SMALL ISLAND ECONOMIC VULNERABILITY TO NATURAL DISASTERS

By

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To Julio, down by the schoolyard

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LIST OF ABBREVIATIONS

ACS	Association of Caribbean States
CE	Certainty Equivalent
CIAT	International Center for Tropical Agriculture
CARICOM	Caribbean Community
CPACC	Caribbean Planning for Adaptation to Global Climate Change
CRED	Centre for Research on the Epidemiology of Disasters
CRRA	Constant Relative Risk Aversion
ECLAC	United Nations Economic Commission for Latin America and the Caribbean
EM-DAT	Emergency Management Database
GDN	Gender Disaster Network
HURTRACK	NOAA's Historical Hurricane Track Database
IFLS	Rand's Indonesian Family Life Survey
IPCC	Intergovernmental Panel on Climate Change
LS	Ligon and Schechter's (2003) Vulnerability to Poverty Measure
NB	Negative Binomial
NOAA	National Oceanic and Atmospheric Association
Oxfam	Oxford Committee for Famine Relief
SIDS	Small Island Developing State
UNSD	United Nations Division for Sustainable Development
UNCTAD	United Nations Conference on Trade and Development
UNISDR	United Nations International Strategy for Disaster Reduction
UNDP	United Nations Development Programme
US$	United States Dollar

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Natural disasters disrupt livelihoods and economies, eroding decades of economic development gains in a matter of minutes or hours and smiting advances in disaster-hardened technologies. Natural disaster impact is not altogether determined by nature but rather contingent upon the economic conditions of the receiving community. Weather hazards, such as windstorms, matriculate to natural disasters when pre-event economic conditions (for example, poverty) compound the effects of the hazard to exceed a devastation threshold. Thus, while natural hazard exposure may be relatively homogenous over a large tract of land, natural disasters do not affect households uniformly.

In spite of the evidence that developing countries account for 95% of disaster deaths and, as a percentage of gross national product, suffer greater financial losses (World Bank, 2005), disaster and development links are obviated by economic and epidemiological research (Kellenberg and Mobarak, 2007; Anbarci et al., 2006; Kahn, 2005; Sen, 1981). We use natural disaster vulnerability approaches to explore how differential exposure, risk and access to resources render some more likely to suffer natural disaster losses. Our focus is on small island states, since these have

characteristics that make them especially vulnerable to the effects of climate change, sea-level rise, and extreme weather hazards (Intergovernmental Panel on Climate Change (IPCC), 2007).

Natural disasters intensify existing economic and social vulnerabilities, disproportionately impacting marginalized persons, such as the poor, persons on island communities, and females. Households on island nations are struggling to smooth consumption with increased natural disaster risk – this increased risk is straining coping mechanisms, such as savings and assets, with long-term implications for economic development. Aggregated to the country level, we find that natural disaster risk is (i) disproportionately impacting consumption-constrained households, (ii) increases projected poverty rates and (iii) economic development factors such as income, urbanization, and institutional strength determine natural disaster losses at the country-level.

This research offers insight on the relationships between economic development and natural disaster risk by examining linkages in exposure to risk, self-insurance, and levels of wealth. The research objective considers important analytical nuances of disaster impacts currently missing from existing literature. These include the analysis of coping with high natural disaster risk and the heightened vulnerability of small islands.

CHAPTER 1
STRUCTURE OF THE THESIS

The focus of this dissertation is to examine small island vulnerability to natural disaster risk. Specifically, we analyze differentiated impacts of natural disasters on island countries and households coping with long-term increases in natural disaster frequencies. This dissertation is organized as follows.

Chapter 2 presents an overview of natural disaster risk. This chapter is intended to inform the reader of the scientific and economic literature related to weather hazard risk and the broader scope of natural disasters and economic development. Specific emphasis is given to the especially vulnerable sub-populations of females and persons on small island developing states (SIDS).

Chapter 3 reviews relevant microeconomic theories, specifically detailing the vulnerability to poverty measures. We motivate our application of the Ligon and Schechter (LS) poverty measure to analyze natural disaster vulnerability on island nations. Key concepts gleaned from related theories of economic development, risk preference, economic vulnerability and welfare are offered.

Chapter 4 adapts the aforementioned theoretical concepts to the context of household vulnerability to poverty on island nations. We empirically analyze the welfare impacts of aggregate, frequent natural disasters on a vector of idiosyncratic risk factors. A sample of Indonesian households over 10 years is used to obtain estimates of individual household vulnerability to poverty and an aggregate measure of Indonesia's likelihood of future poverty. These estimates are used to identify correlates of lower future poverty rates, assessing long-term welfare impacts of coping with natural disaster risk in addition to other forms of aggregate and idiosyncratic risk.

Chapter 5 applies an existing macroeconomic natural disaster risk model to explore determinants of vulnerability to natural disaster risk. As disaster data is scarce, especially within small developing and formerly colonized islands, our examination of differences in disaster losses across thirteen especially vulnerable nations offer important policy applications. Natural disaster risk on small island developing nations is increasing with urbanization and income. Coping with this risk suggests stronger institutions and disaster-hardened infrastructure investments. To analyze the cyclical nature of natural disaster vulnerability, we use long panel data (18-years) towards a better understanding of natural disaster vulnerability causality.

As Chapter 4 presented evidence of household vulnerability to natural disasters and Chapter 5 presented substantiation of macroeconomic impacts of natural disaster risk, Chapter 6 presents policy applications and conclusions gleaned from Chapters 4 and 5, concluding the dissertation.

CHAPTER 2
OVERVIEW OF NATURAL DISASTER RISK

This chapter presents an overview of the economic impact of natural disasters. The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (2007) concluded climate change is now a certainty and that it has begun to affect the frequency, intensity and length of many weather hazards[1]. Natural disasters result from a weather hazard exceeding a recipient community's ability to cope with the hazardous event, a phenomenon of the entwined human-natural environment.

The transformation of a weather hazard into a natural disaster is a human process, evidenced by the even distribution of weather hazards compared to the uneven distribution of natural disaster losses. Exposure to risk is a salient dimension of economic development. As poor persons (or countries) are least protected from risk the potential for loss is elevated: poverty may cause exposure to risk (Smith et al., 2006; Kellenberg and Mobarak, 2008). Whereas high human development countries are exposed to 15% of the extreme weather hazards, these countries account for less than 2% of resulting deaths; low human development countries are exposed to 11% extreme weather events yet result in a majority (53%) of the deaths (United Nations Development Programme (UNDP), 2004). Conversely, the causal direction may reverse such that risk exposure may cause or exacerbate poverty (Carter et al., 2007; Hoddinott, 2006).

This chapter is divided into two sections. First, the global context of natural disaster risk is presented through a brief history. Towards a deeper understanding of

[1] A weather hazard is a "potentially damaging physical event, phenomenon, or human activity that may cause the loss of life or injury, property damage, social and economic disruption or environmental degradation" (United Nations Development Programme (UNDP), 2004).

the relationship between economic development and natural disaster risk, we motivate our study of the especially vulnerable subpopulations of small island nations. In the second section, we review literature guiding our conceptual analysis through exploring relationships between economic development and natural disaster risk.

Overview of the Evolution of Natural Disaster Risk and its Relevance

Disaster events, such as the 2011 earthquake, tsunami and nuclear disasters in Japan and the 2010 earthquakes in Haiti challenge the research community to better understand how human behaviors impact disaster vulnerability on urbanized island nations. “Disaster risk continues to grow as rapid urbanization increases as a result of the drive for economic growth and social improvement” (United Nations Development Programme (UNDP), 2002). Recent experiences indicate extreme weather hazards deliver the strongest physical impacts to coastal urbanized communities, yet increased economic impacts of these weather hazards may be attributable to changes due to urbanization not the hazards. Urbanization agglomerates human and financial resources densely, increasing resources at risk to a natural disaster. Population density is increasingly skewed along the world’s coast: by 2020, 75% of the world’s population will live within 60 km to the coast (United Nations Education, Science and Culture (UNESCO), 2008).

Globally, natural disaster events and losses are escalating (see Figure 2-1 and 2-2). Today, 70% of annual disasters are climate-related whereas two decades ago 50% were climate-related (United Nations, 2009). Since 1970, natural disasters have affected more than 5 billion persons globally with over 1 trillion US$ in financial losses (Emergency Management Database (EM-DAT), 2010).

The human-built environment (for example, the pattern of human settlements) and economic conditions (for example, quality of infrastructure) of an economy foreshadow natural disaster vulnerability (Linrooth-Bayer and Amendola, 2000; Cutter, 2001; Lucas, 2001; UNDP, 2004; Bradshaw, 2004; Kahn, 2005; Neumayer and Plumper, 2007; Strömberg, 2007; Vigdor, 2008). In 1755, a catastrophic earthquake hit the city of Lisbon, Portugal and resulted in the death of over 20% of the population. Prior to the natural disaster, Lisbon was the 4th largest city in Europe. Secondary hazards from the earthquake included fires and floods. A year after the disaster, Rousseau poignantly attributed much of the calamities from the earthquake to human actions: "while the earthquake was an act of nature, previous acts of men, like housing construction and urban residence pattern, set the stage for the high death toll" (as cited in Strömberg, 2007). Within a year, Lisbon learned from the event by rebuilding more earthquake-resilient infrastructure and stymied subsequent impacts of the disaster, such as famine or epidemics. Coping with (recovering from) natural disasters over time hinges on economic characteristics, such as wealth levels and institutional strength, and rebuilding stronger before another event strikes.

Presently, communities are strained in coping with repeated disaster events. For example, Haiti suffered two major earthquakes in 2010 with a secondary epidemic of cholera emerging from post-disaster conditions (attributed to the water provisions in international aid camps). Importantly, these earthquakes did not strike Haiti in a favorable time: the country was still suffering from a string of four hurricane disasters in 2008 which resulted in a secondary flooding disaster and tertiary food crisis. At the time of the 2010 earthquakes, Haiti was very vulnerable to natural disaster shocks due to

their depressed economic characteristics (for example, low per-capita income levels and weak governance) and decimated coping mechanisms which had not recovered (for example, there was still a food shortage attributed to crop losses from the 2008 hurricanes and floods).

Presently, economic globalization distributes natural disaster risk not just to the recipient community but across trade partners and economic markets. Consider the case of Japan, a very globally integrated member of the world economy. Their 2011 disasters impacted most deeply their own macroeconomic markets, yet ripple effects spread to other countries and linked markets. Natural disaster risk manifests locally and globally. Climate change science predicts – with near certainty – increased climate variability (IPCC, 2007). This increased climate variability alters natural disaster risk, through increased weather hazards (for example, increases in the number of hurricane or seismic events) and through increases in societal vulnerabilities from stresses on resource availability and markets (for example, a tourist-dependent economy or an export-based tropical-agriculture economy).

Vulnerability to Natural Disaster Risk

A commonality among the natural disaster literature findings is that countries, regions, economic sectors, and social strata differ in their degree of vulnerability to natural disaster risk (Noy, 2009; Carter et al., 2007; Hoddinott, 2006; Barrett and Carter, 2004; Bradshaw, 2004; Chou et al., 2004; Dercon, 2004; Sen, 1981), a result of the uneven distribution of risk and resources. Numerous researchers have noted the importance of economic development in reducing disaster vulnerability (Sen, 1981; Albala-Bertrand, 1993; Gallup, et al. 1999, Horwich, 2000; Kahn, 2005; Anbarci, et al., 2005; Kellenberg and Mobarak, 2008; Toya and Skidmore, 2007; Strömberg, 2007; and

Vigdor, 2008). A branch of vulnerability analysis considers the relative impacts of disasters to specific sub-populations asserting the deterministic role of the economic conditions prior to a weather hazard in shaping disaster impact. Existing empirical analyses examine the relative vulnerability of various strata, such as females (Neumayer and Plümper, 2007; Bradshaw, 2004; Deare, 2004), the poor (Kellenberg and Mobarak, 2008; Carter et al., 2007) and small island developing states (Noy, 2009; United Nations Division of Sustainable Development, 2009; IPCC, 2007; Brugiglio, 2006; UNDP, 2002).

Small island developing states. Regional (Brugiglio et al., 2006) and global (Noy, 2009) disaster vulnerability studies revealed the higher structural[2] vulnerability of small island developing states (SIDS). Characterized by their economic size (for example, limited natural resource endowments, high import content, small domestic market and dependence on trade markets), insularity and remoteness (for example, high per-unit transport cost and supply uncertainty), and proneness to weather hazards, SIDS are especially vulnerable to the effects of climate change, sea-level rise, and weather hazards (IPCC, 2007). Population and economic development pressures have increased this risk.

SIDS suffer the greatest magnitude of natural disaster damage, both in terms of financial losses (percentage of gross national product) and human losses (percentage of population affected) (Noy, 2009). Between 1970-1989, small islands represented over half of the countries (13 of 25) with the greatest number of natural disasters (UNCTAD, 1997). SIDS have higher relative exposure to many economic and natural

[2] Structural vulnerability manifests from exposure to natural or external hazards whereas vulnerability in general manifests from economic and environmental factors interacting with hazards (Cutter, 2001).

hazards. The United Nations Division for Sustainable Development (UNSD, 2009) identifies a suite of sustainable development challenges facing SIDS:

- Limited resources
- Remoteness
- Susceptibility to natural disasters
- Vulnerability to external shocks
- Excessive dependence on international trade

Globally, there are 51 SIDS[3] in three main regions: the AIMS (Africa, Indian Ocean, Mediterranean, and South China Sea), the Caribbean, and the Pacific. Within the Caribbean region, there are 23 SIDS. Cuba is the largest SID in the Caribbean, with respect to both size and population. Often described to have undesirable geographic qualities (remoteness, small size, insularity, high frequency of weather hazards), it is important to understand the determinants of natural disaster vulnerability on SIDS towards accomplishing their economic development goals and coping with climate change.

SIDS illustrate the intricate human-environment relationship of vulnerability: the high extent of coastal geography increases event likeliness and small scale, dwindling risk-abatement and consumption smoothing options. Small islands face unique constraints from their remoteness and size, such as limited choices in risk diversion and consumption smoothing mechanisms. Increasing population density and urbanization exacerbate these constrictions.

Natural Disaster Risk and Economic Development

Economic development and natural disaster risk are not independent: often the poorest persons are the worst affected by environmental shocks (Briguglio et al., 2006).

[3] This includes both small island developing states and small island developing territories.

While wealthier nations experience greater absolute financial losses, poorer nations suffer greater relative financial losses (as a percentage of gross national product) and more human losses: nearly 90% of disaster-related deaths and 98% of persons affected by disasters between 1991-2005 occurred in developing nations, with more than 25% of these deaths occurring in the least developed countries (World Bank, 2010b). Disaster damage is not only primary; secondary losses from disaster include decreased human capital, depleted savings, and long-term implications on economic development and growth (Easterly and Kraay, 2000; Rasmussen, 2004; Hoddinott, 2006; Toya and Skidmore, 2007; Carter et al., 2007; Vigdor, 2008).

Kellenberg and Mobarak (2008) explored non-linearities in the relationship between natural disaster risk and economic development by fitting a Kuznets-type[4] shape to a cross-section of 73 countries. They identified economic development "turning points" when the relationship between economic development and vulnerability to disasters reversed from positive (increasing economic development and increasing vulnerability) to negative (increasing economic development and decreasing vulnerability). Their empirical findings suggest micro-level behavioral responses from increasing income (for example, locational choice) lead to this non-linear relationship between economic development and disaster losses. Consistent with Kuznets' theory, the demand for increased risk abatement options has a positive income elasticity of

[4] Kuznet (1955) studied the shape of the relationship between economic development and income inequality, coining the phrase "Kuznet's curve". According to the theory, the initial stages of economic development are met with increasing income inequality until economic development reaches a critical threshold or turning-point whereby income inequality wanes with economic development. The reversal of the relationship between economic development and income inequality results from income equality being a luxury good (demand increases at an increased rate with income): increased economic development increases demand for income equality and economic decision-makers respond to this increase in demand by decreasing inequality.

demand, implying a threshold of income must be a priori attained for increased abatement demand. These results affirm the findings of the trifurcation of post-disaster migration responses discussed above: low-income migrate to risk, middle-income migrate away from risk, and high-income have the luxury of insuring risk. This research sheds light on the relationship between risk and economic development. In Chapter 4, we find evidence of coping differences by economic strata: households with self-insurance mechanisms, such as savings and good quality housing, are less vulnerable to consumption shortfalls in the presence of natural disasters.

Quality of Institutions

The United Nations International Strategy for Disaster Reduction (UNISDR, 2009) finds that disaster risk is highly condensed in poorer countries with weaker governance. In tandem, Kahn's (2005) study of 57 nations demonstrated that countries with greater wealth (measured by per-capita GDP) and stronger institutions experience less vulnerability to natural disasters. To illustrate the role of institutional strength on vulnerability to disasters, we may compare cyclone-ravaged communities; tropical cyclone Andrew struck south Florida in 1992 and a similar magnitude cyclone struck Bangladesh in 1991. In terms of their vulnerability,[5] Andrew was a stronger storm in magnitude yet less destructive with fewer secondary effects than the weaker storm in Bangladesh, consistent with Kahn's conclusions on institutional quality's deterministic role in natural disaster vulnerability. The SIDS of the Caribbean suffer negative implications of their petite economic scale: the inability to reach economies of scale in infrastructure investments increases their probability of suffering natural disaster losses.

[5] Hurricane Andrew killed 23 people; the typhoon in Bangladesh killed over 100,000 and displaced millions of people as a result of the secondary event of flooding.

Albala-Bertrand (1993) demonstrated that countries most impacted by a disaster have weaker economies and Kahn (2005) found that countries with less democracy suffer from more natural disasters. Anbarci et al. (2005) estimated a panel of countries with earthquake disaster experience to estimate the role of the political economy on natural disaster losses (deaths). They examine economic development dynamics through explanatory variables of income-based and land-based Gini-coefficients[6]. The lack of significance of the Ginis was attributed to lacking an empirical link between (income or land) equality and earthquake preparedness. Tol and Leek (1999), Horwich (2000) and Kellenberg and Mobarak (2008) offered evidence that lower wealth levels increase disaster vulnerability.

Poverty and Risk-Prone Areas

Economic development pressures are forcing increasing numbers of households to locate in relatively riskier areas: flood plains, on earthquake faults, or below sea level; unsafe dwellings exacerbate this risk. "The vulnerability of those living in risk-prone areas is perhaps the single most important cause of disaster causalities and damage" (Annan, 1999).

Economic theory has documented this phenomenon using the hedonic framework in earthquake zones (Brookshire et al., 1985) and hurricane-prone areas (Smith et al., 2006, Hallstrom and Smith, 2003). Brookshire et al. (1985) find evidence that California housing prices reflect risk and Smith et al. (2006) reveal the economic coping capacity of households through household locational response post-disaster: low-income

[6] The gini-coefficient demonstrates resource distribution, varying between 0 for complete equality (all members of the community have the same amount of a resource) and 1 for complete inequality (one member of the community has all of the resource while other members have none).

households responded ex-post by migrating to risk (areas that experienced heavy damage and thus have lower rents), middle-income households respond by migrating away from risk and upper-income households remain, attributed to their ability to afford insurance. If a (unintended) consequence of natural disasters is high-risk areas resettled by relatively poorer persons with less access to insurance mechanisms, risk in these areas will escalate.

Urbanization. Urbanization is impacting vulnerability to natural disasters. Over 50% of global populations reside in urban areas and is increasing with time[7]: 2.9 billion persons (48%) lived in urban areas in 2001 and estimates project 4.9 billion persons (60%) will live in urban areas by 2030 (United Nations Habitat, 2008). New urbanites demand housing, infrastructure, and services such as sanitation. Urbanization increases both population densities and economic activities, which in turn pressure coastal ecosystems and increase vulnerability to weather hazards. Rapid urbanization cannibalizes post-disaster smoothing options, such as own-food production and water sanitation. The mutually dependent relationship between the poor and their environment is obvious within the rural context: livelihood depends upon public good provision from natural resources (for example, forests offer food and kindling resources, rivers offer fish and irrigation resources) yet obtuse within the urban context. Urban poor lack access to public good resources both in the natural and human-planned environment, the former of which has been a priori expended by the process of urbanization.

To exemplify the relationship between natural disaster risk and the urbanized environment, consider the case of two coastal communities experiencing a tropical

[7] Most global population growth between 2001 and 2030 will be in urban areas with rural areas having nearly static population levels (UN-Habitat, 2008).

cyclone. In the first community, urbanization has not transpired and coastal ecosystems are in tact, with the benefit of absorbing the cyclone's storm surge. In the second community, rapid urbanization has happened and ecosystems have been replaced by residential housing - the missing coastal ecosystem allows the storm surge to come on shore, causing flooding. Urbanization increased exposure to risk (more people were exposed to the hazard) and cannibalized hazard-absorbing public goods. In this second scenario, urbanization increased aggregate risk. On the other hand, ex-post coping mechanisms, such as increasing labor supply or accessing credit, hinge on market access and depth (Carter et al., 2007; Barrett and Carter, 2004). These conditions are often more favorable in urban areas. We find evidence of the impact of urbanization on natural disaster risk on island nations in Indonesia and the SIDS of the Caribbean. In both environments, the high coastal geographic extent and limited smoothing opportunities increase natural disaster risk in urban areas.

Coping with Natural Disaster Risk

Livelihoods are at a variety of risks from exogenous forces such as health risks (accidents, illnesses, death), price risks (food costs, input/output production costs, policy changes), and disasters (wars, epidemics, droughts). While a breadth of literature exists regarding risk and household behavior (Carter et al., 2007; Dercon et al., 2005; Fafchamps, 2003; Ligon and Schechter, 2003), a dearth subsists considering household behavior towards coping over the long-term with persistent natural disasters, especially within a development context. It is generally accepted that ex-ante risk management is cost effective (Sawada and Shimizutami, 2007). However, the rare and unpredictable nature of natural disasters limits this form of risk management. Similarly, many, ex-post strategies that have been shown to reduce consumption fluctuations (Alderman and

Paxson, 1992), yet hinge on a priori savings or market access, such as access to credit or transfers (Sawada and Shimizutami, 2007; Stromberg, 2007; Carter et al., 2005) often incomplete or missing in developing countries.

Many economic studies analyze behavioral responses demonstrating risk coping. Alderman (1998) and Gertler and Gruber (2002) present evidence that disaster persistence makes coping more difficult using data from Pakistan and Indonesia, respectively. Smith and McCarty (2007) analyzed hurricane evacuation behavior. The found housing quality had the greatest impact on evacuation behavior while numerous other demographic characteristics were significant, such as hurricane experience, income and hurricane risk (severity and location of the storm) during the 2004 hurricane season.

Sawada and Shimizutani (2007) empirically analyzed household behavior responses to the 1995 Great Hanshin Awaji (Kobe) earthquake, rejecting the full consumption insurance hypothesis (suggesting insurance mechanisms were ineffective means of coping). They find self-insurance and credit mechanisms effective against negative income shocks, yet contrary results for transfers (higher income households receive transfers, attributed to self-interested exchanges). They offer empirical evidence of a hierarchy of risk-coping mechanisms, with self-insurance first-best and find self-insurance to be a substitute for credit and transfers. Self-insurance was used as a risk-coping mechanism when households suffered minor asset damages, whereas credit was used when the households suffered major asset damages.

Carter et al. (2007) and Hoddinott (2006) develop asset-based approaches to analyzing coping with natural disasters. Carter et al. (2007) examine two disaster-

ravaged communities for evidence of natural disasters acting as poverty traps in Honduras (Hurricane Mitch) and Ethiopia (three-year drought). They find that in both settings, natural disasters act as a poverty trap and have longer implications for poorer households as compared to their wealthier peers. Hoddinott (2006) examined the case of Zimbabwean farmers, finding different reactions to disaster shocks based on their ex-ante poverty status. While farmers a priori above the poverty line cope through consumption smoothing (for example, sell assets), farmers below the poverty line pre-event asset smooth (for example, decrease consumption). The latter bears a heavy human capital cost, affirming Carter et al.'s finding that natural disasters act as poverty traps. Supporting this, Van den Berg and Burger (2008) identified the main response (21%) of Nicaraguan households to Hurricane Mitch was (dramatically) reducing consumption (asset-smoothing), not dissavings or borrowing (consumption-smoothing): credit market access impacted the effectiveness of self-insurance mechanisms.

Coping with natural disasters either through reducing assets (consumption-smoothing) or reducing consumption (asset-smoothing) has long-term poverty implications. Consumption-smoothing may deplete productive household portfolios[8], stymieing future income streams or serving as a poverty trap (Carter et al., 2007) and asset-smoothing may deplete human capital[9] permanently decreasing future capacities (Hoddinott, 2006). Coping with natural disaster risk through consumption-smoothing is more favorable with respect to long-term welfare: households and macroeconomies

[8] Examples may include selling livestock during poor market conditions or with future production implications (ie, not having a cow to provide future milk or an ox to provide future tilling services) or dissavings.

[9] Examples may be impacts of childhood malnutrition on mental and physical development and lower school attendance rates on skill development.

able to smooth their consumption in the presence of natural disaster shocks demonstrate the ability to self-insure their disaster losses. This is especially important to households without access to formal insurance mechanisms, such as wind insurance, and to households without access to formal markets (for example, credit). As macreconomies continue to experience greater frequencies of natural disaster and hazard shocks, self-insurance will become increasingly important as formal insurance markets will deteriorate (as there are fewer "good" states of the world and the "bad" states of the world continue to increase in cost). Consumption-smoothing over time in the presence of repeated, natural disaster events reflects households updating their expectations regarding the increasing risk from natural disasters.

Concluding Remarks

Urbanization and settlement patterns are altering natural disaster risk and repeated disaster events are straining local and macroeconomic coping mechanisms. This is especially pervasive on lower-income island communities who face higher relative natural disaster risk and lower relative resource levels. Economic development factors, such as institutional strength and resource levels, play an important role in shaping the distribution of natural disaster risk.

It is internationally acknowledged that natural disaster loss reduction must be systematically integrated into policies for sustainable development and poverty reduction (UNISDR, 2005). Economic development and disaster management research is experiencing a shift from examining poverty through a static (consumption) lens towards understanding disaster losses as a function of economic development, integrating poverty reduction programs with natural disaster and environmental

management, especially in urban areas[10]. This research contributes to the understanding of how natural disaster risk impacts poverty. Appealing to the poverty-vulnerability relationship described as different sides of the same coin, long panel data permits us to investigate not only these relationships but enhances understanding of the causal directionality of these relationships.

[10] For example, the Bangladesh Urban Disaster Mitigation Project aims to improve the capacity and risk management in urban areas.

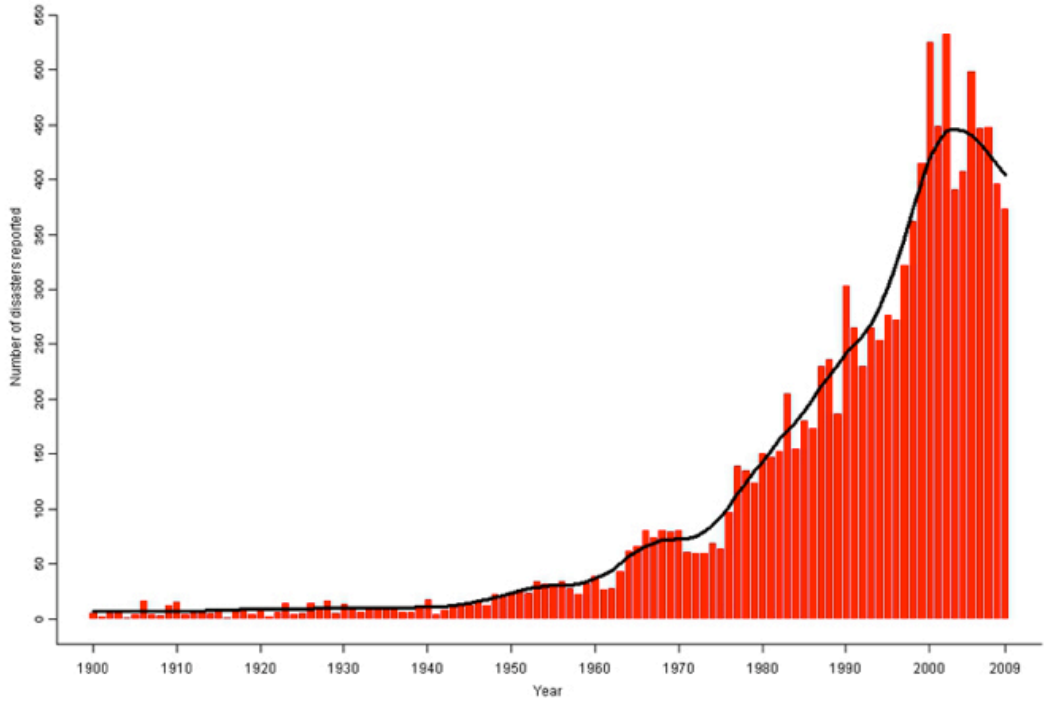

Figure 2-1. Number of annual natural disasters reported (source: EM-DAT)

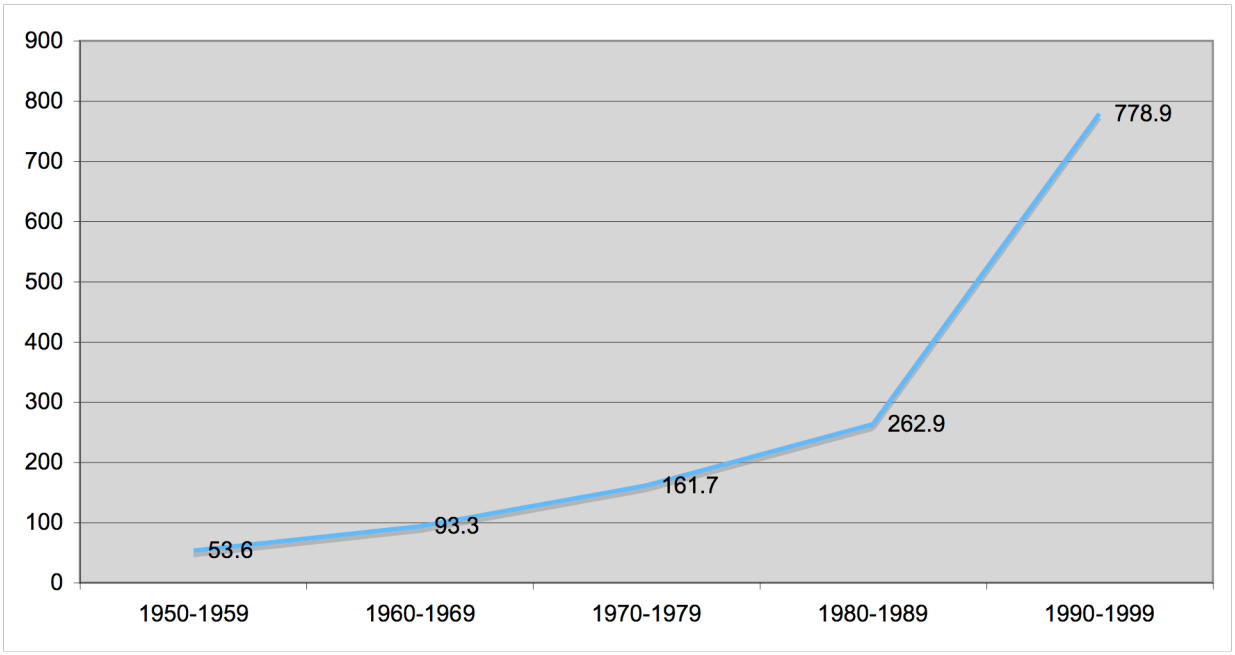

Figure 2-2. Global financial losses (in billions of US$, adjusted for inflation) from natural disasters

CHAPTER 3
VULNERABILITY TO NATURAL DISASTER RISK

Vulnerability studies analyze risk. Some measures of vulnerability encapsulate welfare consequences of risk, usually focusing on households or individuals with low resource endowments. Poverty impacts the probability of suffering from a weather hazard - poverty may dictate that individuals locate in riskier areas, increasing their probability of loss from weather hazards. For example, an urban poor person may live in a tin shanty house more susceptible to cyclone winds compared to their wealthier neighbor living in a concrete house: even though they both face the same risk from the weather hazard, their vulnerability, or likelihood of suffering a loss, differs. Yet, many measures and estimators present in the vulnerability to poverty literature omit welfare consequences of risk (for example, the headcount poverty measure).

This chapter presents an overview of the dominant microeconomic approaches to measuring vulnerability to poverty. As some of these approaches are based on the theory of maximizing expected utility and risk preferences, Appendix A details this theory. The vulnerability as expected utility measure estimated in Chapter 4 demonstrates the self-insurance property of redistributing resources from a favorable to an unfavorable state of the world; we detail the theory of self-insurance in the second section. We close the chapter by motivating our application of a vulnerability to poverty measure to understand welfare consequences of natural disaster risk on especially vulnerable sub-populations. As most vulnerability to poverty studies either analyze poverty in general or a specific natural disaster shock (for example, the Kobe earthquake or Hurricane Mitch), our long-term analysis of how households are coping with repeated disaster shocks contributes importantly to the vulnerability literature.

Measuring Vulnerability

Poverty measures have been used throughout the economics literature as a welfare gauge of the less endowed (Ligon and Schechter, 2003; Foster et al., 1984). The concepts of vulnerability and poverty are closely, though not directly, linked. Vulnerability analyses are forward-looking (ex-ante) predictions of differentiated impacts on various economic (or social) strata whereas poverty status is observed consumption or income level. Chaudhuri et al. (2002) note "poverty and vulnerability (to poverty) are two sides of the same coin." Vulnerability (to poverty) is the ex-ante probability of a household being in poverty in the future whereas current poverty is an ex-post realization of this state.

Future poverty rates depend on the types of risks or shocks that households are exposed to. Aggregate shocks, such as natural disasters, impact poverty rates and cannot be as risk-pooled as idiosyncratic shocks[11], and impact future poverty rates (Carter et al, 2007; Hoddinott, 2006). In order to better understand aggregate risk contributions to future poverty rates, it is important to understand the mechanisms that households use to cope with risk.

Three classes of vulnerability to poverty measures (each with differing estimators) have emerged within microeconomics generally conceived as i) vulnerability as uninsured exposure, ii) vulnerability as expected poverty and iii) vulnerability as expected utility. To motivate our selection of a vulnerability measure to analyze impacts of natural disaster risk, we detail each of the three measures and discuss their appropriateness and limitations.

[11] Idiosyncratic shocks can be insured at the village level, though not fully (Townsend, 1995; Udry, 1990).

Vulnerability as Uninsured Exposure

The vulnerability as uninsured exposure measures household responses to observable shocks, such as natural disasters (Glewwe and Hall, 1998) or unemployment, ex-post. The notable difference in using this approach, compared to the latter two presented, is that it does not call for the construction of an aggregate measure of vulnerability. This approach rather analyzes household level data under the premise that if household consumption, c^i, and a shock (or set of shocks) covary, it may be inferred that these households lack the resources (or acces to resources) to smooth consumption against these shocks.

Household consumption responses to aggregate risk. Glewwe and Hall (1998) use panel data from Peru to examine household consumption responses to a three-year drought. Their measure of vulnerability as exposure to this aggregate risk identifies the change in household consumption associated with aggregate shocks through the β_t parameter:

$$E(c_t^i \,|\, \bar{x}, x^i) = \alpha^i + \eta_t + x^i \beta_t \qquad (3\text{-}1)$$

For each household *i*, after controlling for the level of aggregate variation in mean consumption ($\bar{x}$) and household effects (x^i), their expected consumption over time is equal to the variation in their consumption stream from periods 1 through t. Household *i*'s expected consumption over time, given the level of individual (x^i) and aggregate ($\bar{x}$) characteristics, is modeled as a function of individual, time-invariant household fixed effects (α^i), time-varying household-invariant effects (η_t) and characteristics of the individual household *i* (x^i). Interestingly, they focus on household responses to aggregate shocks identified through the β_t parameter in contrast with Amin et al. (1999)

who estimate a household specific vulnerability parameter, β^i. After estimating expected utility of consumption in (3-1), Glewwe and Hall use the predicted changes in expected consumption ($U^i(c) = \log(c)$) over time as their measure of vulnerability:

$$U^i(c^i_{t+1}) - U^i(c^i_t) \tag{3-2}$$

This measure captures the changes in utility (welfare) following a macroeconomic shock, such as a natural disaster. If a household's utility fell by less than the population-average, that household is regarded as less vulnerable compared to a household who suffered a greater than population-average decrease in utility.

Household consumption responses to individual risk. Amin et al. (1999) follow Glewwe and Hall's conceptualization of vulnerability as exposure by examining household responses to idiosyncratic shocks (for example, disruption in household income from unemployment). In their model,

$$E(c_t \mid \bar{x}, x^i) = \alpha^i + \eta_t + x^i_t \beta^i \tag{3-3}$$

expected consumption after controlling for aggregate variation in mean consumption ($\bar{x}$) and household effects (x^i) is the same as (3-1). On the right hand side, x^i_t is household *i*'s income over time and β^i is the amount of welfare reduction associated with increased risk from consumption co-varying with income over time, what they refer to as household *i*'s vulnerability to idiosyncratic risk. There are two main drawbacks of this measure. First, it does not capture aggregate risk. Second, given two households with equivalent average consumption, it regards a household as more vulnerable to individual shocks if their household's income is more time-variant. To illustrate, consider two households, HH^1 and HH^2, with identical average household income:

$\frac{1}{T}\sum_{t=1}^{T} x_t^1 = \frac{1}{T}\sum_{t=1}^{T} x_t^2$. The household with more variable income over time will be regarded as more vulnerable compared to the household with the same level but less variable income.

Household responses to individual and community risk. Dercon and Krishnan (2000) extended these two measures to develop a measure incorporating both idiosyncratic and aggregate (village) level risk. Compared to most other models using expected consumption, they model actual consumption over the short-run to specifically explore short-run dynamics of poverty (for example, seasonal poverty compared to year-to-year poverty) as they hypothesize household vulnerability is underestimated by other poverty measures which do not account for seasonal incentives (for example, labor demand or prices).

$$c_t^i = \alpha^i + \gamma R_t^i + \beta x_t^i + e_t^i \qquad (3\text{-}4)$$

Because this is an ex-post (backward looking) measure, they use actual consumption, rather than expected. Their measure of vulnerability (3-4) measures household *i*'s actual consumption over the time horizon 1 through t, c_t^i, as a function of time-invariant household fixed effects, α^i, a vector of observed household shocks, R_t^i which vary over time (for example, unemployment or illness), the aggregate, time-varying variables (for example, prices), x_t^i, and an error term, e_t^i. The β parameter measures the household's exposure to aggregate shocks and the γ parameter measures household *i*'s vulnerability to the observed idiosyncratic shocks. Both of the vulnerability parameters are intended to capture the decrease in welfare (consumption) from the additional risk faced by a

household if its consumption co-varies with the aggregate shock or the characteristics of the household.

Vulnerability as Expected Poverty

The class of Foster-Greer-Thorbecke (1984) decomposable poverty measures assume that for a non-negative living standard, y, (for example, income or consumption) and a threshold amount of this living standard, z, y is distributed with density f(y) over the interval 0 to z, defining a poverty measure P as:

$$P = \int_0^z \left(\frac{z-y}{z} \right)^{\alpha} f(y)dy \qquad (3\text{-}5)$$

$$\alpha \geq 0$$

with z equal to a standard of living indicator, usually the poverty line set by the researcher's discretion (say 2 US$ per day), y is the household's level of wealth (perhaps measured in food consumption or income), and α is the sensitivity parameter also set by the discretion of the researcher, set to 0, 1, or 2. The interpretation of taking the expectation over the interval of 0 to z is we are interested in the area under the function: the proportion of the population who fall below the poverty line.

As α increases, P becomes increasingly sensitive to the standard of living indicator of the poorest households: higher values of α weight more heavily to individuals whose standard of living is farther from the threshold line z. Commonly, α=0 is referred to as the headcount measure and summing the P measure yields the total number of persons in a population who live below the standard of living. The implication of setting α=0 is that the function collapses to just a binary indicator as to whether the household is in poverty (=1) or not (=0). α=1 is the poverty gap measure and α=2 is the poverty gap squared measure. The latter two α specifications gives more weight to households

(individuals) further from the standard of living line compared to those below, but near, the line. The interpretation of setting α=1 or 2 and the sum of the measure yields the minimum cost of eliminating poverty, given the assumption of transfers being perfectly targeted. In all three α specifications, higher P-statistics aggregated over the population indicate greater poverty in the economy.

The cohort of measures describing vulnerability as expected poverty adjusts the P_α measure for a non-deterministic setting, implying households (individuals) can move in and out of poverty. Defining P_α^i as the poverty of household i:

$$P_\alpha^i = \frac{\max\{z - c^i, 0\}}{z^\alpha} \tag{3-6}$$

z is set to a poverty threshold level of consumption, c^i is the consumption of household i and α is set to the researcher's parameter of choice (for example, α=0 headcount measure).For any set of I households, poverty of the set is given by $\sum_{i \in I} P_\alpha^i$. The max operator establishes that the household is either in not in poverty or is in poverty by the amount of distance between z and c^i.

Expected headcount measure of expected poverty. Pritchett et al. (2000) and Chaudhuri (2001) estimate vulnerability as the expected headcount of poverty, with α set equal to 0 in P_α. They demonstrate that the expected headcount of poverty varies with household resource levels (wealth), aggregate risk and idiosyncratic risk. The drawback of this measure is that it labels households insuring against shocks (through certainty equivalence, as described previously) as more vulnerable than households not insuring against shocks when the shock is characterized as a low-probability (rare),

high-loss event. Pritchett et al. include uncertainty about the future as risk in their model, with the degree of vulnerability increasing with the time horizon. Risk of poverty is modeled as one minus the probability of no episodes of poverty, yet still structurally disregard the depth of expected poverty. By summing this individual vulnerability measure over N households, the headcount measure is obtained.

Expected poverty gap measure of expected poverty. The expected poverty gap measures of expected poverty include both the expected poverty gap (α=1) and expected poverty gap squared (α=2). We do not detail the first measure as it has not been applied to this type of analysis. Interpretively the poverty gap measures depend on the distance of the poor below the poverty line (z) and the number of poor, not only the latter as in the headcount measure. Ravellion (1998) applied the theory of expected poverty gap squared as a vulnerability measure. Since estimator does not capture the welfare consequence of risk but rather relies on time-varying consumption to estimate dynamics in poverty, we do not consider it appropriate to measure welfare impacts of natural disaster risk.

The set of these measures have additional limitations limiting their applicability in our study. Prohibitively, P_α implicitly characterizes the nature of risk preferences as absolute risk aversion, in stark contrast to existing research on poor household risk preference as displaying constant relative risk aversion (CRRA). For a review of poor household risk preference, see Cardenas and Carpenter (2010) or Resenzweig and Binswanger (1993).

Vulnerability as Expected Utility

Ligon and Schechter (2003) and Calvo and Dercon (2003) use the theory of expected utility as the basis for their vulnerability measures. In both, wealth and various sources of risk are disaggregated and use the von Neumann-Morgenstern utility functions. The strength of these measures rest in the von Neumann-Morgenstern functions reflecting risk preferences (for more information on risk preferences, see Appendix B). The relative risk aversion family of functions has been deemed suitable to evaluate numerous microeconomic applications, including vulnerability. This family of utility functions is specified as:

$$U(c) = \frac{(c)^{1-\gamma}}{1-\gamma} \qquad \text{(3-7)}$$
$$\textit{subject to}: \gamma \geq 0$$

U(c) is the utility gleaned from consumption, c is the amount of consumption (for example, daily food consumption in US$), z is a threshold amount of consumption (for example, daily food consumption allowance of 2 US$) and γ is a curvature parameter. In comparison to the P_α family, which considers z as the lower bound of consumption for only wealthy households (by construction, a household is in poverty if their consumption is below z, acknowledging z is not a lower bound for poorer households), the relative risk aversion utility functions interpret z as a lower-bound parameter for all households and allows for different values of the risk-sensitivity (curvature of the utility function) parameter γ. This second advantage is especially salient as welfare costs of risk decrease as the curvature parameter decreases; the P_α measures will have welfare costs of risk increase as the curvature parameter decreases. Related to the case of

increased natural disaster risk, this utility function reflects increasing risk sensitivity in the presence of increased risk (in accordance with risk vulnerability, Pratt and Zeckhouser (1987) demonstrate that increasing mean zero risk increases risk aversion) to capture increasing sensitivity to natural disaster risk. Within the relative risk averse utility functions, the specification of CRRA is most commonly used in analyzing how poor households cope with risk, with experimental evidence supporting this choice (Cardenas and Carpenter, 2010; Ligon, 2007; Ligon and Schechter, 2003). This is attributable to how the function summarizes attitudes towards risk through the curvature parameter[12].

The researcher selects the level of z within the context of the analysis; often z is set to the poverty line (for example, the poverty line of 2 US$ per day). However, if the context of the analysis is seeking information relative within the population, z may be defined relative to the population rather than set at a specific level (for example, z may be the estimated population-average daily consumption which for one population may be 2 US$ per day but for another population, this average may be 7 US$ per day). Setting z as the normalized population-average level of consumption allows for more within-population relative inference: households with certain characteristics will be identified as more vulnerable than households without these characteristics within the sampled environment.

[12] The CRRA assigns a constant ratio by which households (individuals) give higher weights to negative (downside) risks than to positive (upside) risks. The fact that the function explicitly reflects the preference for a stable (smooth) rate of consumption relative to higher future consumption over time reflects the context of our analysis: households prefer smooth consumption in the presence of natural disaster risk. There are important properties to note in the CRRA utility function. First, as $\gamma \rightarrow 1$, the utility function converges to ln(c)[12]. Second, the kurtosis of the function (U"'(c)>0) implies a positive incentive for precautionary savings. As we are interested in how households use savings to smooth consumption, we select this utility function. Finally, as γ increases, the utility function becomes increasingly sensitive to risk and equality.

Defining the vulnerability of household i as:

$$V^i = U^i(\bar{c}) - EU^i(c_t^i) \tag{3-8}$$

$\bar{c}$ is normalized average consumption for the entire population, and $EU^i(c_t^i)$ is household *i*'s expected utility from their stream of consumption over time. The vulnerability of the entire population is the summation of V^i across all households. Implicit in this model is that if all households consume $\bar{c}$ with certainty, there is no vulnerability. Substituting (3-1) in (3-8) and writing this measure in a discrete probability space helps us explain its meaning:

$$V^i = \left[\frac{(\bar{c})^{1-\gamma}}{1-\gamma}\right] - \left[\left(\frac{(c_1)^{1-\gamma}}{1-\gamma}\right)(p1) + \left(\frac{(c_2)^{1-\gamma}}{1-\gamma}\right)(p2) + \ldots + \left(\frac{(c_t)^{1-\gamma}}{1-\gamma}\right)(pt)\right] \tag{3-9}$$

The expected utility of consumption represented by the second bracketed term includes household *i*'s stream of consumption over time (weighted by time period as p1,…,pt and modified by the risk aversion parameter). Weighting all periods equally, the value of the second term, $EU^i(c_t^i)$ captures the household's ability to smooth their stream of consumption over time by penalizing fluctuations in the stream of consumption through the parameter γ.

To account for differences between poverty and risk, Ligon and Schechter decompose their measure into distinct components:

$$V^i = \underbrace{[U^i(\bar{c}) - U^i(Ec_t^i)]}_{\text{"Poverty"}} + \underbrace{[U^i(Ec_t^i) - EU^i(c_t^i)]}_{\text{"Risk"}} \tag{3-10}$$

The first term is the difference between the function evaluated at the utility from being at the (population-relative) poverty line ($U^i(\bar{c}) = \left[\frac{(\bar{c})^{1-\gamma}}{1-\gamma}\right]$) and household *i*'s utility from their average consumption ($U^i(Ec_t^i) = \left[\frac{(\bar{\bar{c}})^{1-\gamma}}{1-\gamma}\right]$ with $\bar{\bar{c}}$ defined as household *i*'s average consumption over time). The second term, $[U^i(Ec_t^i) - EU^i(c_t^i)]$, represents risk and is consistent with other ordinal measures of risk: it is the difference between household *i*'s utility from their average consumption ($U^i(Ec_t^i)$) and household *i*'s expected utility from their stream of utilities over time: $\left[\left(\frac{(c_1)^{1-\gamma}}{1-\gamma}\right)(p1) + \left(\frac{(c_2)^{1-\gamma}}{1-\gamma}\right)(p2) + \ldots + \left(\frac{(c_t)^{1-\gamma}}{1-\gamma}\right)(pt)\right]$ with p1,…,pt denoting the weight assigned to each time period. We can denote this as $U^i(Ec_t^i) = U^i(\bar{\bar{c}}^i)$ with $\bar{\bar{c}}^i$ denoting household *i*'s average level of consumption over the time period. Risk is captured through variation in consumption over time. If consumption in each period was equal for a household, $c_1^i = c_2^i = \ldots = c_t^i = \bar{\bar{c}}^i$, there would be no risk.

The risk in this measure can be further decomposed into aggregate and idiosyncratic risk by letting $E(c_t^i \mid \bar{x})$ denote the expected value of consumption conditional on a known vector of aggregate variables, resulting in their final measure of vulnerability:

$$V^i = \underbrace{[U^i(\bar{c}) - U^i(\bar{\bar{c}}^i)]}_{\text{"Poverty"}} + \underbrace{[U^i(\bar{\bar{c}}^i) - EU^i(E(c_t^i \mid \bar{x})]}_{\text{"Aggregate Risk"}} + \underbrace{[EU^i(E(c_t^i \mid \bar{x})) - EU^i(c_t^i)]}_{\text{"Idiosyncratic Risk"}} \qquad (3\text{-}11)$$

The second bracket, $[U^i(\bar{\bar{c}}^i) - EU^i(E(c_t^i \mid \bar{x})]$, is the difference in the utility that household *i* gains from certain consumption ($U^i(\bar{\bar{c}}^i)$, household *i*'s average consumption over time)

and $EU^i(E(c_t^i \mid \bar{x})$, household *i*'s expected utility from their expected future stream of consumption (variation of consumption) given the level of aggregate shock faced by all members of the population:

$\left[\left(\frac{E(c_1 \mid \bar{x})^{1-\gamma}}{1-\gamma}\right)(p1)+\left(\frac{E(c_2 \mid \bar{x})^{1-\gamma}}{1-\gamma}\right)(p2)+\ldots+\left(\frac{E(c_t \mid \bar{x})^{1-\gamma}}{1-\gamma}\right)(pt)\right]$. The third term, idiosyncratic risk, is the difference in utility between $EU^i(E(c_t^i \mid \bar{x})$ and household *i*'s stream of utilities over time weighted by period ($EU^i(c_t^i)$).

Following Ligon and Schechter, Calvo and Dercon (2003) added a "kink" in the utility function to acknowledge that a household with expected consumption at or below the poverty line has some probability of realized (actual) consumption above the poverty line with a min operator:

$$\frac{E[\min\{z, c^i\}^{1-\gamma} - z^{1-\gamma}}{z^{1-\gamma}} \tag{3-12}$$

and define z, c and γ as above. This min operation asserts the magnitude of consumption above the poverty line does not matter; what matters is whether consumption is above the poverty line or not.

As we believe the magnitude does matter (and that households would clearly prefer consumption more above the poverty line than closer to it), we select the Ligon and Schechter vulnerability measure over the Calvo and Dercon's. In a series of Monte Carlo experiments, Ligon and Schechter (2002) test the aforementioned vulnerability measures and find their measure performs best under risk sensitivity and in environments with measurement error. In Chapter 4, we apply the LS measure to such an environment.

Vulnerability and Consumption Smoothing

Risk has important consequences on consumption levels and individuals will try to look for ways to smooth their consumption streams in order to maintain a constant level of well being. Collins (2004) summarizes consumption smoothing activities using Friedman's permanent income hypothesis (PIH). Rational individuals will attempt to smooth consumption if income is disrupted implying that transitory shocks have no effect on consumption, but that permanent shocks do alter consumption. Due to missing or faulty insurance markets, many households suffering a shock cope – smooth consumption – using self-insurance mechanisms (Collins, 2004).

The consensus of existing research on shocks in developing countries is that transitory shocks seldom translate into permanent fluctuations in consumption – that is, households are able to smooth their consumption over time in the presence of transitory shocks. This is because households have developed a variety of coping mechanisms, such as depleting household assets or borrowing (Frankenberg, Smith, and Thomas, 2003), increasing family labor supply (Beegle, Frankenberg, and Thomas 2000), and reducing investments in health and education (Frankenberg, Thomas, and Beegle 1999; Thomas et. al. 2004; Bradshaw, 2004). The smoothness of household consumption has been taken to imply that economic shocks are not costly to household in the long-run (Morduch 1995). Contrarily, Jalan and Ravallion (2001) find the poorest wealth decile to be the least insured, with 40% of an income shock passed to current consumption and Carter et al. (2007) and Hoddinott (2006) developed asset-based approaches to analyze shock coping behavior, finding evidence of bifurcation: shocks act as poverty traps for ex-ante poverty-stricken households but not for households a priori above the poverty line. Households below the poverty line prior to a disaster shock were not able

to smooth consumption as a coping response and resorted to decreasing consumption (asset smoothing rather than consumption smoothing), with heavy human capital costs. Restricted credit market access limited self-insurance mechanisms, such as borrowing, which may have alleviated the consumption shortfalls intertemporally for some households.

Ligon and Schechter (2003) conclude individuals self-insure against poverty through the distribution of their consumption over time in a risky world. That is, individuals will distribute their consumption so as to smooth it intertemporally, using consumption surpluses accumulated in "good" times to smooth consumption shortfalls in "bad" times. Self-insurance (smoothing consumption over time) against poverty (consumption shortfalls) is modeled as a function of consumption expenditures, aggregate risk, idiosyncratic risk, and unexplained risk. As vulnerability is relative, Ligon and Schechter intentionally model the distribution of consumption (rather than only the average of consumption) to evoke comparisons between a certainty equivalent (CE) amount of consumption (the poverty line) and a household's expected consumption. The LS model posits the poverty line[13] as analogous to the choice of a CE such that if an individual had expected consumption greater or equal to the poverty line, they are not (relatively) vulnerable to poverty.

Self-insurance

Insurance redistributes income and consumption from a more endowed state of the world to a less endowed state of the world; within the risk context, insurance redistributes wealth (consumption) from a non-shock (good) state of the world to a

[13] The poverty line is a threshold amount of wealth, income, or consumption below which individuals are considered in poverty and above which they are not.

shock (bad) state of the world. The insurance literature delineates forms of diversifying risk as market insurance, self-insurance (reducing severity of damage), and self-protection (reducing likelihood or probability of damage).

Given two states of the world, one with a shock occurring with probability p and one without a shock event occurring with probability (1-p)[14], the initial level of welfare W_1, welfare will remain at W_1 if no shock occurs yet diminish to W_2 in a shock state of the world. This loss of welfare is equal to the difference between W_1 and W_2. Insurance smoothes welfare over two states of the world through charging an insurance premium (W_p) in exchange for replacing two states of the world (W_1 and W_2) with one state of the world, W where $W_1 < W < W_2$. In a shock state of the world, the consumer will have $W_2 + W_{\text{loss covered by insurance}} - W_p = W$; in a non- shock state of the world, the consumer will have $W_1 - W_p = W$.

Self-insurance redistributes wealth and consumption: as economic agents face a budget constraint, wealth used to for self-insurance has a consumption opportunity cost to other goods and services. As example of self-insurance against flooding shock, W_p would be the amount of wealth required to raise a house above the ground by 100 feet such that the loss incurred to elevate the house is known and it is also known that the severity of further uncertain losses from flooding have diminished (risk decreased). Consistent with the definition of self-insurance, the severity of losses was reduced to W_p.

Risk-averse individuals maximizing expected utility behave in accordance with information and choose to locate in relatively safer areas with a self-insurance premium

[14] There are only two states of the world: p + (1-p) = 1.

for locational safety. Brookshire et al. (1985) demonstrated that households are willing to pay a self-insurance premium to locate in safer residences in post-Alquist-Priolo California[15]. Ehrlich and Becker (1972) found market insurance and self-insurance to be substitutes while market insurance and self-protection were compliments (contingent on the probability of loss).

In a state of certainty (state of no risk), market mechanisms allocate resources efficiently among individuals. In the case of uncertain shock events, the conditions for market efficiency may be violated by the non-rival, non-excludable nature of aggregate safety, resulting in market failure through a non-efficient allocation of resources. Self-insurance may be a very important form of wealth smoothing for countries without market insurance available as it demonstrates the necessary insurance principal of wealth redistribution from more favorable states of the world to less favorable states of the world. Clarke and Wallsten (2003) found that remittances act as self-insurance in their two-year panel study of post-Hurricane Georges Jamaica, though not at a fully insured level[16]; Lewis and Nickerson (1989) find self-insurance expenditures to be excessive in the absence of complete market insurance under limited liability (there is some government public relief); and Ligon and Schechter (2003) develop a self-insurance model against poverty, demonstrating that individuals can self-insure against poverty and that poorer households suffer greater losses from aggregate risk, ceteris paribus.

[15] The Alquist-Priolo Earthquake Fault Zoning Act (1972) provides a mechanism for mitigating seismic hazards by preventing construction of human-occupancies on the surface trace of active faults. The act disseminated public information regarding seismic (earthquake) risk, known as Earthquake Fault Zones.

[16] Remittances self-insure $0.25 of a $1 loss, after controlling for moral hazard and aggregate community damages.

The expected utility framework has been deemed appropriate in measuring behavior towards low-probability, high-loss events such as natural disaster shocks (Brookshire et al, 1985; Ligon and Schechter, 2003; Calvo and Dercon, 2003). Risk-averse households with greater future consumption risks ex-ante have lower levels of expected utility. Risk plays a significant role in vulnerability to poverty and smoothing consumption intertemporally decreases vulnerability to poverty in the LS measure by decreasing consumption risk. Households able to smooth consumption intertemporally are less vulnerable to poverty than other households, ceteris paribus. We employ their measure to analyze how households are coping with long-term increases in disaster frequencies in Chapter 4.

The theoretical and empirical literature reviewed analyzes poverty impacts of shocks, dependent on household characteristics, shock characteristics, and coping strategies accessible to households. Much of this literature is limited by the short time-span of the data or analyzes consumption responses to idiosyncratic, not aggregate, fluctuations (Glewwe and Hall, 1998; Skoufias and Quisimbing, 2004; Townsend 1994; and Udry, 1990). Aggregate shocks, such as natural disasters, cannot be as risk-pooled as idiosyncratic risks can[17], heightening the need to understand aggregate risk contributions to poverty vulnerability. Most vulnerability studies[18] use either cross-section or data from 1-3 years, thus are limited in their understanding of consumption responses to temporal changes in natural disaster risk. Our longitudinal (10- and 18-year) analyses therefore reveal important relationships between economic development

[17] Townsend (1995) admits that aggregate risk cannot be fully pooled at the village level, though it can be pooled much more than idiosyncratic risk. We do not agree with Townsend's (1994) conclusion that aggregate risk can be fully pooled at the village level.

[18] With the exception of Duclos et al. (2010) who estimate their model using a 17-year panel from China.

and natural disaster risk over a longer time horizon. We address the need to understand how resource-constrained households and countries cope with increased natural disaster risk - important to governments and global agencies managing increased weather hazards and populations - by estimating the LS measure for a decadal panel of Indonesian households coping with repetitive, frequent natural disasters in the next chapter and by examining macroeconomic impacts of natural disaster risk in Chapter 5.

CHAPTER 4
VULNERABILITY TO POVERTY AND NATURAL DISASTER RISK

This chapter investigates linkages between vulnerability to poverty and natural disaster risk. At low ex-ante consumption levels, the poor cannot afford unexpected losses from natural disaster risk. Using a ten-year panel of Indonesian households exposed to over 100 natural disasters, we examine vulnerability to poverty – a measure of current poverty and risk - on an island nation towards understanding differences in household behavior towards natural disaster risk on islands. Aggregate risk is shown to be the greatest form of risk faced by Indonesian households. Households with savings and pension payments, higher education levels, smaller household sizes, and rural residences suffer less consumption losses from aggregate risk compared to other households in the sample.

This research provides selective evidence of the impact of natural disaster risk on long-term poverty rates. By estimating a decadal panel, we complement existing static poverty analyses with a dynamic perspective. Households unable to sustain consumption over time above the poverty line in the presence of shocks are regarded as vulnerable to poverty; as we are analyzing consumption under uncertainty, vulnerable households not only suffer from consumption shortfalls (level of consumption below poverty line) but are also unable to intertemporally distribute their consumption over time so as to “smooth” their consumption stream. By using expected consumption as our measure of welfare, we focus on changes to both the distribution and the level of consumption from natural disaster shocks in addition to other sources of aggregate and individual risk. To cope with increasing natural disaster events in the absence of market insurance, households substitute self-insurance mechanisms to smooth consumption

(Morduch, 1995; Lewis and Nickerson, 1989; Ehrlich and Becker, 1972). For example, Carter et al. (2007) found that households suffering losses from Hurricane Mitch in Honduras were limited in smoothing consumption (especially the poorest households), because of limits in their borrowing capacity related to credit markets imperfections (Van den Berg and Burger, 2008; Carter et al., 2007).

Household responses to natural disaster risk may have long-term implications for welfare trajectories including permanently lowered consumption levels (Carter et al., 2007), selling of productive assets in the household portfolio (Barrett, 2001), or diverting resources from more productive uses. Important to the natural disaster context, households in high-risk environments confront both income and asset risk during a natural disaster shock. As motivated in Chapter 2, island nations are very high-risk environments and often suffer detrimentally from their isolation, limited resources and trade dependencies.

Natural disasters directly and indirectly impact a household's consumption, especially in their ability to smooth consumption over time in the presence of natural disaster risk as it manifests both idiosyncratically and aggregately. Consider the case of a household suffering a flood disaster. The disaster impact may cause an income shock from permutations to the labor market (perhaps the building the individual worked in was decimated or the crops they farmed were ruined) culminating in unemployment. The income shock is a result of the natural disaster manifesting as aggregate losses. Compounding the income shock (from loss of employment) is the household's asset shock: the natural disaster also caused household asset losses by destroying their dwelling. The depleted asset portfolio, which could have been used to smooth

consumption in the face of the income shock (for example, they could have rented a room in the house for income), was also destroyed.[19]

Households on island nations face the great risk from natural disasters; households in poverty on island nations are the most vulnerable to suffering from natural disaster risk. This research specifically analyzes characteristics of households able to smooth consumption (cope through self-insurance mechanisms) in the presence of natural disaster shocks and other sources of risk. We contribute to the economic vulnerability literature by analyzing the consumption impacts from natural disasters reflected in both aggregate and individual risk (recall the examples of income and asset shocks). By estimating expected consumption (rather than actual consumption), we allow for increased risk to evolve household behavior over time (households update expectations over time)[20].

Theoretical Model

We directly follow Ligon and Schechter (2003) in defining vulnerability to poverty as a positive probability of expected utility from consumption falling below a relative threshold[21].

We suppose a finite number of households, indexed by i = 1, 2, …,n over time t=1,…..T and denote the state of the world as $s \in S$. The distribution of household i's

[19] Other examples are if the household was agrarian and active only in the informal economy: if the hurricane disaster ruined their plots and their dwelling, they also suffer an income and asset shock or if this household was dependent on the credit market for access to agricultural inputs: if the hurricane disaster ruined their plots, it destroyed their future income stream (selling the crop) and destroyed their asset (the inputs) which retains the debt obligation (they must still pay the loan back).

[20] This treatment further lessens the potential for measurement error in consumption conflating with unexplained risk.

[21] We could have alternatively chosen to set a specific threshold, such as the poverty line. Since we are interested specifically in population-relative estimates, we use a population-relative threshold for within-population comparisons.

consumption is given as $c^i(s)$. As risk-averting households seek to smooth consumption over time and states of the world, the assumption of stationarity of consumption is reasonable: we regard a household's realizations of consumption expenditures over time as draws from the same time-invariant distribution (Ligon, 2007). Households also demonstrate relative risk-aversion von Neumann-Morgenstern preferences (household ranks uncertain[22] consumption payouts according to expected utility of the individual consumption payouts which may occur), allowing us to represent household preferences with a continuous utility function, $U^i(c_t^i)$.

Households experience current utility from current consumption, with U denoting an increasing and strictly concave utility function, c_t^i denoting household *i*'s current consumption in time *t* and assuming that this household will continue to exist until time T. For this household's range of consumption, the household maximizes their expected utility. This maximization is based on the utility the household expects (EU) from future consumption (c_{t+j}^i) with j denoting a future time. We can model this expected utility from future consumption expected in period *t+j* as:

$$EU^i(c_{t+j}^i) = \int U(c_{t+j}^i)\, dF_t(c_{t+j}^i) \tag{2-1}$$

the household's expectations at time t regarding the utility they will get from future consumption, given as $EU^i(c_{t+j}^i)$, and with $F_t(c_{t+j}^i)$ denoting household *i*'s speculation in time *t* about the distribution of consumption in the future (time *t+j*). Expected utility from future consumption is equal to the mean of this function, calculated by integrating the

[22] We intentionally use uncertain, rather than risky, here to denote that households do not precisely know the probabilities associated with (potential) future consumption realizations (for example, a sports game score). Risky would imply the probabilities are known (for example, the probability of rolling a 2 on a 6-sided dice).

function. We further assume rational expectations[23] by assuming our errors are random and not systematic, individuals in our analysis speculate about the future, our individual units of analysis are risk-averse utility maximizers and the information set upon which individuals condition expectations include past histories of both exogenous and endogenous variables. As example, expectations over time may change from changes in frequencies of extreme weather events (exogenous) or extreme weather event losses (endogenous).

The first step in measuring vulnerability to poverty from the interaction of time-invariant individual fixed effects (α_i), individual-invariant time fixed effects (η_t), the set of k-observable physical, social, economic and environmental variables ($x_t^i = (x_{1t}^i, ..., x_{kt}^i)$) and random, unobserved disturbances (ε_t^i) is to estimate a household's expected consumption[24], $E(c_t^i)$ for each time period. By letting $\tilde{c}_t^i = c_t^i + \varepsilon_t^i$ under the assumption that the error term, $\{\varepsilon_t^i\}$, satisfies the property $E(\varepsilon_t^i \mid x_t^i, \bar{x}_t) = E(\varepsilon_t^i c_t^i) = 0$, we estimate:

$$\tilde{c}_t^i = \alpha^i + \eta_t + x_t^i \beta + \upsilon_t^i \tag{2-2}$$

to obtain fitted estimates of consumption, $\widetilde{c_t^i}$. The error term, υ_t^i, is equal to the sum of measurement error in consumption and prediction error. Expectation operators are applied to the fitted estimates of consumption, $E(\tilde{c}_t^i)$, and are used to calculate the various components of consumption in the vulnerability measure. The intentional

[23] This is based on the Theory of Rational Expectations (Muth, 1961) whereby the outcome depends partly on what individuals expect to happen. By rational expectations, we assume that individuals form expectations from all available information and when expectations deviate from actuality, we assume these deviationsto be random and non-systematic.

[24] If actual consumption has measurement error, the penalty of using actual – rather than expected – consumption will conflate measurement error with unexplained risk (Ligon and Schechter, 2003).

implication of applying expectation operators is that expected consumption, as a forward-looking variable, is the weighted average of the potential outcomes, with weights based on probabilities of these outcomes. Results from this regression are presented in Table 4-1 and Table 4-2 presents the summary statistics of the fitted consumption estimates.

In accordance with expected utility theory, risk aversion emerges due to the concavity of the utility function and explains aversion to large risks, such as natural disasters (see Appendix A for proof). The Constant Relative Risk Aversion (CRRA) function models risk irrespective to initial wealth (consumption) levels: as wealth (consumption) increases, households will hold the same percentage of wealth (consumption) in risky assets[25]. We set the sensitivity parameter equal to 2 following parameter estimates in the microeconomic literature (see Cardenas and Carpenter, 2010 or Ligon and Schechter, 2003). This yields the relative risk aversion function (3-7) becoming:

$$U(c) = -1[c^{-1}] \tag{2-3}$$

Setting the CRRA sensitivity parameter to 2 is symbiotic with our choice of setting the poverty line relative to the population (by normalizing consumption over all households and time periods) and the linear consumption regression. As we seek a model that is sensitive to changes in risk and inequality, the choice of γ (the sensitivity

[25] By comparison, Increasing Relative Risk Aversion implies that consumption of wealthier households will fluctuate less than that of poorer households because the poor are willing to bear more risk and Decreasing Relative Risk Aversion implies that consumption of wealthier households will fluctuate more than that of poorer households because the wealthier are willing to bear more risk. We assume all households are willing to bear the same amount of aggregate, exogenous, natural disaster risk.

parameter) at 2 reflects this[26]. This is especially important to the context of our analysis – we are quite interested in exploring the welfare implications of differences in risk across the population. Lower values of the sensitivity parameter would deflate the role of risk and equality on household utility. Our results then yield information on the percentage change in utility resulting from a one-unit change in an explanatory variable[27].

The shape and properties of the CRRA function reflect our research context. As we are interested in welfare consequences of risk, this function reflects greater utility impact from losses as compared to gains. When consumption decreases, the magnitude of the utility loss is greater as compared to the magnitude of utility gain from a consumption increase of the same quantity. For example, if a household loses one unit of consumption, their disutility is greater than the increase in utility from gaining one unit of consumption. This assumption further relates to our scope of research. As we are specifically interested in self-insurance mechanisms correlated with being able to smooth consumption (sustain an average level of consumption), the CRRA utility function with $\gamma = 2$ will result in higher utilities from consuming a stable, average level of consumption each period as compared to consuming the same level of consumption as a volatile, expected consumption realization each period: $U\left(\bar{\bar{c}}\right) > EU\left(E(c)\right)$ where $\bar{\bar{c}}$ is

[26] In comparison to setting the sensitivity parameter at 1 for example which would give less sensitivity to the severity of poverty and risk – weaker concavity of the utility function will associate less welfare loss with risk and inequality compared to a more concave utility function.

[27] A result of using log-normal consumption and a linear estimating equation.

the average, stable consumption over time, c is that period's consumption realization and $\bar{\bar{c}}$ = c.

Given our concave utility function and following LS, we define vulnerability of the individual unit of analysis as:

$$V^i = U^i(z) - EU^i(c_t^i) \tag{4-4}$$

with z equal to some certainty equivalent amount of consumption. As we seek to understand the relative vulnerabilities of persons within a population as compared to their broader population, we select z as relative to the sample: it is set equal to normalized average consumption over all households and time periods[28], $\bar{c}$ =1.

If a household has average consumption over time, $\bar{\bar{c}}^i$, greater than or equal to population-average consumption over time, $\bar{c}$ (or $\bar{\bar{c}}^i$ >1), we do not regard them as vulnerable to poverty. Admitted by the concavity of the utility function, the LS measure regards households as relatively vulnerable based on the marginal utility of the loss of a unit of welfare. As an example, consider two households with different consumption levels. Household a, HH_a, has relatively greater than average consumption levels; household b, HH_b, has relatively below average consumption. If each household loses the same quantity of welfare, HH_a loses relatively less utility as compared to HH_b due to diminishing marginal utility of consumption; HH_b suffers a greater relative loss than HH_a. Setting the sensitivity parameter at 2 reflects this.

[28] Specifically, we normalize consumption so that average consumption over all households and time periods equals 1.

Applying expectation operators to our concave utility function establishes vulnerability depends on the mean and the variance of consumption, allowing decomposition of the components of poverty and risk as detailed in Chapter 3:

$$V^i = \underbrace{[U^i(\bar{c}) - U^i(E(c_t^i))]}_{"Poverty"} + \underbrace{[U^i(E(c_t^i)) - EU^i(c_t^i)]}_{"Risk"} \tag{4-5}$$

where $[U^i(\bar{c}) - U^i(E(c_t^i))]$ is the difference, in utils, between the utility from consuming at the population average, $\bar{c}$ (=1) less the utility from consuming at household *i*'s average consumption over time, $\bar{\bar{c}}$. Rewriting the poverty term to reflect this yields $U^i(\bar{c}) - U^i(\bar{\bar{c}}^i)$ or $U^i(1) - U^i(\bar{\bar{c}}^i)$. The first term is interpreted as the utility the household gets from consuming at the population average level of consumption over all time periods ($U^i(\bar{c})$ or $U^i(1)$) and is the highest achievable utility. The second term, $U^i(Ec_t^i) = U^i(\bar{\bar{c}}^i)$, is household *i*'s utility from their average consumption over all time periods. Therefore the poverty bracket measures the difference, in utils, between household *i*'s average consumption over time ($\bar{\bar{c}}^i$) and the (sampled) population average consumption ($\bar{c}$ =1). A household with utility from their average consumption $U^i(\bar{\bar{c}}^i)$ less than the utility from the population average consumption $U^i(\bar{c}^i)$ is considered in current poverty.

The second bracket, $[U^i(\bar{\bar{c}}^i) - EU^i(c_t^i)]$, measures total risk faced by household *i*. $EU^i(c_t^i)$ is household *i*'s expected utility from their stream of consumption weighted by probablized time period: $\left[-1\left[(c_1)^{-1}\right](p1) + -1\left[(c_2)^{-1}\right](p2) + ... + -1\left[(c_t)^{-1}\right](pt)\right]$ with p denoting the probability of consumption realizations of the respective time period. We

are very interested in the dynamics of this term as it captures consumption smoothing over time.

This risk term can be further disaggregated into sources of risk by accounting for various sources of risk (aggregate, idiosyncratic and unexplained):

$$V^i = \underbrace{[U^i(\bar{c}) - U^i(\bar{\bar{c}}^i)]}_{\text{"Poverty"}} + \underbrace{\left\{U^i(\bar{\bar{c}}^i) - EU^i[E(c_t^i \,|\, \bar{x}_t)]\right\}}_{\text{"Aggregate Risk"}}$$
$$+ \underbrace{\left\{EU^i\left[E(c_t^i \,|\, \bar{x}_t)\right] - EU^i\left[E(c_t^i \,|\, \bar{x}_t, x_t^i)\right]\right\}}_{\text{"Idiosyncratic Risk"}} + \underbrace{\left\{EU^i[E(c_t^i \,|\, \bar{x}_t, x_t^i) - EU^i(c_t^i)\right\}}_{\text{"Unexplained Risk \& Measurement Error"}} \tag{4-6}$$

The first term is poverty as defined above. The second term, aggregate risk, is the difference in utility between the household *i*'s average consumption over time, $\bar{\bar{c}}^i$, and the expected utility from the variation in consumption given the level of aggregate shock faced by the entire population.

Detailing this with respect to the Constant Relative Risk Aversion (CRRA) function, aggregate risk is measured as $-1\left[(\bar{\bar{c}})^{-1}\right]$ minus

$\left\{-1\left[\left(E(c_1 \mid \bar{x}_t)\right)^{-1}\right](p1) + -1\left[\left(E(c_2 \mid \bar{x}_t)\right)^{-1}\right](p2) + \ldots + -1\left[\left(E(c_t \mid \bar{x}_t)\right)^{-1}\right](pt)\right\}$ and captures welfare consequences of aggregate risk.

Individual, or idiosyncratic, risk is measured in terms of uncertain, expected utility. The bracket measures the difference between two streams of consumption: the household's expected utility of expected consumption which varies only across levels of aggregate risk ($EU^i\left[E(c_t^i \,|\, \bar{x}_t)\right]$) and this household's expected utility from their expected consumption which varies across levels of individual and aggregate risk, $EU^i\left[E(c_t^i \,|\, \bar{x}_t, x_t^i)\right]$. Detailing this to the CRRA utility function, it represents the variation in

household *i*'s stream of consumption over time given their level of individual, x_t^i, and aggregate, $\bar{x}_t$ variables as $\left\{-1\left[\left(E(c_1 \mid \bar{x}_t, x_t^i)\right)^{-1}\right](p1) + -1\left[\left(E(c_2 \mid \bar{x}_t, x_t^i)\right)^{-1}\right](p2) + \ldots + -1\left[\left(E(c_t \mid \bar{x}_t, x_t^i)\right)^{-1}\right](pt)\right\}$. After estimating the vulnerability measure, we examine household correlates of overall vulnerability to poverty and its components (poverty, aggregate risk and idiosyncratic risk).

Empirical Application

We apply the LS measure to the case of Indonesian households experiencing long-term increases in weather hazards and natural disaster rates. Using Rand's Indonesian Family Life Surveys (IFLS) rounds 2 (1997), 3 (2000) and 4 (2007), we estimate the LS measure for 3269 households over 10 years.

Indonesia

Indonesia, the world's 4th most populous country, has a unique geography, demography, and economic environment spanning the equator and Pacific and Indian Oceans. The country has more than 17,000 islands with five main islands (Irian Java, Java, Kalimantan, Sulawesi, and Sumatra) and over 6000 uninhabited islands.

The Republic of Indonesia is the world's largest archipelago with a total land area of 1,919,317 km^2 exposed to a plethora of natural disasters, especially related to seismic activity (volcanoes, earthquakes and tsunamis). Table 4-1 presents Indonesia's natural disaster experience from 1997-2007. Indonesia has a high extent of mountainous territory and a climate characterized by two seasons: dry (June – September) and rainy (December – March).

Indonesian demography. The 2009 population of Indonesia was estimated at 240.3 million with an average population growth rate of 1.14% (US Department of State Bureau of East Asian and Pacific Affairs, 2010). Java is the world's most populous island with roughly 124 million inhabitants (2005 population estimates) and one of the world's most densely populated areas (Central Intelligence Agency, 2010).

By percentage of population, the dominant ethnic groups are Javanese (40.6%), Sundanese (15%), Madurese (3.3%), and Minangkabau (2.7%) and the dominant religion is Muslim (86.1%) followed distantly by Protestant (5.7%), Catholic (3%) and Hindu (1.8%).

Indonesian economy. Indonesia is classified as a low-middle income developing country (World Bank, 2010a) and an island developing state by the United Nations. Indonesia has a market-based economy and is a global emerging market with dependence on oil export revenues. The Indonesian currency is the Rupiah (Rp). In 2010, Indonesia's gross domestic product (labor force) had the following sectoral decompositions: 14.4% (42.1%) agriculture, 47.1% (18.6%) industry, and 38.5%(39.3%) services (Central Intelligence Agency, 2010). The major agricultural products are timber, rubber, rice, palm oil, and coffee. Indonesia's major exports are within the energy industry, including oil, natural gas, palm oil (crude), and coal. In terms of quality of life, the average life expectancy at birth is 71 years and the adult[29] literacy rate is 92% (World Bank, 2010a).

Indonesia suffered an economic crisis (part of the Asian Financial Crisis) beginning in mid-1997 during which the government intervened and then a financial

[29] People aged 15 and older.

crisis in late 2005 attributed to international oil prices. The poverty impacts of the 1997 financial crisis have been discussed in the literature: while poverty rates increased dramatically from 12.4% to 24.5% between 1997 to 1999, the rates returned to between 13.1 – 14.2% by 2002 (Suryahadi et al. 2003). In 2006, 17.8% of the Indonesian population lived below the international poverty line, ranking 69th in the world. The Gini index was 39.4 in 2005 and Indonesia is ranked 108th (as a medium development country) in the 2010 Human Development Index.

Indonesian Family Life Survey

Our main data source is longitudinal survey data drawn from the Indonesian Family Life Survey (IFLS), a survey of households and communities in Indonesia. Our empirical application uses three rounds of the survey: IFLS2, conducted in late 1997, IFLS3, conducted in 2000, and IFLS4, conducted in 2007 (we do not include information from IFLS2+ which sampled only 25% of IFLS households specifically assessing the impact of the Asian financial crisis). While numerous researchers have used the survey data to estimate impacts of financial and health shocks, this is the first study to our knowledge to use this data to estimate the impact of natural disasters on vulnerability to poverty. The IFLS surveys include a plethora of household information including consumption (expenditures and own-produced), assets, livelihood and employment, assets, demographic information (age, sex, education level), and household decision-making. Rational expectations and the belief that (research) advances should rest on an enhanced empirical understanding of how households respond to economic and physical environments and on the role of government policy in shaping those environments directly influenced the IFLS survey design (Deaton, 1997).

IFLS sample. IFLS is representative of 83% of the Indonesian population, surveying individuals in 13 of the 27 providences. Households were assigned a unique 7-digit household id number in round 1 (1993) that was maintained for each survey wave in rounds 2, 3 and 4. This allowed merging across waves to obtain a data set containing only those households that participated in each round of the survey for a total of 3269 households with complete information for our selected variables. We restore random sampling by applying household weights to account for both attrition and full population representation. Table 4-3 defines the variables used in this study.

The 3269 households tracked for 10 years have an average household size of 6.03 members, with an average of 1.03 workers and 0.38 pensioners per household. The average head of household is aged 56.4 years old with 19.1 years of education. 33.5% of the heads of households were female and 53% of households reside in rural areas. IFLS contains detailed consumption information by item, food and non-food, including items purchased and own-produced and their price in time t. Our consumption variable was constructed by summing total food consumption (in Rp), purchased and own-produced, by household. We use consumption in price times quantity, rather than just quantity, to account for heterogeneity of purchasing power across space[30].

Natural disaster data

Indonesia is located on an arc of volcanoes and fault lines known as the "Ring of Fire;" the country is prone to recurrent seismic activity with approximately 400 total (150 active) volcanoes. Many volcanoes are located on the most densely populated island,

[30] Consider the case of urban versus rural prices: if the price of one kilogram of rice is 100 Rp in the urban area and 50 Rp in the rural area and both households consume one kilogram of rice, including only quantity would imply that the households are consuming the same amount. Including prices would indicate that the urban household has greater consumption.

Java. Indonesia has a long history of natural disaster shocks. In 1883, the Krakatoa (Krakatau) volcano erupted causing a tsunami to strike Western Java and Southern Sumatra, resulting in over 36,000 deaths (Dasgupta, 2010). Tsunami waves engulfed coastal towns and villages within 2 hours of the eruption; some villages were swept away with the tide as parts of the Krakatau island submerged with the implosion of the volcano. One hundred and twenty one years later, an earthquake just off the coast of Sumatra (Sumatra-Andaman earthquake) caused the 2004 Indian Ocean tsunami. Over 225,000 people were killed with Indonesia accounting for 73% of the tsunami-related deaths (EM-DAT, 2010).

Natural disaster context. During the period of our analysis, Indonesia suffered 145 natural disasters with an average of 13 disasters per annum (see Table 4-4). Table 4-5 reports annual natural disaster losses in financial terms and Table 4-6 reports annual natural disaster deaths. Table 4-7 presents total natural disaster losses, by disaster type, for the entire study period. Floods were the most frequent disaster type, accounting for 31.7% of the natural disasters between 1992-2007, followed by earthquakes (24%), and wet mass movements[31] (18%).

The most costly form of natural disaster during the study period was wildfire, accounting for 47% (9,315,800 in 2000 US$) of the financial losses, followed by earthquakes, accounting for 43% (8,652,600 in 2000 US$). While floods were the most frequently experienced natural disaster, they only accounted for 8% of the financial losses. However, in terms of deaths caused by natural disasters, earthquakes account

[31] Includes avalanches, landslides, and debris flows.

for 95.8% (173,639 of the 181,086); the 2004 earthquake-tsunami accounted for 165,816 (95.5%) of these deaths.

Natural disaster losses in IFLS. Natural disaster household experience was included in each round of IFLS. Households were asked to recall a 5-year history of shocks, including natural disasters and weather events. We include this household-level information as a dummy variable = 1 if the household reported a natural disaster or weather shock causing an economic disturbance in their household (= 0 otherwise). In round 2 (1997), 2.3% of surveyed households reported experiencing a natural disaster shock in the last 5 years, in round 3 (2000), 1.9% of the surveyed households reported experiencing a natural disaster shock in the last 5 years, and in round 4 (2007), 21.2% of the surveyed households reported experiencing a natural disaster shock in the last 5 years. Across the panel, 11.5% of the surveyed households experienced a natural disaster disturbance. Table 4-8 presents evidence of natural disaster persistence: households who experienced a disaster shock in one period were 155% more likely to experience a second disaster shock compared to households who did not experience the first disaster disturbance.

Housing quality

Rodrik (2004) emphasizes the need for good instruments – those with sources of exogenous variation, which are an independent determinant, not a consequence of, poverty. For this reason, data scarcity and measurement error[32], and following the economic development literature, we not use survey-reported income as our measure of income but rather follow Filmer and Pritchett (2001) by constructing a housing quality

[32] For our final estimated sample of N=10887 (n=3269, t=3) we have 559 observations with reported income and 10328 missing observations.

index as our measure of income. We construct A_t^i as household *i*'s housing quality in time period *t*:

$$A_t^i = \frac{f_{1t}}{s_{1t}}\left(a_{i1t} - a_{1t}\right) + ... + \frac{f_{Nt}}{s_{Nt}}\left(a_{iNt} - a_{Nt}\right) \qquad (2\text{-}4)$$

where

$$\begin{aligned} f_{1t} &= \textit{scoring factor asset } 1 \textit{ in year } t \\ a_{i1t} &= i^{th} \textit{ household value for asset } 1 \textit{ in year } t \\ a_{1t} &= \textit{sample mean for asset } 1 \textit{ in year } t \\ s_{1t} &= \textit{sample standard deviation for asset } 1 \textit{ in year } t \\ \mu_A &= 0 \textit{ by construction} \end{aligned}$$

The assets for household *i* ($a_{i1\text{-}14}$) include the type of dwelling, number of rooms, type of flooring, roof and walls, size of house and yard, presence of waste, trash or stagnant water, ventilation, whether the kitchen is inside or outside, presence of a stable and whether household members sleep in the same room as the kitchen. Higher values of the index indicate higher housing quality.

Self-insurance mechanisms

We include self-insurance mechanisms of savings, asset ownership, and number of pensioners. Self-insurance redistributes wealth accumulated during a favorable state of the world to an unfavorable (disaster) state of the world[33].

Savings. We include the total amount of Rupiah in savings reported by the household as a form of self-insurance (dissavings) available to households. In times of economic shocks, households dissave to smooth consumption. Savings are especially important to households when market mechanisms stifle other forms of self-insurance (such as borrowing or transfers).

[33] A complete description of self-insurance is offered in Chapter 3.

Asset ownership. Home ownership is a major asset for many households. It offers both security and liability during economic shocks, especially within the natural disaster context. We include a dummy variable to indicate whether one or more members of the household own the home they reside in. Home ownership may offer security in the form of households having a place to live, land ownership and alleviating the need to pay rent. On the other hand, within the disaster context, home ownership implies households must rebuild their shelter if destroyed by the storm – the home may be a liability in that repairs may be costly or materials to rebuild may be unavailable. Further, there may be a relationship between evacuation and homeownership. It has been documented through post-disaster qualitative interviews that some homeowners are reluctant to evaluate for fear of looting.

We also include a dummy variable to indicate if a household has animals. Animals offer many consumption-smoothing benefits such as potential income (from selling the animal, selling their offspring, or selling by-products such as eggs or milk), potential labor (using the animal for traction), or food (consuming the animal). Akin to the motivation above regarding home ownership, the risk-relationship may reverse at the individual level as animal ownership represents greater household resources exposed to risk.

Pensioners. We include the number of pensioners per household as a form of self-insurance. Devereax (2001) presented evidence that pensions – a form of income entitlement often given to the elderly - offer consumption stabilization in the face of economic shocks as it contributes an additional stream of income to the household, often redistributed for household uses. The pension also serves as guaranteed income

to the household; this is salient in the disaster context as other paid labor – formal and especially informal – may be interrupted by the disaster's impact. Consider two forms of employment as examples. If a worker is a formal agricultural laborer and the disaster decimated the crops or land, this individual faces a great possibility of losing their income. If a worker rather is an informal entrepreneur (for example, they sell clothing at a local market which they make at home) and the disaster decimates the local community, this individual faces a great possibility of losing their income stream as a result of other household's not being able to afford their goods or services. In both cases, having a pensioner in the household will offer stable income during the shock time. In the self-insurance context, a pension is a certain, known transfer.

Household characteristics

The set of k-observable household variables includes household head characteristics of sex, age, age^2, employment status and level of education; household characteristics of residential type (urban or rural), region of the household, household size and household self-insurance mechanisms (housing quality (proxy for income), asset ownership, savings and pensioners) and reported natural disaster shock experience. Table 4-9 presents the summary statistics for variables used in calculating the consumption estimates, the vulnerability to poverty measure and correlates of the vulnerability measure.

Calculating the Vulnerability to Poverty Measure

The first step in calculating the vulnerability to poverty measure was obtaining the fitted consumption estimates ($\widetilde{c_t^i}$) from equation (4-2) by regressing log-consumption on the set of individual risk variables (x_t^i), household fixed effects (α^i) and year fixed-

effects (η_t). Results of this regression are presented in Table 4-1 and Table 4-2 presents the summary statistics for $\widetilde{c_t^i}$. The highest attainable level of $\tilde{c}_t^i$ is 1 and the average for the sample over the timeframe is 0.50. The fitted consumption estimates, $\widetilde{c_t^i}$ obtained from (4-2), are used to calculate each household's average consumption ($\overline{\overline{c^i}}$) and their expected consumption for each period ($E(\widetilde{c_t^i})$). The expected consumption estimates are used in the risk measurements ($EU^i\left[E(\widetilde{c_t^i}\middle|\overline{x_t})\right]$, $EU^i\left[E(\widetilde{c_t^i}\middle|\overline{x_t}, x_t^i)\right]$, and $EU^i\left[E(\widetilde{c_t^i})\right]$). Second, we select the "poverty line" as population relative. By defining the poverty line, $\bar{c}$, as 1, households with average predicted consumption, $\overline{\overline{c^i}}$, less than 1 are considered in current poverty. The final step ahead of estimating the vulnerability measure was assuming CRRA risk preferences, specifying the utility function as equation (4-3).

Results

The interpretation of the vulnerability measure is direct, given our consumption normalization: the vulnerability measure represents the population average percentage utility loss resulting from the presence of poverty and risk (Table 4-10 row 1 column 1) as the sum of current poverty (Table 4-10 row 1 column 2), aggregate risk (Table 4-10 row 1 column 3), idiosyncratic risk (Table 4-10 row 1 column 4) and unexplained risk/measurement error (Table 4-10 row 1 column 5). Table 4-10 presents the vulnerability to poverty measure estimates in the top row and correlates to the measure in the rows below.

The utility of the average Indonesian household sampled is 62% lower than it would be in the absence of consumption risk and inequality, assuming costless redistribution. In terms of consumption risk, aggregate risk is the greatest form of risk faced by Indonesian households and the greatest contributor to vulnerability to poverty in Indonesia. This is partially attributable to their island scale – for example, small size, limited resource base and limited spatial scale to smooth aggregate risk. It is also partially attributed to their strong social insurance programs smoothing individual risk[34] and household's ability to self-insure their risk through savings and assets. While aggregate risk includes macroeconomic shocks such as financial or currency crises in addition to natural disasters, our results demonstrate that natural disaster risk is impacting household consumption decisions through the highly significant correlations of household natural disaster experience and the various components of vulnerability to poverty. Indonesia suffers recurrent natural disaster shocks and households with greater self-insurance mechanisms (savings and assets) and greater levels of human capital (education) are coping with these repeated shocks better than less endowed, less educated households.

Vulnerability to Poverty

Indonesian household vulnerability to poverty as the sum of a) poverty, b) idiosyncratic risk, c) aggregate risk and d) unexplained risk is presented in row 1 of Table 4-10. Aggregate risk is the greatest form of risk faced by Indonesian households and increases a household's future probability of being in poverty. It accounts for nearly 40% of the vulnerability to poverty measure (aggregate risk comprises 24.68 of 62.4%).

[34] For example, Indonesia had health insurance and food subsidy programs available to households during the time frame.

Compared to the magnitude of aggregate risk's contribution to future poverty in Bulgaria, Indonesian households face much greater aggregate risk. We expected this result of living on an island exposed to extreme weather events. In accordance with poverty trap findings of Carter et al. (2007) and Hoddinott (2006), the inability to consumption smooth leads to natural disaster shocks sending households near the poverty line into poverty. Interestingly, we find current poverty status roughly equal in magnitude to the impact of aggregate risk on future poverty rates. This is a very important result for island communities such as Indonesia who tout decreasing poverty levels as economic development; yet their long-term economic development – in terms of the poverty lens – is being hampered by aggregate risk.

We find current poverty status to be smaller than LS, contributing 40% to vulnerability to poverty (they found current poverty status accounted for 57% of vulnerability to poverty in Bulgaria). Idiosyncratic risk is small but highly significant, accounting for less than 1% of vulnerability to poverty. Unexplained risk (and potential measurement error) accounts for 13% of vulnerability to poverty. Our estimate of unexplained risk is much lower than Ligon and Schechter's (32%). This was expected as we took significant investment to find high quality, detailed household information, use a proxy rather than reported income and included more idiosyncratic controls in x_t^i as compared to Ligon and Schechter (2003) thus do not have as many unobserved sources of idiosyncratic risk as Ligon and Schechter (2003) (their estimate of unexplained risk was greater in magnitude than both aggregate and idiosyncratic risk). We also attribute this result to our inclusion of observed household-level shocks and numerous insurance-type mechanisms (while Ligon and Schechter include only number

of workers, pensioners and income level, we additionally include savings and some assets[35]).

There are some important caveats in comparing our results from Indonesia with results from Bulgaria. First and most importantly, we use a decade of household information (from 1997 to 2007) to analyze consumption smoothing whereas Ligon and Schechter use one year (1994 with 12 monthly observations) of household information. Appealing to the need for longer-term analysis as articulated by Ligon and Schechter, the scope of our analysis is much more long-term and thus captures enduring coping more so than Ligon and Schechter. Whereas their conclusions regarding household vulnerability to poverty reflect how households cope in the short-term with risk, our conclusions shed light on how households are coping over longer time horizons with frequent shocks, especially natural disaster shocks. Second, Bulgaria is a European nation comprised of one single landmass, exposed to one coast (the Black Sea) with much lower geographic risk of natural disasters. During 1994, Bulgaria experienced zero natural disasters; in 1993, they experienced one storm disaster with zero reported deaths, zero reported financial losses and 5000 persons affected (EM-DAT). Therefore, comparisons of our results with Ligon and Schechter's should be tempered by differences in time horizons and geographic natural disaster risk, the latter strengthening our case for differences in natural disaster vulnerability on islands.

There are notable differences between rural and urban households with respect to risk and poverty rates. Urban households face greater overall vulnerability to poverty and current poverty rates. Yet, rural households face a great deal more idiosyncratic

[35] Ligon and Schechter include animal, but not home ownership and do not include savings.

risk than their urban peers. This is partially attributed to the distribution of resource levels: urban areas have better access to credit markets and greater human resource levels compared to rural areas. For example, housing and land values are higher in urban areas; food prices are often higher as well. The result is also partially attributed to the distribution of common-pool and public goods: in rural areas, there are more common-pool and public goods available at the aggregate level to smooth consumption. For example, while an urban household must rely on the formal market to purchase their consumption bundle (water, food, fuel), a rural household may rely on many common-pool and public good resources available as rural amenities. These amenities may include fishing waters, sources of fuel for cooking, and fresh water sources. While rural aggregate risk is smaller, their individual risk is much greater as they do not have individual access to many insurance-type mechanisms integrated into the formal economy. For example, aid distribution and labor market opportunities are greater in urban areas. If we consider the case of a household suffering the loss of their home dwelling to a disaster, the urban household faces greater aggregate risk of secondary impacts (for example, disease outbreak) but lesser individual risk (for example, loss of income) than their rural peers. The urban household has access to temporary shelters, but lack access to individually sustain their provisions of basic needs (such as shelter, food and water) at the aggregate level as rural households do. Aggregate risk is less correlated with consumption shortfalls in rural households. Yet rural residence is correlated with higher levels of individual risk implying urban and rural households face different risk from interactions of their local environment.

Explaining Vulnerability to Poverty

Subsequent to calculating the vulnerability to poverty measure, we estimate a linear regression of each component of vulnerability on the average household characteristics to identify correlates of vulnerability to poverty and the within components, mirroring Ligon and Schechter (2003). The overall sample mean of household characteristics are used as the independent variables in the regression in addition to household and time fixed-effects (for sample averages of these characteristics, refer to the summary statistics in Table 4-9). By identifying coping correlates, we offer a deeper understanding of how natural disaster risk impacts future poverty rates and how consumption-constrained households are coping with permanent upswings in natural disaster rates.

Vulnerability to poverty correlates

Significant correlates of the overall future likelihood of poverty are presented in column 1 of Table 4-10. As the vulnerability to poverty measure relies on variations in utility from consuming at the population average level of consumption ($U\left(\bar{c}\right)$), the utility from consuming at household *i*'s respective average level of consumption ($U\left(\bar{\bar{c}}^{i}\right)$), and expected utility from household *i* consuming at their expected consumption realizations each period ($EU\left(\tilde{c}_{t}^{i}\right)$), it is important to recall the assumption of CRRA risk preference shaping the utility function. This assumption explicitly states that a household will garner higher utility from stable (or average) consumption as compared to the expected, each period, utility from same level of consumption. Further, the utility impact of a change in average consumption for a household ($\Delta\bar{\bar{c}}^{i}$) when $\bar{\bar{c}}^{i} < \bar{c}$ is greater in magnitude of

utility change compared to the change in utility from a change in one period's expected consumption ($\widetilde{c_t^i}$). Therefore, the magnitude of correlations will be greater in the poverty measure (comparing $U\left(\bar{c}\right)$ to $U\left(\overline{\overline{c^i}}\right)$) as compared to the risk measures (comparing $U\left(\overline{\overline{c^i}}\right)$ to EU($\widetilde{c_t^i}$)). To exemplify this, consider a household consuming at the population average $\left(\overline{\overline{c}} = \bar{c}\right)$. This household suffers a consumption loss such that their average consumption ($\overline{\overline{c}}$) is now less than $\left(\bar{c}\right)$. As the CRRA function acknowledges a greater amount of utility from consuming the same amount at a stable, average level of utility as compared to a probabilistic, each period consumption realization ($U\left(\overline{\overline{c^i}}\right)$ > EU($\widetilde{c_t^i}$) given $\overline{\overline{c^i}} = \widetilde{c_t^i}$), the utility impact of a household having average consumption less than $\bar{c}$ results in a greater loss of utility in the difference between U($\bar{c}$) and U($\overline{\overline{c^i}}$) as compared to utility loss from a change in expected consumption (EU($\widetilde{c_t^i}$)).

Natural disaster experience. Household natural disaster experience is highly correlated with the vulnerability measure and is time-sensitive to the conditions of the economic environment. While household disaster experience in the early 1990's (between 1992-1997) significantly increases vulnerability to future poverty (by nearly 68%), households who experienced a disaster shock during the late 1990's (between 1995-2000) are 36% less vulnerable to poverty. The timing of natural disaster shocks matter as they interact with the economy upon strike. Considering Indonesia's economic and political history during this timeframe reveals support for our findings. Indonesia's

President Suharto is considered the most corrupt leader of all time (Transparency International, 2004); he was in power from 1968-1998. Recalling the case of Hurricane Katrina discussed in Chapter 2, the slumping economic indicators of New Orleans portended a more vulnerable environment for disaster to strike. And so with the case of Indonesia: as discussed in an earlier section of this chapter, Indonesia rebounded from the Asian financial crisis in 1997, attributed by many to the government's intervention and social protection schemes available to households (between 1995 – 2005) and has steadily improved their institutional strength in the post-Suharto era (after 1998)[36]. During this time, government assistance was available for poor households and thus households were able to recover from disaster shocks riding on the coattails of interventions to alleviate the financial crisis (for example, there was a very beneficial rice subsidy program).

Self-insurance mechanisms. Households with savings are 43% less vulnerable to future poverty compared to households without savings. The presence of savings indicates the household is able to smooth their consumption intertemporally in the presence of shocks. Consistent with findings from across the world, self-insurance mechanisms decrease the likelihood of shocks acting as poverty traps. Not only do we find that households with savings are overall less likely to be in poverty in the future, they are also 88% less likely to be in current poverty and are better able to smooth consumption in the presence of aggregate risk (by 12%). Another self-insurance mechanism we examined was the number of pensioners in the household. As pensions continue to provide household income even during economic disturbances, they are

[36] For example, a common measure of institutional strength is the corruption index (see Table 4-12 for Indonesia's historical corruption rankings).

often a consumption-smoothing safety net to recipient households. Households with pensioners are more than 25% less vulnerable to poverty than households without.

Animals offer consumption-smoothing benefits to households. Animals serve as a potential source of income (by selling the animal), labor (by using the animal to work fields), or as a consumable (food). Households with animals were 33% less vulnerable to poverty than households without animals.

Household characteristics. Larger households are 16% more vulnerable to future poverty. Interestingly, sex of the female headed-households is significantly correlated with lower vulnerability to poverty and lower current poverty status. This suggests strong gender institutions in Indonesia. Reflecting on country statistics presented earlier, Indonesia has strong institutions reflected in successful crisis interventions (for examples, Asian crisis of 1997, oil crisis of 2005), alleviating food and price market frictions (for example, a rice subsidy) and the availability of heath care and insurance (for example, Kartu Sehat and Dana Sehat are available to households). In 2005, Indonesia's gender-related development index was ranked 94th, yet their human development ranking was only 107th.

Poverty correlates

Natural disaster disturbances. Households that reported natural disaster disturbances between 1992-1997 are correlated with greater current poverty levels as compared to households not experiencing these shocks. Yet, households reporting natural disaster disturbances between 1995-2000 are correlated with lower current poverty levels than households not experiencing these shocks. These results offer support for our hypotheses regarding the deterministic role of economic conditions at the time of a natural disaster. Between 1995-2005, numerous social safety net

programs were available to households to thwart poverty inducement. These provisions were not available during the first period.

Self-insurance mechanisms. The significant self-insurance correlates of current poverty status include savings (negative), pensioners (negative) and animals (negative). Households who have the ability to accrue financial and asset surpluses during good times are better able to smooth their consumption in bad times by spending down these surpluses. Further, households with a permanent income source (pensioners) have a certainty level of minimum income significantly correlated with being able to smooth consumption over time.

Household characteristics. In the sample, 34% of the households have female heads. These households are 24% less in current poverty and face less total risk than male-headed households. There is a significant difference in the number of workers per household between male and female heads: the average number of workers in female headed-households is 1.8 while in male is only 0.63. Yet, male-headed households have greater probabilities of savings: 61.8% of male-headed households have savings while only 28.7% of female-headed households have savings.

Households with greater numbers of pensioners are 48% less impoverished compared to households without pensioners. This is consistent with other findings of the consumption-smoothing benefits of pensioners: they receive a stable income used to benefit the household and not just the individual recipient. We find that greater number of pensioners is also negatively correlated with greater aggregate risk, though the magnitude is less. The results regarding household animal ownership are similar: households who own animals are less impoverished than households without.

Households in rural areas face 25% less current poverty than households in urban areas. Over the time period studied, Indonesia faced very volatile commodity prices[37]. These price volatilities impact households with greater reliance on purchasing (rather than own-producing) their consumption needs. Urban households are often more reliant on purchasing their commodities. In Indonesia, rural agriculture has significantly reduced rural poverty (Suryahadi et al., 2008). Supporting our findings regarding rural areas, the headcount of rural households living at the poverty line has been declining from 21.8% in 2006 to 16.6% in 2010 (World Bank, 2010a).

Aggregate risk correlates

Significant correlates of aggregate risk are presented in column 3 of Table 4-10.

Natural disaster disturbances. Similar to current poverty correlates, households reporting disaster disturbances between 1992-1997 are correlated with higher levels of aggregate risk and households with disaster disturbance reports between 1995-2000 are correlated with lower levels of aggregate risk.

Self-insurance mechanisms. Households with savings, pensioners and animals are correlated with lower levels of aggregate risk. As the vulnerability to poverty measure is an aggregate, population-level measure, aggregate risk represents consumption shocks experienced by all. Households with self-insurance accruals are able to cope with aggregate risk better than households without self-insurance available. These self-insurance mechanisms decrease aggregate risk by presenting households with the ability to smooth their consumption losses in the presence of aggregate risk.

[37] For example, domestic prices, especially food (increased by 118%), skyrocketed in 1998 with 78% inflation (Surhahadi and Sumarto, 2003).

Household characteristics. Female heads of households are much more prominent in rural areas: within this sample, 60% of the female-headed households lived in rural areas compared to 52% of male-headed households (difference of means was significant at the 1% level; see Table 4-11). Other characteristics of households facing lower aggregate risk include greater rates of educational attainment (at the primary and post-secondary, but not secondary levels), younger head of household (sample average age of household head is just older than 54).

We find household size positively correlated with aggregate risk. While larger family sizes increase the number of (potential) laborers available and may diversify the human capital of the household, which may smooth labor market impacts from shocks[38], it relies on availability of work and regardless of work availability, still presents more mouths to feed.

Urban households face greater aggregate risk compared to rural households, a result we attribute to not only characteristics of urban areas in general (higher agglomerations of resources, for example) but also the risk-proneness of where Indonesia's urban areas lie spatially. Recall Indonesia's historic experience with seismic activity and their geography: Jakarta, the most dense urban area in Indonesia is located on the island of Java, the most densely populated island in the world. Java is also located on the "Ring of Fire" chain of volcanoes. Their increased aggregate risk is a result of the interaction of geographic characteristics and locational decisions of millions

[38] Consider as example a household with only two members, one in the formal economy and one in the informal economy. They face less current poverty due to lower consumption-needs (less mouths to feed) but cannot diversify their aggregate risk. On the other hand, a household with ten members may have more consumption needs to fulfill, but there are more laborers with potentially different skills, implying greater probability of employment across the formal and informal economies.

of households. The choice to locate in the higher risk areas only serves to exacerbate the aggregate risk of the area.

Idiosyncratic risk correlates

The individual household characteristics that are significantly correlated with greater individual levels of risk include: disaster experience (decreases household risk), animals (increase household risk by increasing exposed resources), having a male head of household, and living in a rural area. This last correlate is especially interesting to our scope of analysis. Significant correlates of idiosyncratic risk are presented in column 4 of Table 4-10.

Natural disaster experience. Natural disaster experience is a significant and negative correlate of individual risk for both the first (1992-1997) and last (2002-2007) time periods. This is the only component of our vulnerability measure that is significantly correlated with disaster experience in the last period. Households that experienced a disaster shock between 1992-1997 face lower idiosyncratic consumption risk. Yet, households with 1992-1997 disaster experience are also correlated with higher levels of aggregate risk and current poverty. This suggests that these households are better able to smooth consumption against risk individual to their household, but not able to smooth consumption in the presence of aggregate risk (risk common to all). Interestingly, disaster experience from 2002-2007 is significantly (negatively) correlated only with individual risk. Global and national support for recovery from the 2004 tsunami explains the negative correlation with individual risk: households were able to defray this risk with exogenous recovery support.

Households with disaster experience in these two time periods are correlated with lower individual risk, offering some evidence that households may learn from natural

disaster experiences. By experiencing a household-level disaster disturbance, a household may glean new information regarding natural disaster risk and impacts. This information may be used to rebuild stronger, thwarting future consumption losses from future natural disasters. For example, consider a household living on the coast. During a natural disaster, the household is directly impacted by a tsunami disaster. After this experience, the household may gain information on how to increase their self-protection in the future (perhaps they consider building a house on stilts or migrating further inland). Adding further credibility to these significant correlates, these results are consistent with our assumption of rational expectations.

Self-insurance mechanisms. At the idiosyncratic (household) level, self-insurance accruals represent additional resources at risk. Further, these mechanisms may be expended only once (you can only spend your savings one time just as you can only sell or consume an animal one time). Households with animals are correlated with higher individual risk, yet pensioners and savings are not significant correlates.

Household characteristics. Urban and rural areas present different aggregate and individual levels of risk: urban areas are correlated with greater aggregate risk while rural areas are correlated with greater individual (household) levels of risk. We explain this as a result of differences in the levels and distributions of resources to smooth consumption. Urban areas present greater overall resource levels, especially formal market goods and services, which implies more to lose (recall that risk emerges from volatility of consumption). Further, the households are much more dependent on the formal market in urban areas compared to rural areas, especially with respect to labor, food consumption (purchased not own produced), and health. Yet, rural areas ex-ante

offer different resource provisions: as the aggregate services and market integration are less in rural areas, there is less aggregate risk but greater individual risk. There are not as many individual-level smoothing mechanisms for households to smooth their losses. In the presence of a natural disaster shock, informal risk sharing is not fully effective (Sawada and Shimizutani, 2007). As urban households have significantly greater rates of savings and better access to borrowing (as a result of greater market integration), urban households have less individual risk to future poverty than their rural peers.

Differences across correlates

Certain household characteristics are correlated across all components of the vulnerability measure yet other correlates show dissonance with some components and high correlations with others. We briefly discuss these dissentions.

Self-insurance correlates. Animal ownership is correlated with lower vulnerability to poverty, lower current poverty status, and lower aggregate risk (perhaps suggesting a relationship with wealth level). Yet, it is correlated with higher individual risk. This reflects the nature of assets in crisis times: they present the household with increased resources exposed to risk but importantly offer households an asset which may be used to smooth their consumption in the presence aggregate risk (animals are negative correlated with aggregate risk). Animal ownership represents a consumable resource, as households may directly consume them or indirectly consume their value by selling the animal. As a source of guaranteed income, households with a pension recipient have a safety-net level of income available to their household in times of crisis. As this is also the time when the labor market may be disrupted causing income disturbances for households, pensions guarantee a minimum (certain) level of consumption for the household.

Household characteristics. Greater levels of education attained by the household head are correlated with lower vulnerability to poverty, lower current poverty and lower aggregate risk but have no bearing on individual risk. For example, a more educated head of household may have improved access to (or understanding of) information on aggregate risk, such as forecast information or self-protection information. However, this information has no bearing on individual shocks, such as a health shock. The magnitude of the correlation is much smaller in aggregate risk as compared to overall vulnerability to poverty and current poverty status reflecting the permanent impact of human capital investments. Increased education levels have more salience in staving off poverty and future poverty as compared to coping with aggregate risk. This may be evidence that more educated heads of households have better information regarding aggregate risk and thus make better decisions regarding this risk. For example, these heads of household may have more information regarding disaster history or regarding geographic risk (such as fault line information), reflected in better household decision making (for example, building a house on a less risky plot of land).

Concluding Remarks

In this chapter, the LS poverty measure was used to analyze Indonesian household vulnerability to poverty, with a focus on assessing aggregate risk impacts of natural disasters. The decomposable measure shed light on the impacts of aggregate risk to future poverty rates in the long-term by estimating a 10-year panel of representative households. This research contributed to research needs identified by Ligon and Schechter whom called for longer panel data to extend their inferences. Further, as this measure employs a utilitarian framework, the impact of sources of risk on household welfare are more accurately represented as compared to the FGT-class

of poverty measures, which, as noted by Ligon and Schechter (2003), detrimentally underestimate risk-reducing schemes such as self-insurance. Our results contribute additional evidence that shocks, such as natural disasters, affect expected poverty (Ravallion, 1998) and that poor households are less well (consumption) insured than their wealthier peers (Jalan and Ravallion, 2001). Natural disasters, as unexpected, aggregate shocks, can have a significant influence on the relatively poor household's welfare, including poverty inducement and persistence (Carter et al., 2007).

To further investigate some of the intriguing results from the timing of household natural disaster experience, we examine the interaction of the economic and political environment on aggregate natural disaster risk by comparing a panel of small island developing states in Chapter 5. As these islands face similar risk for weather hazards yet dissimilar economic development characteristics (for example, per-capita income levels, urbanization and institutional strength), examining differences in natural disaster risk reveals some of the intricacies of the entwined human-environment relationship. Building on our results regarding the sex of the head of household, we present a gendered perspective of natural disaster risk on islands in Chapter 6.

Indonesian households face risk, the greatest form of which is aggregate risk. As aggregate risk is not locally diversifiable, governments and policy makers alike require enhanced understanding of welfare impacts of this form of risk and how it impacts future poverty rates. We found that certain households are able to diversify risk through consumption smoothing over time. For example, receiving a pension offers a permanent, expected transfer payment, especially important for negative risk realizations such as natural disasters.

Social planners and policy makers seeking to decrease natural disaster losses should acknowledge the poverty consequences of increased risk from natural disasters and seek policies empowering households to minimize this risk, as this will also implicitly decrease risk at the aggregate level. By estimating correlates of coping with this risk, our conclusions offer insights into household behaviors that decrease consumption risk. Policies promoting self-insurance mechanisms at the household level, such as household savings, decrease natural disaster risk at the aggregate and household levels. Self-protection mechanisms decrease the likelihood of a loss and are very important in coping with natural disasters, especially at the country-level as increased self-protection decreases aggregate risk. Appealing to our results regarding urban versus rural risk, governments seeking to decrease natural disaster risk should publicly disseminate information regarding high-risk prone areas to improve household expectations of long-term risk associated with their locational decisions. For example, public information regarding fault zones may improve household settlement decision-making. Similarly, public information regarding housing quality related to natural disaster performance will assist households in better rebuilding decisions. For example, public information regarding disaster-hardened building materials such as concrete will improve self-protection and decrease future housing losses from natural disasters. Another example of self-protection relates to human capital. Publicly available education on survival skills, such as swimming, will increase self-protection available to households.

The ex-ante conditions of an economy impact a household's ability to cope with a natural disaster shock. During spells of economic turmoil, natural disasters exacerbate

suffering as coping mechanisms (for example, savings) are already strained. We demonstrated that households are less able to cope with natural disaster shocks during less favorable economic times (in the middle to late 1990's), yet are more able to cope in times of greater social protection and improving macroeconomic indicators (late 1990's through 2007). Households living on island nations are especially sensitive to these macroeconomic conditions. Indonesian households benefiting from their strong and improving economy, though not all households reap the same benefits. Households with low endowments of assets (housing, animals), human capital (education), and self-insurance mechanisms (savings, pensioners) are the most vulnerable to poverty because they cannot smooth their consumption in the presence of aggregate risk. As macroeconomic conditions are more favorable in Indonesia as compared to small island developing states with much lower resource and wealth endowments, Indonesia is a good example of an island nation coping with increased natural disaster risk concurrent with improving economic conditions. Next, we will examine how differences in these economic conditions on small islands determine macroeconomic vulnerability to natural disasters.

Future Research

There are a few avenues warranted further examination. First, we will incorporate raw disaster data from EM-DAT into the empirical application. It is currently only serving as background evidence on the macroeconomic impact of natural disaster shocks. Second, and related to our explicit analysis of unique features of island economies, economic crises experienced by Indonesia during this time frame (for example, the Asian Financial Crisis of 1997) were transmitted across geographic borders. While social protection schemes were shown to be effective at alleviating the impact of these

crises (Suryahadi et al., 2003), we do not explicitly include information at the household level regarding impacts of these shocks other than price transmissions in food consumption expenditures. We hedge this impact by using housing quality as a proxy for income – this income proxy will not capture income variation from the economic crisis. Yet, this may also be a limitation in that we are disregarding this income variation. We are currently exploring using a measure of other economic shocks excluding natural disasters. We are also exploring interactions of government interventions with natural disasters as we hypothesize that natural disaster shocks transpiring during economic crises will only aggravate the impacts of the economic crises further.

Finally, we are very intrigued by the significant but small estimate of idiosyncratic risk. While this may be a result of strong social support already documented in the literature as effectively thwarting Indonesian poverty, both formal (for example, health insurance and rice subsidies) and informal (village networks and local risk-pooling), the nature of this small contribution of individual risk to future poverty suggests a puzzle warranting greater attention.

Table 4-1 Predicted consumption regression results

Ln(Consumption)	Parameter		Standard Error
Disaster 92-97	0.14		(0.10)
Disaster 95-00	0.22		(0.15)
Disaster 02-07	-0.05		(0.05)
Savings	0.15	***	(0.03)
House quality	0.04		(0.04)
Animals	-0.06		(0.04)
Own house	0.07		(0.05)
Sex (Female)	-0.06		(0.14)
Age	0.01	**	(0.01)
Age^2	0.00	***	(0.00)
Ed, primary	0.07	**	(0.03)
Ed, secondary	0.15		(0.16)
Ed, post-secondary	0.04	*	(0.03)
Rural	0.04	**	(0.02)
Household size	0.06	***	(0.01)
Workers	-0.01		(0.01)
Pensioners	0.04		(0.05)
Constant	13.76	***	(0.03)
sigma_u	0.56		
sigma_e	0.48		
rho	0.57		
N	10887		
n	3269		
R^2	0.7164		
F(4,3628)	336.33		
Prob > F	0.00		

Parameter estimates include household and year fixed effects; standard errors are robust standard errors.

Table 4-2 Fitted consumption predictions.

Consumption Predictions ($\bar{c}$)	Mean	Standard Deviation	Min	Max		Observations
Overall	0.50	0.31	0.00	1.00	N	10887
between		0.01	0.44	0.60	n	3269
within		0.31	-0.09	1.06	T	3

Table 4-3 Description of variables

Household characteristics	Description
Household size	Number of members in the household
Food consumption	Annual purchased and own-produced food consumption (quantity x $price_t$)
Residential type	Dummy variable; =1 if reside in rural area and =0 if reside in urban area
Age	Age of head of household, in years
Pensioners	Number of household members receiving a pension
Natural disaster	Dummy variable indicating if the household reported a natural disaster disturbance during the last 5 years
Education, < primary	Dummy variable = 1 if head of household has less than primary school completion; = 0 otherwise
Education, primary	Dummy variable = 1 if head of household has primary school completion; = 0 otherwise
Education, secondary	Dummy variable = 1 if head of household has secondary school completion; = 0 otherwise
Education, post-secondary	Dummy variable = 1 if head of household has post-secondary school completion; = 0 otherwise
Housing quality	Housing quality index (higher values indicate better quality); function of 14 housing-related characteristics
Employed	Head of household formal employment (= 1 if formally employed)
Sex	Head of household sex (=1 if female; = 0 if male)
Savings	Reported amount of total household savings, in Rp
Homeowner	Dummy variable = 1 if household owns; = 0 otherwise

Table 4-4 Frequency of Indonesian natural disasters

Natural Disaster Type	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Drought	1	0	0	0	0	0	1	0	0	0	0
Earthquake	1	2	1	5	2	4	3	6	2	5	4
Epidemic	2	2	3	2	0	1	1	1	2	0	3
Flood	0	1	1	4	4	7	8	1	3	9	8
Mass movement wet	0	0	2	4	4	1	4	4	2	3	2
Storm	0	0	0	0	0	0	0	2	0	0	0
Volcano	1	1	0	0	0	1	0	4	1	1	2
Wildfire	1	1	1	1	0	1	0	0	1	1	0
Total	6	7	8	16	10	15	16	18	11	19	19

(source: EM-DAT)

Table 4-5 Financial Losses (in 2000 USD) from Indonesian natural disasters

Natural Disaster Type	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Drought	88000	0	0	0	0	0	1000	0	0	0	0
Earthquake	1100	200000	3900	73000	0	0	0	4519600	0	3155000	700000
Epidemic	0	0	0	0	0	0	0	0	0	0	0
Flood	0	0	0	113000	10000	351600	0	60000	0	107300	971000
Mass movement wet	0	0	0	54600	10000	0	3961	3500	5000	37943	0
Storm	0	0	0	0	0	0	0	0	0	0	0
Volcano	0	0	0	0	0	0	0	0	0	0	0
Wildfire	8000000	1300000	1800	0	0	0	0	0	0	14000	0
Total	8089100	1500000	5700	240600	20000	351600	4961	4583100	5000	3314243	1671000

(source: EM-DAT)

Table 4-6 Deaths from Indonesian natural disasters

Natural Disaster Type	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Drought	672	0	0	0	0	0	0	0	0	0	0
Earthquake	20	34	5	149	0	11	1	165816	916	6592	95
Epidemic	197	1449	56	25	0	17	0	658	87	0	403
Flood	0	4	12	264	402	230	414	5	154	645	438
Mass movement wet	0	0	89	126	185	32	119	119	168	184	43
Storm	0	0	0	0	0	0	0	4	0	0	0
Volcano	1	0	0	0	0	0	0	2	0	0	0
Wildfire	240	3	0	0	0	0	0	0	0	0	0
Total	1130	1490	162	564	587	290	534	166604	1325	7421	979

(source: EM-DAT)

Table 4-7 Total natural disaster losses from 1997-2007

Natural Disaster Type	Total number of disasters	Total people affected	Total people killed	Total damage (US$ '000)
Drought	1	1080000	672	89000
Earthquake	35	4939893	173639	8652600
Epidemic	19	133650	2892	0
Flood	46	3009810	2568	1612900
Mass movement wet	26	332325	1065	115004
Storm	2	3715	4	0
Volcano	11	125845	3	0
Wildfire	7	34470	243	9315800
Total	145	9659708	181086	19785304

(source: EM-DAT)

Table 4-8 Persistence of household natural disaster shocks.

	No Disaster$_t$	Disaster$_t$	Total
No Disaster$_{t+1}$	6291 (88.56%)	813 (11.44%)	7104
Disaster$_{t+1}$	128 (83.12%)	26 (16.88%)	154
Total	6419 (88.44%)	839 (11.56%)	7258

Table 4-9 Summary statistics

Variable		Mean	Standard deviation	Minimum	Maximum	Observations	
	overall	6.22	(2.51)	2.00	22.00	N	10887
Household size	between		(2.34)	2.00	18.33	n	3629
	within		(0.91)	-1.45	13.55	T	3
Residential type	overall	0.55	(0.50)	0.00	1.00	N	10887
(= 0 urban = 1 rural)	between		(0.20)	0.00	1.00	n	3629
	within		(0.45)	-0.12	1.22	T	3
	overall	54.64	(16.02)	16.00	115.00	N	10887
Age, household head	between		(15.26)	24.33	104.33	n	3629
	within		(4.87)	23.64	84.98	T	3
Pensioners	overall	0.38	(0.49)	0.00	2.00	N	10887
	between		(0.14)	0.33	1.67	n	3629
	within		(0.47)	-0.62	1.38	T	3
	overall	0.01	(0.09)	0.00	1.00	N	10887
Natural disaster (Round 1)	between		(0.05)	0.00	0.33	n	3629
	within		(0.07)	-0.33	0.67	T	3
	overall	0.01	(0.08)	0.00	1.00	N	10887
Natural disaster (Round 2)	between		(0.05)	0.00	0.33	n	3629
	within		(0.07)	-0.33	0.67	T	3
Natural disaster (Round 3)	overall	0.07	(0.26)	0.00	1.00	N	10887
	between		(0.14)	0.00	0.33	n	3629
	within		(0.22)	-0.26	0.74	T	3
	overall	0.35	(0.48)	0.00	1.00	N	10887
Education: < primary	between		(0.33)	0.00	1.00	n	3629
	within		(0.35)	-0.32	1.02	T	3
	overall	0.20	(0.40)	0.00	1.00	N	10887
Education: primary	between		(0.26)	0.00	1.00	n	3629
	within		(0.30)	-0.47	0.87	T	3
	overall	0.00	(0.04)	0.00	1.00	N	10887
Education: secondary	between		(0.02)	0.00	0.33	n	3629
	within		(0.03)	-0.33	0.67	T	3
	overall	0.45	(0.50)	0.00	1.00	N	10887
Education: post-secondary	between		(0.30)	0.00	1.00	n	3629
	within		(0.40)	-0.22	1.11	T	3

Table 4-9 Summary statistics, continued

Variable		Mean	Standard deviation	Minimum	Maximum	Observations	
Housing quality	overall	0.94	(1.29)	0.00	20.36	N	10887
	between		(1.29)	0.00	20.36	n	3629
	within		(0.00)	0.94	0.94	T	3
Employed household head	overall	0.78	(0.41)	0.00	1.00	N	10887
	between		(0.20)	0.00	1.00	n	3629
	within		(0.36)	0.12	1.45	T	3
Sex household head	overall	0.34	(0.47)	0.00	1.00	N	10887
	between		(0.03)	0.00	0.67	n	3629
	within		(0.47)	-0.33	1.00	T	3
Savings(Rp)	overall	3.91E+07	(1.47 E+8)	0.00E+00	4.30E+09	N	10887
	between		(7.97 E+7)	0.00E+00	1.44E+09	n	3629
	within		(1.23 E+8)	-1.39E+09	2.90E+09	T	3
Homeowner	overall	0.89	(0.32)	0.00	1.00	N	10887
	between		(0.26)	0.00	1.00	n	3629
	within		(0.18)	0.22	1.55	T	3

Table 4-10 Correlates and breakdown of vulnerability in consumption

Average Value (in utils)	Vulnerability	=	Poverty	+	Aggregate Risk	+	Idiosyncratic Risk	+	Unexplained Risk
Variable	62.4***		24.81***		24.68***		0.2416***		12.95***
	[59.80, 64.90]		[22.30, 27.20]		[24.30, 25.90]		[0.22, 1.44]		[9.9, 14.8]
Disaster 92-97	0.47	**	0.39	**	0.06	***	-0.02	*	0.03
	(0.22)		(0.18)		(0.02)		(0.01)		(0.05)
Disaster 95-00	-0.18	*	-0.13	*	-0.02	**	0.00		-0.04
	(0.10)		(0.08)		(0.01)		(0.02)		(0.07)
Disaster 02-07	-0.03		-0.01		0.00		-0.02	***	0.00
	(0.03)		0.02		(0.00)		(4.64E-03)		(0.02)
Savings	-0.27	***	-0.22	***	-0.03	***	0.00		-0.02
	(0.03)		0.02		(0.00)		(0.00)		(0.02)
Animals	-0.21	***	-0.16	***	-0.02	***	0.01	***	-0.02
	(0.06)		(0.05)		(0.01)		(3.58E-03)		(0.02)
Own House	-0.01		-0.01		0.00		-0.01		0.04
	(0.03)		(0.02)		(0.00)		(0.01)		(0.05)
Pensioners	-0.16	***	-0.12	***	-0.02	***	0.00		-0.02
	(0.03)		(0.02)		(0.00)		(0.00)		(0.02)
Sex	-0.07	**	-0.06	**	-0.01	***	-0.01	**	0.00
(Female)	(0.03)		(0.02)		3.13E-03		(0.00)		(0.02)
Age	0.01	***	0.01	***	6.85E-04	***	0.00		0.00
	(0.00)		(2.62E-03)		(3.39E-04)		(0.00)		(0.00)
Age^2	0.00		-2.66E-05	*	-2.07E-06		5.41E-06	*	0.00
	(0.00)		(2.04E-05)		(2.64E-06)		(3.28E-06)		(0.00)
Ed, primary	-0.20	***	-0.17	***	-0.02	***	0.00		-0.02
	0.02		0.02		(0.00)		(0.00)		(0.02)
Ed, secondary	-0.19		-0.20	*	-0.03	*	*(dropped)*		*(dropped)*
	(0.14)		(0.12)		(0.02)				
Ed, post-sec.	-0.23	***	-0.20	***	-0.03	***	0.00		0.00
	(0.02)		(0.02)		(0.00)		(0.00)		(0.01)
Rural	-0.08	***	-0.06	***	-0.01	***	0.01	***	0.00
	(0.02)		(0.01)		1.82E-03		(2.97E-03)		(0.01)
Household size	0.10	***	0.09	***	0.01	***	0.00		0.01	**
	(3.12E-03)		(2.59E-03)		(0.00)		(0.00)		(2.29E-03)
Workers	0.01		0.01		0.00		0.00		0.00
	(0.01)		(0.01)		(0.00)		(0.00)		(0.01)
R^2	0.29		0.28		0.29		0.24		0.17

N=10886; n=3629. Regressions include regional dummies. Numbers in parenthesis are bootstrapped standard errors and those in brackets are 90% confidence intervals. *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, and * indicates significance at the 0.10 level.

Table 4-11 Head of household by residential type.

Head of Household	Observations	Mean		Standard Error	Standard Deviation	[95% Confidence Interval]	
Male	7237	0.53		(0.01)	0.50	0.52	0.54
Female	3650	0.59		(0.01)	0.49	0.58	0.61
Combined	10887	0.55		(0.00)	0.50	0.54	0.56
Difference in Means		-0.07	***	(0.01)		-0.09	-0.05

*** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, and * indicates significance at the 0.10 level.

Table 4-12 Indonesia's ranking in the Corruption Perception Index.

	Corruption Perception Index	
Year	Score	Ranking
1995	1.94	41/41
1996	2.65	45/54
1997	2.72	46/52
1998	2.00	80/85
1999	1.70	96/99
2000	1.70	85/90
2001	1.90	88/91
2002	1.90	96/102
2003	1.90	122/133
2004	2.00	133/145
2005	2.20	137/158
2006	2.40	130/163
2007	2.30	143/179

Source: Transparency International. Score related to perceptions of the degree to which corruption is seen by business persons and reported in surveys. A perfect 10.00 indicates a completely corruption-free country while a 1.00.

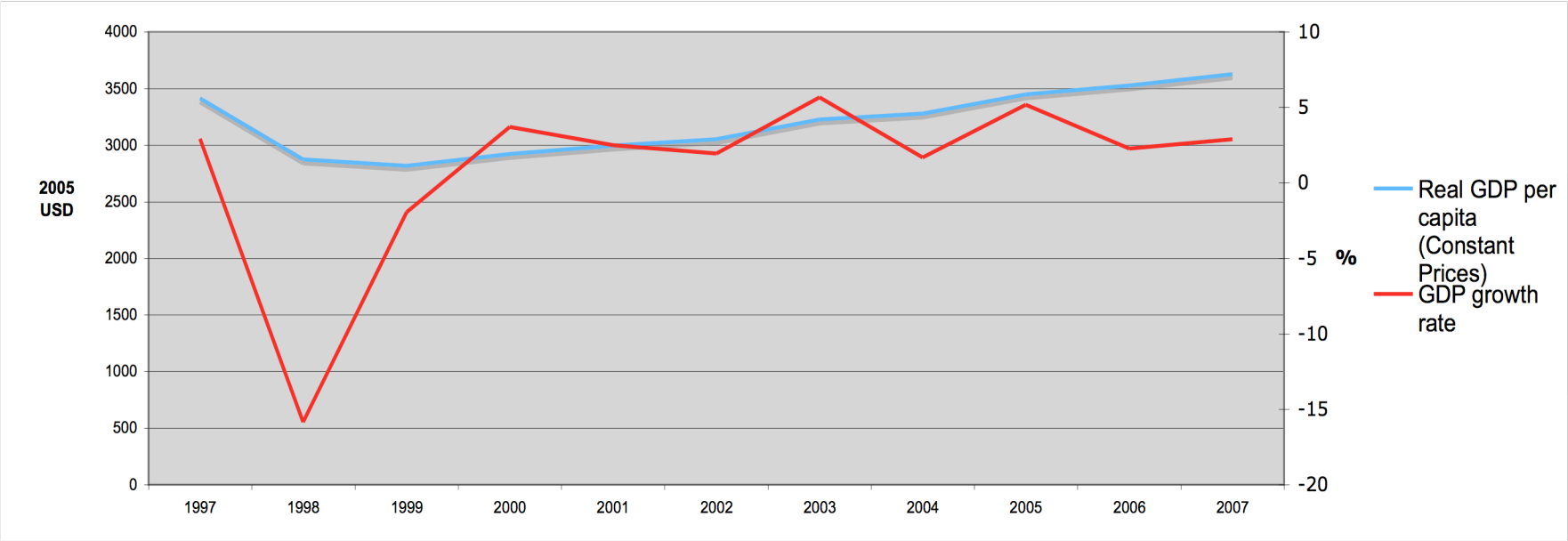

Figure 4-1. Per capita real gross domestic product (in 2005 USD) and real gross domestic product growth rate (source: World Penn Table)

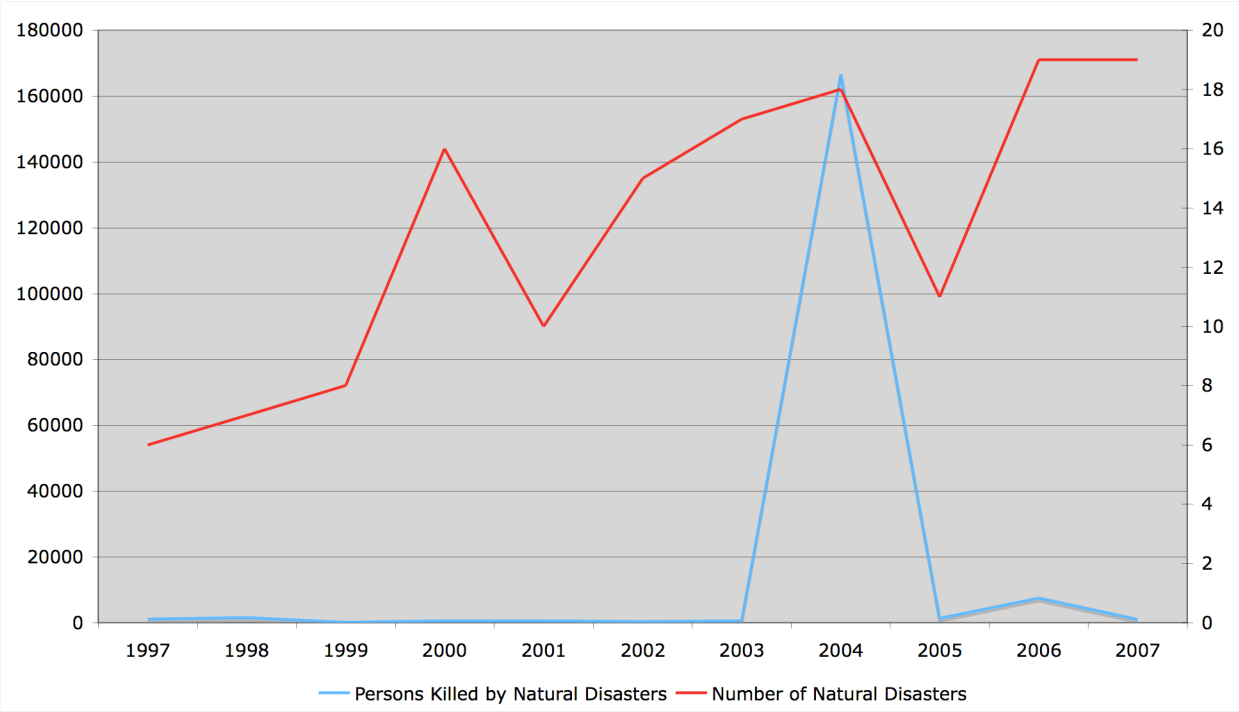

Figure 4-2. Number of persons killed annually by natural disasters and number of natural disasters (source: EM-DAT)

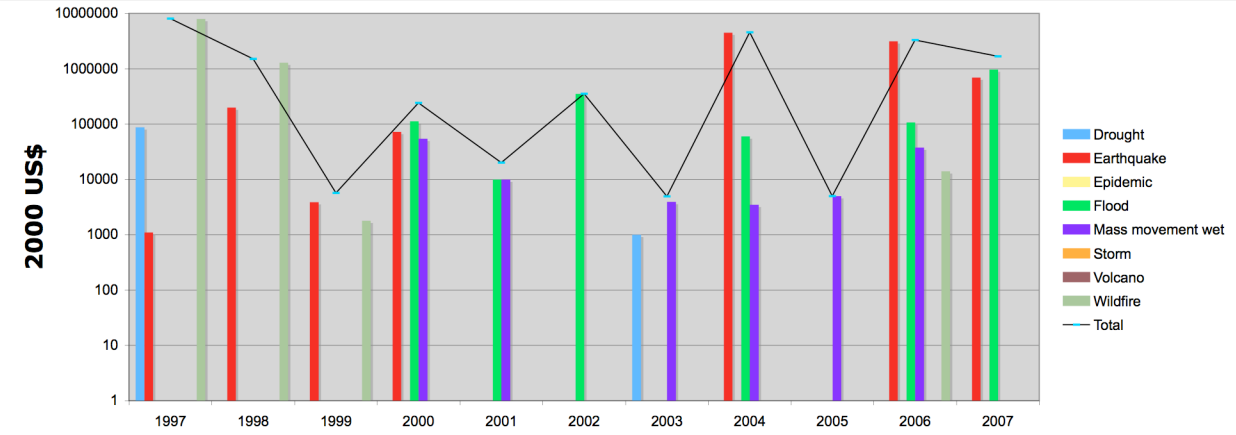

Figure 4-3. Annual financial losses, by natural disaster type (source: EM-DAT)

CHAPTER 5
SMALL ISLAND MACROECONOMIC VULNERABILITY TO NATURAL DISASTERS

This chapter explores natural disaster vulnerability across a panel of small islands in the Caribbean. Chapter 4 revealed aggregate risk as a significant contributor to future poverty rates on island nations. In small island developing states (SIDs), poverty rates are already undesirably high and economic development measures (for example, institutional strength) are undesirably low. Governments and individuals on SIDs seek economic improvement concomitant to coping with increased natural disaster risk. Yet, SIDs may demonstrate differences in natural disaster vulnerability because of the unique and unfavorable economic characteristics delineated in Chapter 2.

By estimating an existing macroeconomic risk model with a panel of SIDs experiencing increased weather hazard frequencies and low levels of economic development (for example, high poverty and low human capital levels), we specifically analyze how differences in economic development characteristics determine natural disaster vulnerability on small islands. SIDs are classified according to geographic and economic distinctions. It is these characteristics that make them especially vulnerable to natural disaster risk. Yet, this risk is not evenly distributed between SIDs, even within the same hazard risk region. This implies that economic conditions – not the weather hazard – determine vulnerability to natural disasters.

By analyzing an 18-year panel of SIDs in the same geographic hazard risk region yet with dissimilarities regarding their economic development, we contribute a deeper understanding of the effect of economic development on natural disaster vulnerability in SIDs to the economic vulnerability literature. This is an important contribution as global models only shallowly include a fixed effect representing the unique economic character

of SIDs but do not explore differences between SIDs, only noting that SIDs are different as compared to other economies.

Between 1970-2004, windstorms (hurricanes, cyclones, and tropical storms) and floods accounted for over 90% of the total economic costs of weather-related events worldwide (Kunreuther, 2010). The Caribbean has experienced an increase in windstorm events (increased risk), with SIDs paying the cost of this increased risk through increased financial and human disaster losses. In our 18-year analysis, we estimate a backward-looking measure towards understanding the determinants of natural disaster vulnerability (measured in disaster deaths). By controlling for strength of a hazard and geographic risk (high likeliness of events), we find natural disaster vulnerability is (partially) explained through economic development characteristics (for example, low wealth and resource levels). Urbanization and infrastructure investments demonstrate perverse implications on a small island's probability of experiencing disaster losses as the spatial distribution of resources at risk to natural disasters matters. This may imply that infrastructure investments are not diminishing natural disaster risk for their citizens. It may also imply that concentrating resources and investments in risk prone areas increases natural disaster vulnerability, as motivated in Chapter 2. It also contributes further evidence that natural disaster vulnerability is not evenly distributed; rather, natural disaster vulnerability is skewed disproportionately to the poverty-stricken with long-term implications on welfare trajectories. While economic characteristics (poverty and risk) determine vulnerability, increased vulnerability to natural disasters deteriorates these already-depressed economic measures by incurring greater losses from the increased risk.

Our findings reveal nuances in the relationship between economic development, population density and vulnerability for economically disadvantaged communities. The findings are edifications regarding economic impacts of frequent and increasing hazard events in a sample of especially vulnerable persons and environments to natural disasters: persons in poverty on island nations. As hazard frequencies increase, coping with repeated hazards becomes untenable for persons without access to adequate resource levels and at the aggregate level, erodes economic development progress (for example, infrastructure investments).

Small Island Developing States of the Caribbean

Geography is a significant determinant of disaster vulnerability (Kellenberg and Mobarak, 2008; Anbarci, et al., 2005; Briguglio et al., 2006; Kahn, 2005; and Gallup et al., 1999). With higher relative exposure, the SIDs of the Caribbean are especially vulnerable to weather hazards from their coastal extent, petite scale, and geographic location within a high risk region for extreme windstorm (tropical cyclone) events (see Figure 5-1).

In Chapter 2, the unique economic characteristics of SIDs were presented within the context of natural disaster risk. As these states face higher geographic and economic risk to natural disasters (for example, smaller scale, limited resource base and trade dependencies), they suffer differently from natural disasters compared to larger economies. The 13 SIDs sampled share the usual characteristics of SIDS, yet with individual distinctions. The political geography of the SIDs in the Caribbean is highly complex, exemplified by numerous languages and ethnicities, differences in territorial status, and the economic isolation of Cuba.

SIDS from the Leeward Islands include Antigua and Barbuda and St. Kitts and Nevis. Grenada, St. Lucia, St. Vincent and the Grenadines, and Trinidad and Tobago are located in the Windward Islands. The Netherlands Antilles (Aruba, Bonaire and Curaçao) is in the Leeward Antilles region. The Bahamas are in the region known as the Lucayan Archipelago. Cuba, Dominican Republic, Haiti, Jamaica and Puerto Rico are in the Greater Antilles. The island of Hispaniola is home to both Haiti and Dominican Republic, who a share a border. The Greater Antilles region is the most disaster prone area in the Caribbean (UNSD, 2009).

The sovereign states sampled include Antigua and Barbuda, Bahamas, Cuba, Dominican Republic, Haiti, Grenada, Jamaica, Puerto Rico, Saint Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, and Trinidad and Tobago. Non-sovereign territories include the Netherlands Antilles (Kingdom of the Netherlands) and Puerto Rico (United States Commonwealth). The political evolution of the Caribbean SIDS includes colonized histories for many of the sampled nations, with some still having colony or dependent territory status, and some whom were colonized more than once. The former British colonies (Anglophone Caribbean) sampled include: Antigua and Barbuda, Bahamas, Grenada, Jamaica, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, and Trinidad and Tobago. The former Francophone colonies sampled include: Grenada, Haiti, St. Lucia, St. Vincent and the Grenadines, (and briefly Antigua and Barbuda, Dominican Republic, Tobago). The former Spanish colonies include: Cuba, Dominican Republic, Haiti (until 1609), Jamaica (until 1655) and Puerto Rico. In addition to European colonization, this region has strong historical connections to slavery.

Geography

SIDs from the Leeward Islands include Antigua and Barbuda and St. Kitts and Nevis. Grenada, St. Lucia, St. Vincent and the Grenadines, and Trinidad and Tobago are located in the Windward Islands. The Netherlands Antilles (Aruba, Bonaire and Curaçao) are in the Leeward Antilles region. The Bahamas are in the region known as the Lucayan Archipelago. Cuba, Dominican Republic, Haiti, Jamaica and Puerto Rico are in the Greater Antilles. The island of Hispaniola is home to both Haiti and Dominican Republic, who a share a border. The Greater Antilles region is the most disaster prone area in the Caribbean (UNSD, 2009).

The persons sampled are the most vulnerable to natural disaster risk. First, they are in the zone of high natural hazard risk (Figure 5-1; Munich Re, 2010). Second, they experience depressed economic development levels. And third, they live on island nations. (The latter two define the unique characteristics of SIDs). Vulnerability cannot be explained by exposure to natural hazards alone: the sampled nations experience similar hazard risk but dissimilar disaster frequencies over the time period studied (see Table 5-1) , motivating our investigation into the determinants of a weather hazard matriculating to a natural disaster. Presently, small island nations of the Caribbean suffer average annual disaster losses of $3B USD (Alleyne, 2010). These losses cause disruptions to numerous economic development links, such as human capital and infrastructure.

Persons living in various SIDs of the Caribbean illustrate the nuanced relationship between disaster vulnerability and its determinants. Although they experience similar geographic and physical risk, they experience dissimilar frequencies of disasters (see Figure 5-2). For example, persons on Cuba and Haiti suffer the greatest number of

natural disaster frequencies. These countries also experience differences in losses from natural disasters with individuals in the Dominican Republic and Haiti experiencing the greatest number of natural disaster-related deaths (see Figure 5-3). Due to data scarcity on many explanatory variables, the estimated balanced panel followed the 13 countries for 18 years (t=1983-2000)[39].

The complete data set represents an unbalanced[40] panel of 13 SIDs (Antigua & Barbuda, Bahamas, Cuba, Dominican Republic, Grenada, Haiti, Jamaica, Netherlands Antilles, Puerto Rico, St. Kitts & Nevis, St. Lucia, St. Vincent & the Grenadines, and Trinidad & Tobago; n=13) over 31 years (t=1970-2000). Table 5.2 describes the variables used in the regression.

Weather Hazards and Natural Disasters

The central source of disaster data, used in this and many other disaster vulnerability studies (for example, Kahn, 2005; Anbarci et al., 2005; Kellenberg and Mobarak, 2007), is the Emergency Management Database (EM-DAT) from the Centre for Research on the Epidemiology of Disasters (CRED). It is the most comprehensive, publicly available disaster database. EM-DAT data is self-reported by countries. Using data from EM-DAT, country-level measures of vulnerability aggregated by year are constructed. We follow previous studies using the dependent variable of persons killed (DEAD) (Kellenberg and Mobarak 2008; Anbarci, et al. 2005; Kahn 2005) as our measure of vulnerability. Table 5.3 presents summary statistics for the estimated sample.

[39] Grenada was dropped from final estimation due to zero disaster occurrence.

[40] The unbalanced sample includes observations for lagged variables from 1970 – 2000; due to data limitations in some explanatory variables, the estimated balanced panel has observations from 1983 – 2000 over 13 countries.

For the complete data set of 160 natural disasters causing total financial losses of $14,077,731 USD from 1970-2000, there were 81 windstorm (hurricane and tropical storm) disasters causing financial losses of $13,333,201 USD, 52 flood disasters causing $556,530 USD in financial losses, 1 earthquake and 1 volcano causing no financial losses, and 11 droughts with only 2 having financial losses reported. Examining deaths as the dependent variable (as used in peer studies), there were a total of 3765 deaths resulting from 81 windstorms (hurricanes and tropical storms), 1264 deaths from 60 floods, 2 deaths from 3 volcanoes, 1 death from 2 earthquakes, and none resulting from the 14 droughts. The final estimated sample suffered 139 natural disasters resulting in 3064 total deaths: 12 droughts, 2 earthquakes, 6 epidemics, 53 floods, 62 windstorms, 1 volcano and 3 wildfires (see Table 5.4).

To illustrate the increase in weather hazards concluded by the scientific community (NOAA, 2008; IPCC, 2007), we examine the raw data on extreme windstorms (tropical cyclones, also known as tropical depressions, tropical storms and hurricanes) in this area. Using spatial data was from NOAA, landfall[41] extreme windstorm events (tropical cyclones attaining the classification of tropical storm or hurricane) for the 13 sampled nations are presented in Figure 5-4. This figure documents the increase in frequency of these hazards with the black 5-year moving average trend line. Over the sampled timeframe, the SIDS in our study experienced 125 tropical cyclone hazards (80 between 1983-2000) manifesting into 81 (62 between 1983-2000) natural disasters. Otherwise stated, approximately 65% of these hazards

[41] We define landfall in symmetry with NOAA as events within 60 nautical miles (approximately 69 miles) of the island.

caused losses exceeding the disaster threshold[42] between 1970-2000 and more narrowly, 77.5% of the windstorm hazards between 1983-2000 caused losses sufficient to classify the hazard as a natural disaster. We are interested in the determinants of a hazard matriculating to a disaster, as 35% (22.5%) of these hazards did not manifest into disaster losses implying the potential for averting disasters. As averting disaster may be related to the strength of the hazard, we control for disaster magnitude in the economic model.

Economic models of natural disaster vulnerability give considerable attention to the magnitude of a shock (Noy, 2009; Anbarci et al., 2005). Noy (2009) concluded the magnitude of disaster impact was greatest on small islands, as compared to other economies, measuring magnitude as both percentage of population killed by a disaster and financial losses as a percentage of gross national product. Larger countries, such as the United States or Brazil, may be able to internally insure against natural disasters, a small island cannot[43]. We examined numerous measures of natural disaster magnitude (as examples, windstorm strength and earthquake magnitude), but most are insignificant affirming our suspicions about the disposition of natural disasters on SIDs. Hazard characteristics account for a magnitude and several measures of hazard characteristics, including windstorm maximum wind speed, minimum pressure, and category and earthquake magnitude were examined; due to insignificance, all hazard

[42] Recall from chapter 2 that a weather hazard matriculates to a natural disaster based on losses exceeding the disaster threshold. This threshold is defined as 10 or more dead persons, 100 or more affected persons or significant financial damage.

[43] For example, consider the impact of Hurricane Katrina on the US economy: economic losses were approximately $125B USD with $66B of the losses insured GDP growth slowed in 2005 between quarter 3 (3.8%) and quarter 4 (1.8%) but bounced back in quarter 1 of 2006 to 1% above quarter 3 (4.8%) (Bureau of Economic Analysis, 2006).

characteristics were dropped from the final estimated model with the exception of a dummy variable indicating if a windstorm was category 4 or 5[44].

Macroeconomic Determinants

We include numerous macroeconomic controls, including exposure and economic development characteristics such as income and urbanization.

Exposure. Exposure is measured as total persons at risk to the hazard event, as increased persons at risk to a disaster may increase vulnerability. The number of persons at risk to a disaster (POP) was collected from the Penn World Table and is lagged by one year to represent populations at risk in the year of the disaster[45] (for other applications of lags applied to independent variables see Dercon and Krishnan (2000) or Dasgupta and Mäler (1995)). Figure 5-5 demonstrates that countries within our sample are quite constrained by their slight surface area. Hence, positive relationship between POP and vulnerability is anticipated. To account for the petite scale of small islands, we use population density $\left(\frac{POP_{it-1}}{SURFACE\_AREA_i}\right)$ as our measure of population and in symmetry with Kahn (2005). A positive relationship between population density and vulnerability is expected, as per capita resource levels wane with higher population densities.

Income. Turning to measures of capacity to respond to shocks, a number of economic measures from the Penn World Tables and the World Bank are used. To

[44] See Table 5.6 for detail on the robustness checks performed for event characteristics and other variable specifications.

[45] If POP_{it} was used the population would include persons who were not present at the time of the disaster; for example, persons killed by the disaster or persons who subsequently migrated out of the country post-disaster.

account for the lag between procuring increased income and subsequent consumption, we employ a t-1 lag on economic development variables (GDP, DA and TELE). To account for potential effects of income available at the individual and country level, affording increased abatement options, we include per-capita income (GDP) and official development and disaster assistance (DA). Countries with higher incomes (ceteris paribus) are expected to be less vulnerable to suffering disaster losses.

Disaster aid. We importantly include official disaster aid as a measure of formal, external transfers. It is expected that DA is related to disaster vulnerability: disaster assistance is received in response to especially devastating disasters and media attention. It is well documented that disaster assistance is not equitably distributed, often excluding those needing aid the most and incurring unintended consequences such as food aid dependency (Barrett, 2001) and while we expect a relationship between natural disaster vulnerability and official disaster assistance, we do not interpret these results as fodder for economic development policy and are ambiguous about the expected sign of the relationship.

Institutional strength. We use infrastructure investments as our proxy for institutional strength. Institutions and infrastructure are strongly correlated (see Figures 5-6 and 5-7)[46]. Infrastructure investment is measured using fixed-line teledensity: the number of telephone lines per 100 persons (TELE). This data was obtained from the World Development Indicators. The data was not available for the full panel and the final panel estimated suffered the loss of twelve years. While previous studies have used this proxy (Reece and Sam, 2010), it is no longer used in modern cellular phone times.

[46] However, disaster losses and infrastructure investments are not correlated (less than 5% of the TELE heterogeneity is explained by our vulnerability measure).

However the timing of this panel admits its relevance. Increased infrastructure investments are expected to decrease vulnerability, yet perverse implications of investment are increased resources at risk and this may be especially true in risk-prone areas. Related to the natural disaster case, infrastructure investments are aimed at protecting citizens (for example, a levee to protect from flooding). Yet these investments may not guarantee protection against natural disaster risk in economies with weak institutions (for example, high levels of corruption or weak democracy).

Other proxies[47] for institutional strength were disregarded due to data limitations for SIDS, including the World Bank's Corruption or Democracy Index, the gini-coefficient, the World Bank measure of trade openness and Acemoglu et al.'s (2002) settler mortality. We specifically investigated trade openness [(Exports-Imports)/Gross National Product] but the nature of SIDS – net importers with small gross national products – offered slight heterogeneity across countries and time; in fact, for many countries and years, the value for trade openness was negative[48]. TELE is expected to have a positive relationship with disaster vulnerability as greater infrastructure investments portend greater resources at risk in very risky areas. While all countries experienced growing infrastructure investments over the timeframe, Puerto Rico had the greatest infrastructure investments, distantly followed by the Dominican Republic and Cuba, respectively.

Urbanization. The persons living on SIDS do not have the luxury to migrate within the country to a less hazard-prone geography due to the small size of islands and

[47] As examples, paved roads, the Gini-coefficient and the Democracy Index were examined yet disregarded due to missing data for most years and countries sampled.

[48] See Table 5.7 for robustness checks on explanatory variable specifications.

the overall proneness to hazards. Increasing numbers of urbanized areas on these small islands represent per-capita deteriorations of numerous self-insurance-type of risk abatement options as afforded in rural areas (for example, agriculture and other natural-resource based sectors). Conversely, rural dwellers do not have access to infrastructure (Ravallion and Lokshin, 2010). Yet it has been assumed that urbanites have greater assets (physical, financial, or labor) compared to their rural peers; poor urban areas do not offer these increased provisions. We expect urbanization in poor communities increases disaster vulnerability.

Urbanized areas (URB) were created using spatial decadal[49] data from the Center for International Tropical Agriculture (CIAT) for d = 1960, 1970, 1980, 1990, and 2000, since historical data on urban areas is not available for this region in the timeframe. The raw data was obtained in raster format and adjusted within ArcGIS to identify urban areas. The coarse resolution[50] compounded with the small size of the islands prohibited other more granular methods to generate the urban variable. Urban areas were identified as continuous grid cells with in the upper 75% of the quartile population distribution, relative to the median value in the data set[51]. As example, Figure 5-5 presents the urbanized areas from 2000, denoted in red.

Economic Model of Macroeconomic Disaster Vulnerability

Vulnerability assessments are predictions accounting for the potential effects of hazardous events with explicit assumptions regarding the nature of natural hazards and

[49] CIAT estimated population densities ex-post based upon census data collected between 1996 – 2003.

[50] Each grid cell was 1955 hectares, or 193 km^2.

[51] Numerous census definitions of urban were explored; quantitative definitions failed from the aggregation level of the data and magnitude of the grid cells.

social systems at risk. Whereas in the previous chapter we conceptualized vulnerability as the difference, in utils, between a household consumption at the population-relative poverty line (U(z)) and at their expected utility from their expected consumption (EU(c)), we now conceive vulnerability as an aggregate, country-level measure. Rather than conceiving z as a poverty threshold amount of consumption, we conceive z as a threshold level of loss from a natural disaster – what we will refer to as the disaster line to intentionally evoke comparisons with the poverty line. We measure disaster losses in human deaths and define the disaster threshold as 10 or more deaths from one hazard event in accordance with EM-DAT and existing literature. Our utility measure becomes a measure of disutility and we can write

$$V = -U(z) + EU(c) \tag{5-1}$$

If we set z equal to 0 (implying no deaths from a hazard event), -U(z) is zero and reflects utility loss as the main criteria of a weather hazard matriculating to a disaster. Therefore, V is equal to the expected disutility from the number of disaster deaths, for which the actual number of deaths from a disaster is the best proxy. While the LS measure is not appropriate at the aggregate level (due to aggregate utility not being well defined), we do build upon their measure reflecting the two main components of vulnerability: poverty and exposure to risk. From this, we hearken the importance of controlling for variables influencing poverty, the means to cope with natural hazards (for example, gross domestic product), as well as variables reflecting natural hazard exposure (for example, population and resources) and other relevant controls.

The relationship between disaster vulnerability and its components may expressed as:

$$
\begin{aligned}
y_{it} = \beta_1 \ln(POPDEN_{it-1}) + \beta_2 \ln\left(GDP_{it-1}\right) + \beta_3 \ln\left[\left(GDP_{it-1}\right)^2\right] + \beta_4 \ln(URB_{id}) \\
+\beta_5 \ln\left(DA_{it-1}\right) + \beta_6 \ln(TELE_{it-1}) + \beta_7 (Windstorm\_Dummy_{it}) \\
+\beta_8 (Flood\_Dummy_{it}) + \beta_9 (Drought\_Dummy_{it}) + \beta_{10} (Earthquake\_Dummy_{it}) \\
+\beta_{11} (Category_{it}) + e_{it}
\end{aligned}
\tag{5-2}
$$

The observable y (persons killed by natural disasters in country *i* in year *t*) is used as the dependent vulnerability variable in the reduced-form model, which determines vulnerability to a disaster as a function the recipient economic and hazard (as defined in Chapter 2) characteristics. As done in previous studies, a hazard is classified as a disaster if losses exceed the established threshold of 10 or more people killed, 100 or more people affected (injured or displaced), significant damage, declaration of state of emergency and/or appeal for international assistance. As seen in Table 5.4**,** nearly 80% of countries with zero natural disasters staved off disasters the following year (20% suffered one or more natural disaster the following year) whereas 36.5% of countries suffering one natural disaster suffered another the following year. This suggests countries suffering a natural disaster are more prone to suffering a subsequent natural disaster; better stated, there is evidence of disaster persistence.

Estimating Natural Disaster Vulnerability

Our vulnerability proxy is limited by attenuation at zero, large outliers and excess zeros, rendering conditional mean estimators, such as ordinary least squares, inconsistent and biased (Cameron and Trivedi, 1998). Within the econometric literature, this limited dependent variable is referred to as a count variable.

Linear Estimating Methodology

Some accommodate this limited dependent variable by transforming it to ln (1+y). The detriment of this transformation is continuing to assume the errors are independent

and identically distributed with a mean of 0. As discrete data do not often follow the underlying assumptions of normality, transformations do not usually yield normally distributed data, limiting coefficient interpretation because they are not based on their original scale.

The least squares fixed effect model (LSDV) allows for individual specific constants to capture unobserved characteristics yet does not account for the limited nature of the dependent variable. The LSDV estimates rely on distributional assumptions for the dependent variable[52] and normality of the error term; this violation renders maximum likelihood estimators inconsistent. The panel-wise heteroskedasticity evidences that our errors are not independently and identically distributed across individual observations, but rather across panel-groups (countries). Panel-specific robust standard errors may be employed to accommodate this but would still not compensate for the limited nature of the dependent variable.

Count Data Methodology

Econometric methods for count data allow dependent variables to be discrete proxies for unobserved continuous variables (Cameron and Trivedi, 2001) and are the best empirical models to describe the theoretical model aforementioned. The strong assumption of equidispersion[53] of the Poisson estimator is not satisfied for this data set. The summary statistics (Table 5.3) revealed potential overdispersion (conditional variance exceeding conditional mean), confirmed with a test estimating α, a dispersion

[52] The dependent variable takes only non-negative integer values, thus the assumption that ε_{it} with a continuous y has a continuous PDF is not valid here as E[y|x] may lie outside of the probability lower bound of 0; as such, LSDV is not appropriate.

[53] Equidispersion refers to the conditional mean equaling the conditional variance, something that rarely occurs in real data (Hilbe, 2007) and does not hold for our disaster data sets: $E[\lambda_{it}] = Var[\lambda_{it}] = \exp(x_{it}\beta)$

parameter (Cameron and Trivedi, 2005)[54]. For this dataset, α was estimated to be 27.01 (see Figure 5-8). Overdispersion may be caused by positive correlation between responses, excess variation between response counts, or violations in the distributional assumptions of the data; the consequence of unattended overdispersion includes underestimated standard errors, wrongly appearing as a significant predictors (Hilbe, 2007, 51).

Overdispersion is commonplace in datasets having excess zeros which arise when there are two processes generating a zero count in the dependent variable: a zero count of persons killed from a non-zero count of disasters and a zero count of persons killed from a zero count of natural disasters. The negative binomial (NB) mixture estimator has earned strong favor for empirical research with disaster datasets (Kahn, 2005; Kellenberg and Mobarak, 2007) and is the selected estimator for this research.

To account for this additional source of heterogeneity, we specify the underlying probability distribution function as the Negative Binomial and include conditional fixed effects. A panel fixed effect refers to an effect that is does not vary across individuals units of time (time fixed effect) or space (country fixed effect). For example, a country fixed effect refers to a time-invariant effect of living specifically in that country; the effect is the same for all individuals within that country, but differs by country[55]. It accounts for the unobservable but significant effect of living in that country. Econometrically, the fixed effect allows for a panel-level (for example, country) intercept.

---

[54] Using information from the Poisson regression, $\frac{(y_{it} - \hat{y}_{it})^2 - y_{it}}{\hat{y}_{it}} = \alpha + \mu_{it}$ was computed where $\hat{y}_{it}$ are the fitted values from the Poisson regression.

[55] Similarly, if it were a time fixed-effect, it would be the country-invariant effect of that specific year.

In the negative binomial approach, the fixed effect (ζ_I,) is different. It represents the overdispersion parameter -- rather than a panel fixed effect -- allowed to take any value[56]. Therefore, the negative binomial fixed effect models the level of overdispersion through the fixed effect parameter. The conditional fixed effects model is derived by conditioning out the individual fixed effects (heterogeneity parameter) from the estimated parameters ($\eta_i = x_{it}\beta + \varsigma_i$ for each *i*) and conditioning on the sum of the responses within each panel, $\sum y_{it}$ (Hilbe, 2007).

The negative binomial model is specified as:

$$\Pr(y_{it}) = f(y_{it}) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(1+y_{it})}\left(\frac{1}{1+\varsigma_i}\right)^{\lambda_{it}}\left(\frac{\varsigma_i}{1+\varsigma_i}\right)^{y_{it}} \tag{5-3}$$

with mean $$E[y_{it} \mid \varsigma_i] = \lambda_{it}\varsigma_i \tag{5-4}$$

and variance $$Var[y_{it} \mid \varsigma_i] = \lambda_{it}(\varsigma_i + \varsigma_i^2) \tag{5-5}$$

Equations 5-4 and 5-5 reflect the log of the conditional mean is linear in parameters: ln $E[y_{it}|x_{it}]=x_{it}\beta$ (also referred to as a log-linear model) and the overdispersed nature of our dataset necessitating conditioning on the estimated dispersion parameter, ς_i.

The dispersion fixed effect, or all terms involving ζ_I, is conditioned out of the estimated equation, resulting in the final estimating equation:

$$\Pr(y_{it}) = f(y_{it},.....y_{iT} \mid \sum_t y_{it}) = \frac{\Gamma(\sum \lambda_{it})\Gamma(\sum y_{it}+1)}{\Gamma(\sum \lambda_{it} + \sum y_{it})}\prod_t \frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)} \tag{5-6}$$

accounting for the within group correlations (and does not assume independence of

[56] Follows from the use of a conditional likelihood, resulting in the dispersion parameter dropping out of the estimation.

observations within clusters). Equation 5-6 states that the probability of disaster loss is a function of the mean (log λ_{it}) and is estimated 5-6 using maximum likelihood.

Table 5-5 reports parameter estimates from the negative binomial regression and Table 5-6 reports the incident rate ratios. The interpretation is not direct; to illustrate, let κ represent a specific predictor variable: the estimated β coefficients are difference between the log of expected count at a one-unit increase (log κ_{x+1}) and the log of the expected count (log κ_x); as the difference between two logs is also the log of the quotient, the parameter estimate may also be expressed as log (κ_{x+1}/κ_x). These parameter estimates are used to calculate incidence rate ratios, obtained by exponentiation of the regression coefficients (exp[β]), expressed as 100*(exp[β]-1) or the percentage change in the incidence of disaster death for each unit increase in the independent variable.

Empirical Results

The negative binomial model predicting the number of deaths caused by a natural disaster from the set of macroeconomic explanatory variables was statistically significant at the $p<0.001$ level[57]. We discuss the results using incidence rate ratios below for ease of discussion and interpretation: for a one-unit increase in the explanatory variable in discussion, holding others constant, the rate for natural disaster deaths would be expected to increase (negative parameter estimate) or decrease (positive parameter estimate) by a factor of the coefficient.

[57] Chi-squared = 144.07 and log-likelihood = -214.52.

Natural disaster risk and human behavioral choices are linked. Increasing income has a negative effect on natural disaster losses (disaster deaths increase as income increases), but this effect wanes with increasing levels of income. Our finding that income takes a non-linear shape is expected, as we have enough income variability in the sample, and consistent with existing findings from vulnerability studies using deaths as the dependent variable (Kellenberg and Mobarak, 2007; Strömberg, 2007). For a one-unit increase in log per-capita income, disaster deaths are expected to increase by a factor of 1.26e+17. As increased income at the per-capita level offers increased consumption of smoothing mechanisms, the positive relationship between increasing income and disaster risk reaches a watershed point whereby the relationship between per-capita income and disaster deaths begins to wane in magnitude. The point at which additional income (in logarithmic terms) becomes decreasingly positive in natural disaster deaths is estimated at 34.51 US$, well above the mean (8.88) and range of income within this dataset ([7.44, 10.00]). Countries in our sample have not attained the per-capita income levels to deteriorate the positive relationship between disaster deaths and income. Increased income affords micro-level behavioral responses, which alter risk[58]. For this dataset, a one-unit increase in the log of GDP, disaster deaths are predicted to increase by 66 persons and for a one-unit increase in GDP-squared, disaster deaths are predicted to decrease by 33 persons. Both parameters are significant at the 10% level.

[58] For example, an individual lives in a rural mud hut and experiences increased income sufficient to afford moving to an urban area. The increased income though is only enough to afford living in an urban slum with inferior housing materials. This residential location decision has increased risk compared to the former dwelling. As time goes on, the individual's income continues to increase such that they can afford better housing materials (say concrete walls) and their risk then decreases.

Among this panel of SIDS, population density was not a significant determinant of disaster vulnerability as the islands have similar surface areas and population levels. Yet urbanization was a positive, significant (at the 10% level) determinant of disaster vulnerability. This dissonance is worth further exploration. Population density and urbanization, as defined herein, demonstrate that the pattern of population density matters and portends the per-capita availability of smoothing mechanisms. Islands with greater numbers of urban areas (areas of dense populations) suffer greater disaster deaths, ceteris paribus; for a one-unit increase in the number of urban areas within a country, disaster losses are expected to increase by a factor of 1.95. It is especially important that these small islands proactively plan their urbanization towards diminishing disaster vulnerability. The spatial distribution of population (see Figure 5-5) is more significant in determining disaster vulnerability compared to just an aggregate measure of population density.

According to the UNSD (2009), SIDS economic development is stymied by their disproportionately expensive infrastructure and little opportunity to create economies of scale (a result of their small size). Infrastructure investments herald increased resources at risk. A one-unit increase in the number of telephone lines per 100 persons (TELE) increases expected disaster losses by a factor of 1.07. While this is a perverse implication of governments investing in infrastructure, the results do not support diminishing investments. Rather, infrastructure investments should be disaster-hardened, as made clear by recent disaster events in Japan with out-dated utility infrastructure increasing vulnerability to the 2011 earthquake and tsunami, escalating to

a tertiary nuclear disaster and the United States' experience with Hurricane Katrina in 2005 where infrastructure failures caused a secondary flooding disaster.

Disaster assistance (DA) was not significant, affirming the results that low-income countries, such as the countries in this sample, have characteristics limiting the effectiveness of disaster relief (Collier and Dollar, 2002). It has also been documented that aid has distributional inequities, often not reaching those most needing aid (Barrett, 2001). Our results suggest that disaster aid is not effective in reducing future probabilities of experiencing natural disaster losses.

Country fixed effects contribute to existing empirical evidence regarding the deterministic role of the geography to human vulnerability. The between-country heterogeneity was estimated through country fixed-effects, accounting for unobservables at the country-level. Time fixed-effects were estimated using a measure of accumulated cyclone energy (ACE). ACE indicates the strength of a hurricane season, also accounting for climactic impacts of El Niño and La Niña. For a one-unit increase in ACE, the number of disaster deaths decreases by a factor of 0.99. Stemming from the assumption of rational expectations, we find a significant (at the 1% level) negative relationship between disaster deaths and ACE as information regarding El Niño and La Niña impacts are widely dispersed and enhance expectations for extreme weather hazards. For example, more windstorm events are expected during El Niño and individuals and governments respond to these expectations with ex-ante disaster-mitigating provisions such as windstorm advisories, evacuation plans and preparedness provisions (candles, canned goods, etc).

To control for natural disasters by type, the final model included dummy variables for the disaster types windstorm, flood, drought, and earthquake[59]. Windstorms and floods were statistically significant (at the 0.001 level): a country experiencing a windstorm disaster (dummy equals 1 in time *t*) is predicted to suffer an increase in disaster deaths by a factor of 8.6. A country experiencing a flood disaster (dummy equals 1 in time *t*) is predicted to suffer an increase in disaster deaths by a factor of 7.91.

The Caribbean is the second greatest risk area for tropical cyclones with documented scientific increases in these event frequencies (NOAA, 2008; Kunreuther, 2010). We explored numerous controls on strength of windstorm hazard events, including hurricane category, barometric pressure and maximum sustained wind speed (see Table 5.4); the final model uses a dummy variable to indicate if a windstorm hazard was a category 4 or category 5 event[60]. A country experiencing a windstorm hazard as a strong hurricane, as captured by category encompassing both wind speed and barometric pressure, is predicted to suffer an increase in disaster deaths by a factor of 2.31.

Concluding Remarks

Differences in population levels do not explain vulnerability to natural disasters and increased income increases vulnerability (GDP is positively correlated), positing urban areas - agglomerations of human and financial resources - as especially important to

[59] Initial model used all disaster types, including wildfires, epidemics and volcanoes, which were insignificant and subsequently dropped from the final estimated model, which was robust to this specification.

[60] We do not include controls on other forms of weather hazards due data limitations on other types of hazards that do not manifest into disasters (for example, a drought) or the hazard event manifests to a natural disaster on each occurrence (for example, earthquakes and volcanoes).

investigate in developing countries in that provisions of increased market access often assumed in developed countries (for example, access to labor and housing markets) do not hold.

This research explored country-level differences in disaster losses from hurricanes across countries in the Caribbean , the second most hazard-prone region globally (Munich Re, 2010). As abatement and internal migration options may be limited by the small size of SIDS, there are different determinants of vulnerability to natural disasters in SIDS than previously identified by larger and non-regional studies, affirming the relevance and necessity of regional and sub-population studies.

Empirical evidence is offered to ameliorate the hypothesis that economic development and vulnerability reduction are not always complementary. Rather, urbanization may support deterring or incurring secondary effects of disasters, such as famine and disease outbreak, depending on access to public goods provided in the local area from per-capita income and self-insurance mechanisms. Urban areas increase vulnerability of poverty-stricken communities due to limited (or non-existent) formal and self-insurance options and market failures (for example, labor or housing market failures).

Under increased population densities, small islands quickly face binding size limitations and suffer diminished per-capita resources from sustained population increases. The isolated, high-risk geography of SIDS in the Caribbean exacerbate the scale of a natural disaster shock, rendering many risk-pooling local mechanisms ineffective; disaster assistance flows were also shown to be ineffective in this study. In an environment of increasing weather hazards and resources at risk, it is imperative to

understand the determinants of natural disaster vulnerability towards future loss mitigation. Importantly, disaster-thwarting policies must consider perverse implications of economic development measures, such as per-capita income, and infrastructure investments interacting with increased population densities.

Table 5-1 Natural disaster losses in sampled countries, 1983- 2000

Country	Total Disasters	Total Affected	Total Killed	Total damage (US$ '000)
Antigua and Barbuda	7	94714	8	530000
Bahamas	5	1700	5	700400
Cuba	35	3E+06	131	3499558
Dominican Republic	17	2E+06	490	2005200
Grenada	2	1210	0	5500
Haiti	27	4E+06	1700	321386
Jamaica	12	1E+06	147	1163640
Netherlands Antilles	2	40000	13	1050000
Puerto Rico	10	157915	538	2902000
St. Kitts and Nevis	7	14280	6	684900
St. Lucia	6	3950	49	1001290
St. Vincent and the Grenadines	5	1660	3	10300
Trinidad and Tobago	6	1427	5	25127
Total	141	1E+07	3095	13899301

(source: EM-DAT)

Table 5-2 Variables in the study

Variable	Name	Description	Source
Number killed by natural disasters	$DEAD_{it}$	Persons killed by natural disasters in country *i* in year *t* (government reported)	EM-DAT
Financial losses from natural disasters	$FIN\ LOSS_{it}$	Total financial losses (in 2000 US$) from natural disaster in country *i* in year *t* (government reported)	EM-DAT
Drought disaster	$Drought_{it}$	Dummy variable for 1 or more drought disasters in country *i* in year *t*	EM-DAT
Earthquake disaster	$Earthquake_{it}$	Dummy variable for 1 or more earthquake disasters in country *i* in year *t*	EM-DAT
Flood disaster	$Flood_{it}$	Dummy variable for 1 or more flood disasters in country *i* in year *t*	EM-DAT
Windstorm disaster	$Windstorm_{it}$	Dummy variable for 1 or more windstorm disasters in country *i* in year *t*	EM-DAT
Volcano disaster	$Volcano_{it}$	Dummy variable for 1 or more volcano disasters in country *i* in year *t*	EM-DAT
Income	GDP_{it-1}	Gross national product, per capita in country *i* in year *t-1* (2000 US$ equivalent)	Penn World Table
Population	POP_{it-1}	Total population of the country in country *i* in year *t-1*	Penn World Table
Urban	URB_{id}	Discontinuous areas with density in the upper population density quartile relative to the rest of the nation were considered urban areas, by decade (d=1960, 1970, 1980, 1990, 2000)	International Center for Tropical Agriculture (CIAT)
Disaster Assistance	DA_{it-1}	Official development assistance and aid, per capita, in country *i* in year *t-1*	World Bank Development Indicators (WDI)
Surface Area	$Surface\_Area_{i}$	Total surface area of country *i*, in square kilometers	Penn World Table
Telephone Lines	$TELE_{it-1}$	Telephone lines per 100 persons, in country *i* in year *t-1*	World Development Indicators (WDI)
Magnitude, Wind	Max_wind_{it}	Maximum sustained wind speed of a landfall hurricane in country *i* and year *t*	HURTRAK (NOAA)
Magnitude, Pressure	$Min\_pressure_{it}$	Minimum barometric pressure of a landfall hurricane in country *i* and year *t*	HURTRAK (NOAA)
Magnitude, Category	C_{it}	Dummy variable indicating a landfall windstorm of category 4 or 5 strength in country *i* and year *t*	HURTRAK (NOAA)
Strength of Hurricane Season	ACE_{it}	Annual measure of total cyclone energy in Caribbean Basin in year *t*	HURTRAK (NOAA) NOAA

Table 5-3 Summary statistics

Variable		Mean	Standard deviation	Minimum	Maximum	Observations
$DEAD_{it}$	overall	13.051	84.843	0.00	1122	N 234
	between		26.386	0.00	94.444	n 13
	within		80.949	-81.39	1040.607	T 18
$FIN\ LOSS_{it}$	overall	59798	266684.7	0.00	2180000	N 234
	between		61809.8	3.17	194419.9	n 13
	within		259959.6	-134621.90	2045378	T 18
ACE_{it}	overall	89.73	62.69	17.00	228	N 234
	between		3.6198	87.61	98.667	n 13
	within		62.594	8.06	230.12	T 18
$TELE_{it-1}$	overall	16.755	12.791	0.43	49.654	N 234
	between		10.433	0.64	32.089	n 13
	within		7.917	-4.53	40.021	T 18
$\ln[URB_{id}]$	overall	1.532	1.146	0.00	4.11	N 234
	between		1.1877	0.00	4.07	n 13
	within		0.0742	1.27	1.791	T 18
$Windstorm_{it}$	overall	0.248	0.4327	0.00	1	N 234
	between		0.108	0.11	0.444	n 13
	within		0.42	-0.20	1.137	T 18
$Earthquake_{it}$	overall	0.004	0.065	0.00	1	N 234
	between		0.015	0.00	0.056	n 13
	within		0.064	-0.05	0.949	T 18
$Drought_{it}$	overall	0.038	0.193	0.00	1	N 234
	between		0.066	0.00	0.222	n 13
	within		0.182	-0.18	0.983	T 18
$Flood_{it}$	overall	0.163	0.37	0.00	1	N 234
	between		0.199	0.00	0.667	n 13
	within		0.316	-0.50	1.107	T 18
$\ln[POP_{it-1}]$	overall	5.151	0.739	2.76	6.059	N 234
	between		0.765	2.92	5.99	n 13
	within		0.058	4.97	5.306	T 18
$\ln[GDP_{it-1}]$	overall	8.885	0.624	7.45	10.009	N 234
	between		0.625	7.60	9.823	n 13
	within		0.162	8.42	9.342	T 18
$\ln[GDP_{it-1}^2]$	overall	17.768	1.248	14.88	20.01	N 234
	between		1.252	15.20	19.656	n 13
	within		0.326	16.83	18.67	T 18
$\ln[DA_{it-1}]$	overall	15.376	5.161	0.00	20.395	N 234
	between		4.814	0.00	19.232	n 13
	within		2.271	-2.13	18.244	T 18
C_{it}	overall	0.111	0.315	0.00	1	N 234
	between		0.072	0.00	0.222	n 13
	within		0.307	-0.11	1.056	T 18

Table 5-4 Natural disaster persistence

	No Disaster$_t$	Disaster$_t$	Total
No Disaster$_{t+1}$	135 (79.88)	34 (20.12)	169
Disaster$_{t+1}$	33 (63.46)	19 (36.54)	52
Total	168 (76.02)	53 (23.98)	221

Table 5-5 Negative binomial regression results, parameter estimates

	Deaths					Financial Losses				
Variable	Parameter		Standard Error	[95% Confidence Interval]		Parameter		Standard Error	[95% Confidence Interval]	
$\ln[POP_{it-1}]$	-0.80		(0.75)	-2.27	0.67	0.07		(0.42)	-0.76	0.89
$\ln[GDP_{it-1}]$	57.57	**	(23.24)	12.02	103.13	107.69	***	(29.20)	50.47	164.91
$\ln[GDP_{it-1}^2]$	-29.27	**	(11.68)	-52.17	-6.38	-54.90	***	(14.68)	-83.67	-26.13
$\ln[URB_{id}]$	0.64	**	(0.30)	0.06	1.23	0.21		(0.23)	-0.25	0.66
ACE_{it}	-0.01	***	(0.00)	-0.01	0.00	-0.01	***	(0.00)	-0.02	-0.01
$TELE_{it-1}$	0.08	**	(0.03)	0.02	0.15	0.13	***	(0.03)	0.08	0.19
$\ln[DA_{it-1}]$	0.03		(0.06)	-0.09	0.15	-0.11	**	(0.05)	-0.21	-0.01
$Windstorm_{it}$	2.16	***	(0.29)	1.60	2.72	2.06	***	(0.48)	1.12	3.01
$Flood_{it}$	2.09	***	(0.35)	1.41	2.77	4.02	***	(0.47)	3.10	4.94
$Earthquake_{it}$	-13.07	**	(830.36)	-1640.55	1614.40	3.76	***	(1.14)	1.52	5.99
C_{it}	0.73		(0.34)	0.06	1.39	0.02		(0.49)	-0.94	0.98
N[i]	216					216				
Number of non-zero observations	54					46				
Log-likelihood[ii]	-215.29	***				-469.95	***			
α	21.7					29.14				

[i]N=216, n=12 (Grenada is dropped because of all zero outcomes) and t=18 (1983-2000). [ii]Log-likelihood statistic for the overall model estimated. *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, and * indicates significance at the 0.10 level.

Table 5-6 Negative binomial regression results, incident rate ratios

	Deaths					Financial Losses				
Variable	Incidence Rate Ratio		Standard Error	[95% Confidence Interval]		Incidence Rate Ratio		Standard Error	[95% Confidence Interval]	
$\ln[POP_{it-1}]$	0.45		(0.34)	0.10	1.96	1.07		(0.45)	0.47	2.44
$\ln[GDP_{it-1}]$	1.01E+25	**	(2.34E+26)	1.66E+05	6.13E+44	5.88E+46	***	(1.72E+48)	8.27E+21	4.17E+71
$\ln[GDP_{it-1}]^2$	0.00	**	(0.00)	2.20E-23	0.00	0.00	***	(0.00)	0.00	0.00
$\ln[URB_{id}]$	1.90	**	(0.57)	1.06	3.41	1.23		(0.29)	0.78	1.94
ACE_{it}	0.99	***	(0.00)	0.99	1.00	0.99	***	(0.00)	0.98	0.99
$TELE_{it-1}$	1.09	**	(0.03)	1.02	1.16	1.14	***	(0.03)	1.08	1.21
$\ln[DA_{it-1}]$	1.03		(0.06)	0.91	1.16	0.89		(0.05)	0.81	0.99
$Windstorm_{it}$	8.69	***	(2.48)	4.97	15.20	7.87	**	(3.80)	3.05	20.30
$Flood_{it}$	8.07	***	(2.81)	4.08	15.95	55.71	***	(26.14)	22.21	139.72
$Earthquake_{it}$	0.00	**	(0.00)	0	0	42.74		(48.71)	4.58	399.03
C_{it}	2.07	**	(0.70)	1.06	4.03	1.02	***	(0.50)	0.39	2.65
N[i]	216					216				
Number of non-zero observations	54					46				
Log-likelihood[ii]	-214.520***					-469.95	***			
α	21.7					29.14				

[i]N=216, n=12 (Grenada is dropped because of all zero outcomes) and t=18 (1983-2000). [ii]Log-likelihood statistic for the overall model estimated. *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, and * indicates significance at the 0.10 level.

Table 5-7 Robustness checks on explanatory variables

Variable	Parameter[i]	(Standard Error)
Rescaling development assistance to take only non-negative values	0.25	(0.16)
Examining disaster flows from Relief Web for potential reporting bias	1416.41	(2687.28)
Minimum barometric pressure	0.00	(1.77)
Maximum wind speed	0.00	(1.48)
Category 1 Dummy	0.61	(0.74)
Category 2 Dummy	-15.57	(11887.00)
Category 3 Dummy	1.42	(0.62)
Category 4 Dummy	1.36	(0.61)
Category 5 Dummy	0.22	(0.57)
Category 1-5	0.82	(0.42)
Category of storm and interacting category of storm and strength of storm season	0.00	(0.00)
Dummy variable for category 3, 4 or 5 and interacting category dummy and strength of storm season	0.01	(0.01)
Openness to trade	0.00	(0.00)
Controlling for surface area	0.00	(0.00)
Controlling for coastal extent	0.00	(0.00)

[i]The estimates are from panel negative binomial regressions. Standard errors are shown in parentheses. The regressions include country fixed effects. Cells contain coefficient estimates of the respective variable.

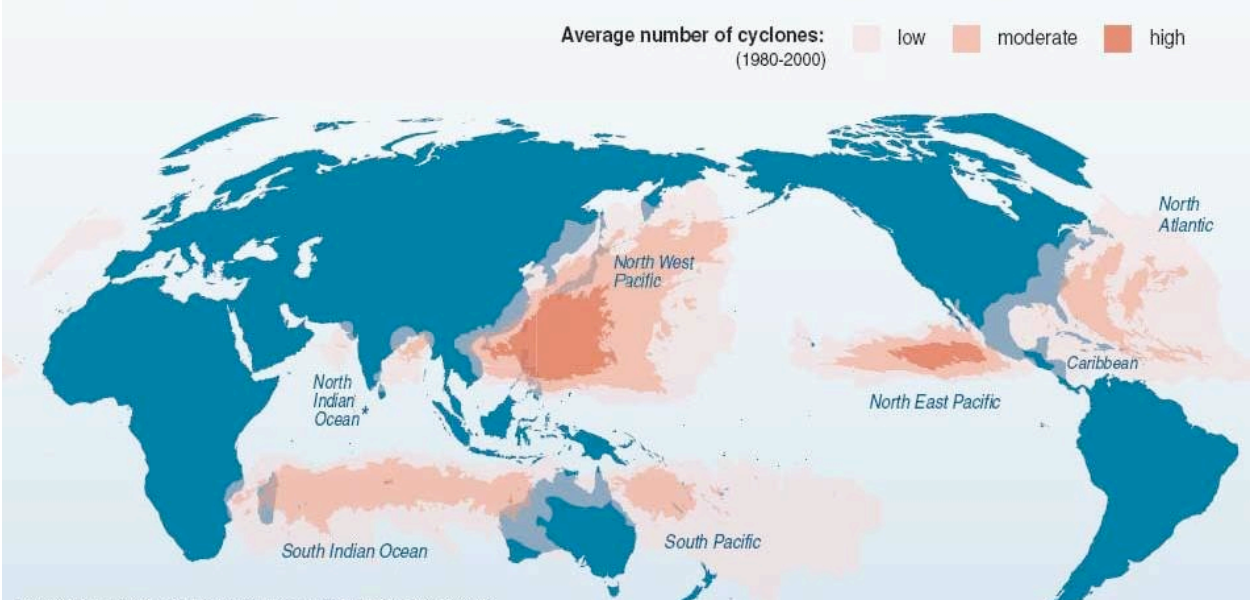

Figure 5-1. Tropical cyclone global frequency (source: UNEP/GRID-Europe)

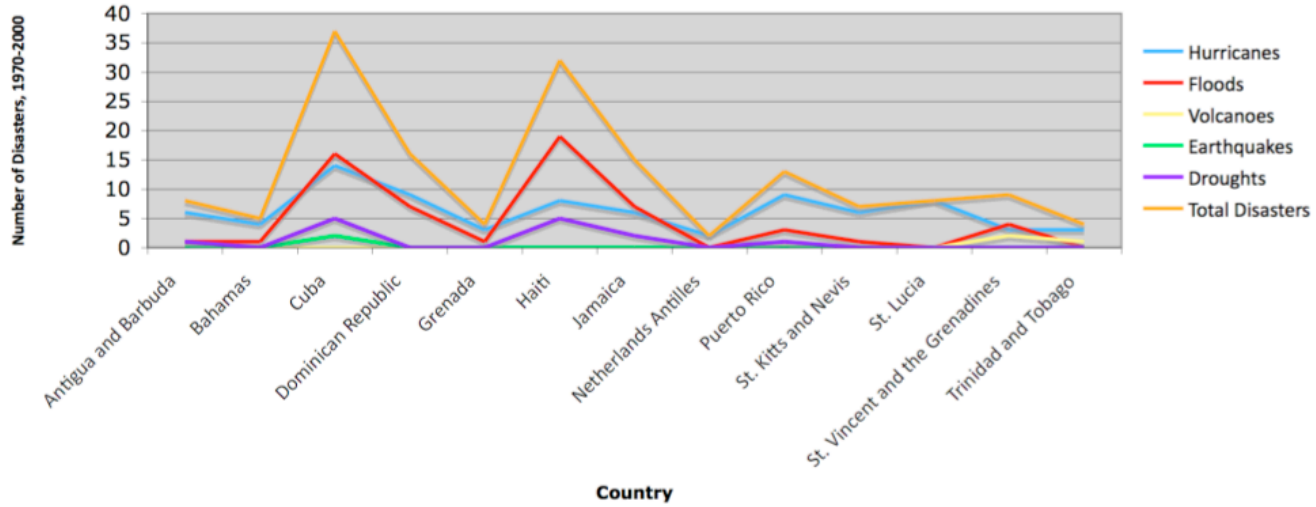

Figure 5-2. Frequency of natural disasters, by sampled country, 1970-2000

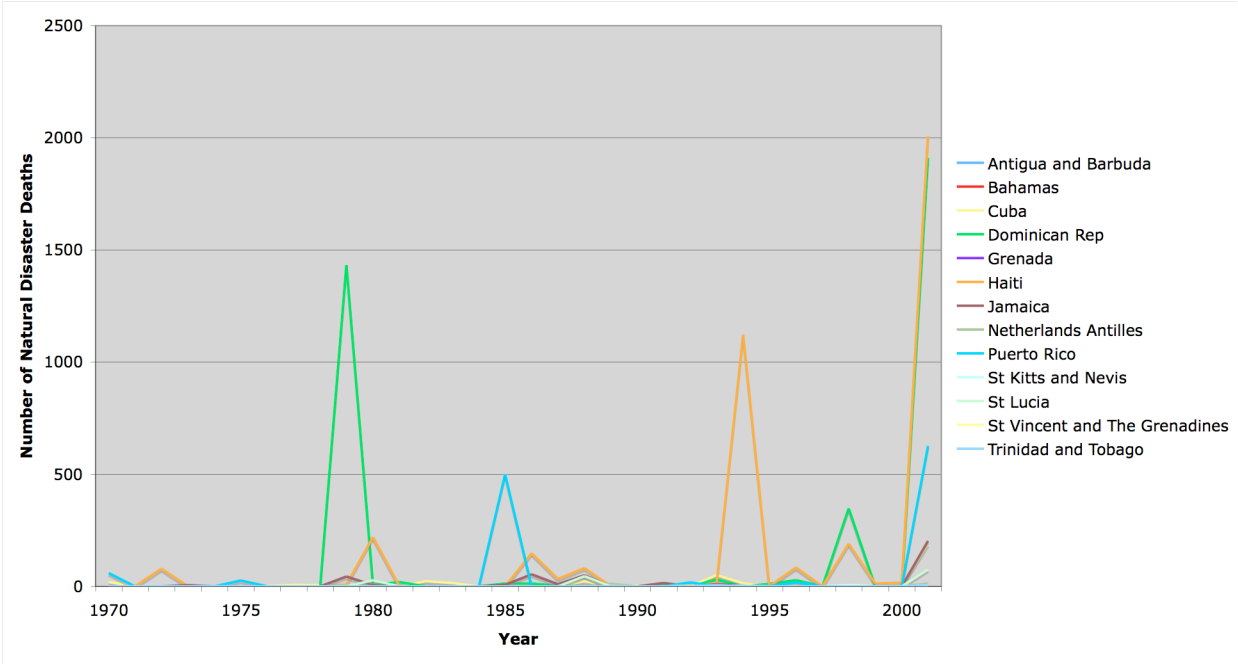

Figure 5-3. Number of annual natural disaster deaths, by sampled country and year

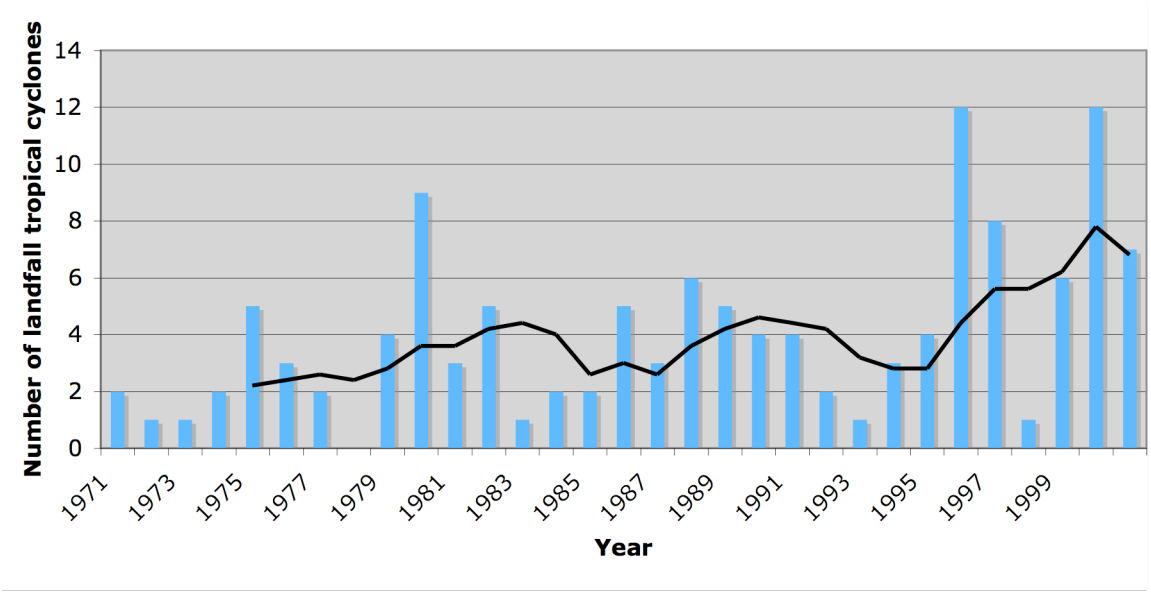

Figure 5-4. Number of annual landfall windstorms for sampled countries

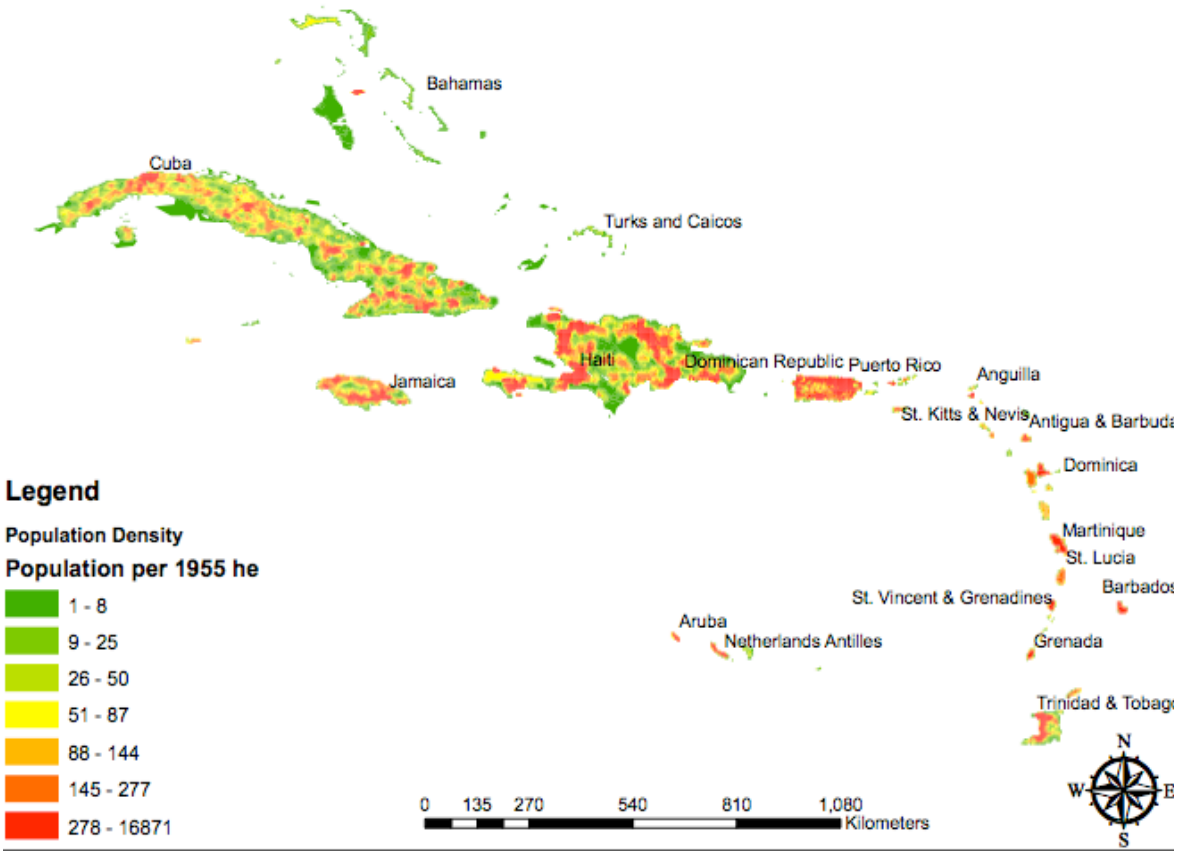

Figure 5-5. Spatial distribution of populations in sampled nations, 2000 (source: CIAT)

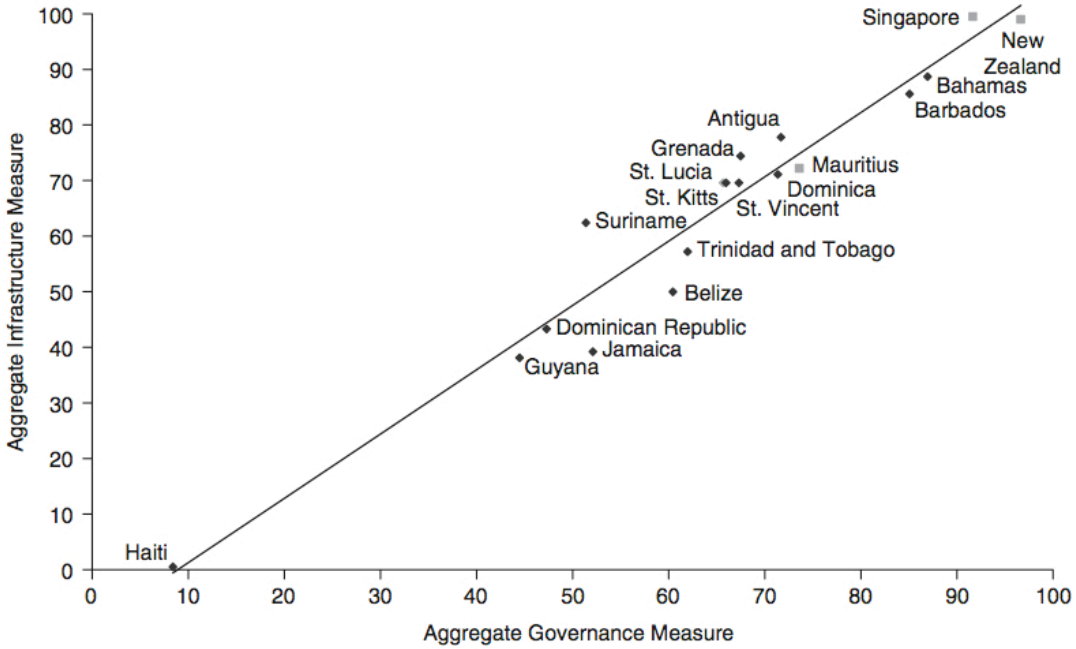

Figure 5-6. Correlation between institutional strength and infrastructure (source: World Bank, 2005)

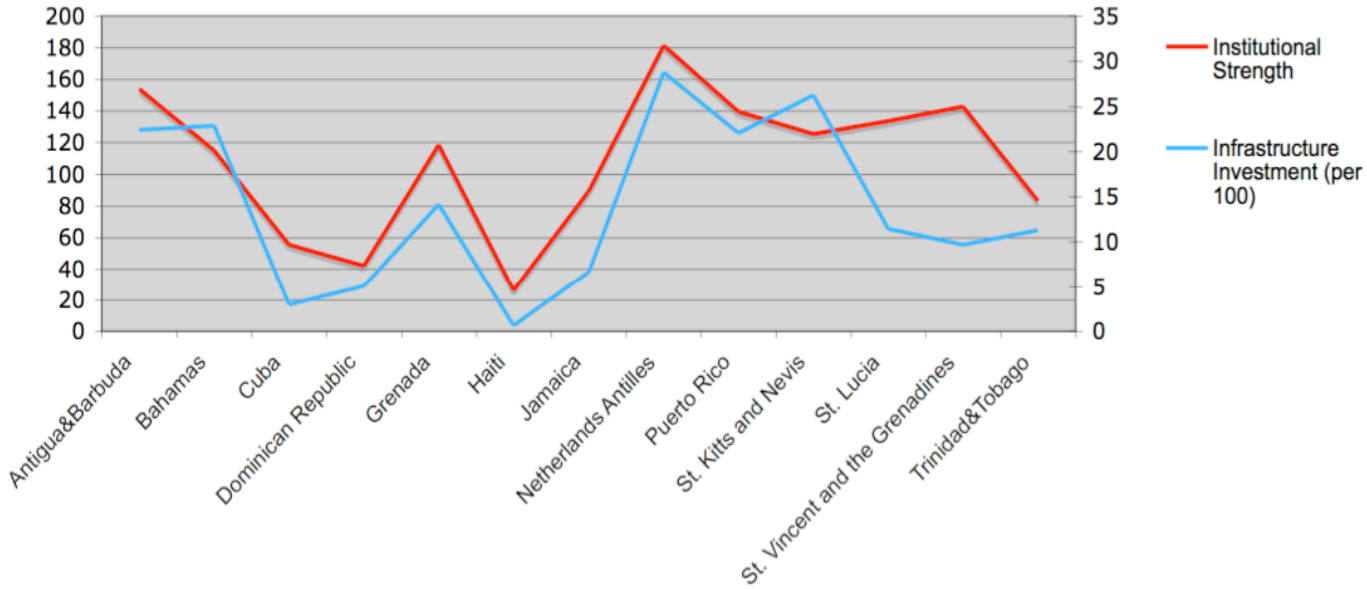

Figure 5-7. Correlation between institutional strength and infrastructure

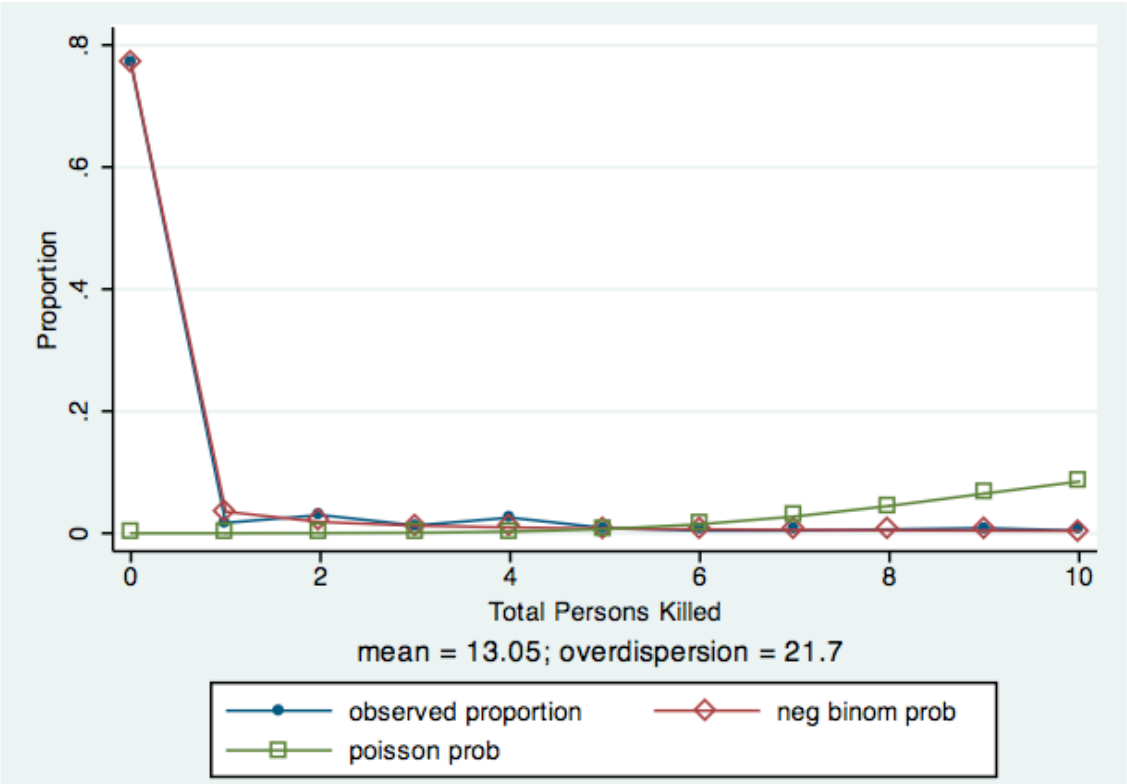

Figure 5-8. Distribution of persons killed by natural disasters in sampled nations

CHAPTER 6
POLICY APPLICATIONS AND CONCLUSIONS

The vulnerability analyses presented at the household and country levels concur with existing conclusions that natural disasters affect people heterogeneously. The vulnerability approach explored in Chapter 4 suggests aggregate risk is unevenly distributed with certain sub-populations systematically disadvantaged in this distribution. In Chapter 5 we presented the disproportionate aggregate risk borne by persons in small island developing states (SIDs).

Natural disaster losses are escalating and risk to suffering from these events is unevenly distributed to the most vulnerable: poor households on small island developing states. The empirical results confirm that relatively poorer households and countries bear a disproportionate share of natural disaster risk. This natural disaster risk has significant implications for poverty levels, especially in risk-prone areas. Small islands are among the high-risk areas and urbanization is serving to only increase their risk.

Summary of Key Findings

Natural disaster risk is impacting future poverty rates. By examining household behaviors correlated with smoothing consumption over time in the presence of natural disaster risk in Chapter 4, we find smaller, rural and more educated households are less likely to be in poverty in the future. Importantly, these household characteristics are correlated with lower levels of aggregate risk, the largest contributor of future poverty induction in Indonesia. As a tropical island archipelago in a risk-prone area (especially related to seismic activity), Indonesia's natural disaster risk supports our hypotheses about higher structural vulnerability of small islands. It is important that households have support for self-insurance mechanisms which smooth consumption losses, like savings

and assets. Additionally, entitlements, as a certain income, are especially important for households to stave off poverty implications of realized natural disaster risk.

In Chapter 5, we specifically analyzed relatively poor, small island communities. The sample included thirteen small island developing states (SIDs) in the Caribbean. This geography is characterized as high risk for natural disasters, especially hurricanes, yet the sampled countries differed vastly in terms their macroeconomic natural disaster risk. Haiti, the most vulnerable country in our sample, also has the weakest institutions and the lowest level of per-capita income. As a result of petite size, SIDs quickly face binding resource constraints with increasing population densities. Urbanization and infrastructure investments are increasing natural disaster risk on SIDs by increasing concentrations of resources in risk-prone areas.

Policy Recommendations

The results presented in this analysis have policy relevance for small island states, especially those pursuing improved economic development such as SIDs. As these economies face the greatest risk from natural disasters, they are especially interesting to analyze with respect to coping behavior. Household behavior that demonstrates the ability to effectively cope with natural disaster losses (negative realizations of the natural disaster risk) by smoothing consumption is important to understand as natural disaster rates and resources at risk continue to increase.

Natural disaster risk is a function of the human-planned environment, not just nature. Individuals, such as households and governments, make decisions with implications for natural disaster risk. There is a need for improved disaster forensic data towards disaster-hardening infrastructure investments – without this information, not only may these investments be wasted in the presence of weather hazards decimating

them but these investments may actually have perverse impacts of escalating natural disaster losses by placing more resources at risk or by causing secondary disasters, such as the case in Haiti in 2010. Further, information regarding the risk-proneness of areas should be publicly available and regarded when setting prices, such as housing and insurance policies. As natural disaster risk is both individual and aggregate, it is important that policies consider those who may be forced by economic pressures to locate in the least desirable – and most hazard prone areas. To benefit the poorest households and islands, improving institutional strength should be prioritized and information on the risk-proneness of areas should be more widely disseminated.

Urbanizing island environments urgently need further investigation. For example, locational (choosing to live rural or urban) and dwelling (quality of housing) decisions at the household level are impacting natural disaster risk. Households need access to information regarding locational and dwelling risk prior to settlement decisions to decrease both individual and aggregate natural disaster risk. Future research needs include improved data, especially spatial, to study human settlement and risk patterns in urban agglomerations.

With lower access to self-insurance mechanisms, poor households suffer greater consumption losses from natural disasters. Poor countries with weak institutions have inadequate access to formal self-insurance mechanisms, such as borrowing, which may alleviate some of these intertemporal consumption shortfalls. Policies supporting self-insurance accruals may alleviate household losses and macroeconomic crises following massive natural disasters. At the household and country level, improved access to self-

insurance may improve future poverty prospects and lessen the long-term consequences of natural disasters.

Future Research

Chapters 5 and 6 highlighted the need for more natural disaster related data, especially data at the intra-household level and within SIDs. While it is recognized that this requires significant investment, inadequate data will continue to mask realities related to coping with natural disasters. SIDs suffer detrimentally from natural disasters; this is a result of both their high-risk environment and economic characteristics escalating this risk.

As we revealed the risk implications of urbanization in Chapters 4 and 5, further analysis is needed regarding the relationship between urban areas and natural disasters. For example, spatial data at a fine resolution may reveal certain parts of an urban area – rather than the entire urban area – as riskier than others (for example, urban households living in the riskiest part of an urban area).

Second, the idea that there are gender differences in natural disaster risk concurrent with the feminization of poverty mandates a closer, empirical analysis regarding female bargaining power in the household and household ability to cope with natural disasters on SIDs. Yet, the necessary data for such analysis is not available. Further, nuances in the gender-poverty-disaster relationship deserve further exploration; for example, St. Lucia's higher male-to-female poverty rates accompany higher natural disaster mortality rates. Behavioral analysis is needed to understand this more completely.

Next, the Indonesian Family Life Survey presents information on other forms of aggregate and household shocks, such as currency crisis or loss of employment. These

other forms of household shocks should be included in the analysis. Specifically, I will investigate the differences in magnitudes and signs of among the various sources of risk.

Finally, an extension of this work should include estimating household risk preferences on small islands towards natural disasters. While natural disasters have been taken previously as rare, extreme shocks in the economic literature, their increase in frequency challenges this disposition. Are there differences in household natural disaster risk preferences when the events are persistent? Further, we seek understanding in how households learn from natural disaster experience: are households which experience a natural disaster shock not only able to recover, but able to recover stronger than before the event as a result of knowledge acquired during the experience (for example, if a household loses their dwelling to a flood but learns to rebuild a house on stilts, how does this impact their future natural disaster risk?). In the case of Indonesian households, we found this learning was correlated with time-sensitive characteristics of the macroeconomy: in good economic times, household level disaster experience improved their ability to cope with shocks yet the reverse was true in unfavorable economic times.

APPENDIX
RISK PREFERENCE

Preferences may be analyzed under certainty (no risk) and uncertainty (greater than 0 risk). In both scenarios, consumption is subject to a budget constraint and economic models seek to find the optimal choice for a consumer by considering the consumer's preferences and budget constraint. Preferences introduce necessary conditions of completeness (consumer prefers A to B, prefers B to A or is indifferent between A and B) and transitivity (consistency) (if consumer prefers A to B and B to C, they prefer A to C). The satisfaction gleaned from consumables is referred to as utility: the utility from consuming Y is U(Y).

Decision makers prefer the alternative within a choice set that maximizes expected utility according to three axioms (ordering and transitivity, continuity and independence). As a continuous, twice differentiable function (C^2) function, utility functions reveal consumer behavior and risk preference. Given risky outcomes, a decision maker maximizes expected utility, preferring risks (lotteries) with higher expected payoffs (or lower expected losses). This individual is referred to as an expected utility maximizer.

As an individual is choosing between playing the lottery[61] (taking a risk) or not prior to the outcome (Y) being known, expectation operators are applied to both the certain outcome (with E(Y) denoting the expected value of the certain outcome) and the uncertain outcome (with E(U(Y)) denoting the expected utility from the expected value of the outcome). Individuals prefer a lottery with the highest expected utility and we can represent the space of lottery L as a utility representation in expected utility form. In other words, we can assign a value to each outcome such that for any two lotteries,

[61] We define risk as a lottery because the probability of outcomes of a lottery are unknown ex-ante.

$L=(P_{1,....}P_n)$ and $L'=(P_1',....P_n')$, we have L $\succeq$ L' if and only if $\sum_{i=1}^{n} U_i P_i \geq \sum_{i=1}^{n} U_i P_i'$ with P_i notating the probability of an outcome occurring. The utility from this lottery L is denoted as U = E(U(Y)).

Building upon the expected utility hypothesis of Bernoulli, von Neumann & Morgenstern's (1944) axiomitized the hypothesis, allowing the typology of three risk preferences, revealed by the second-order conditions of the utility function. A risk-averse utility maximizer has a convex utility function (U">0), preferring a risk-free choice (certain outcome, E(Y)) to a riskier choice (lottery's uncertain outcome, E(U(Y))), given that they have the same expected value: a risk-averse person achieves greater utility from a certain outcome compared to an uncertain outcome, given they both have the same expected value. This person therefore prefers to pay an insurance premium, or a certainty equivalent, rather than risk an uncertain, probabilistic outcome.

By letting a lottery L = ((P, Y_1), (1-P, Y_2), the certain outcome E(Y) = P*Y_1+(1-P)*Y_2 have utility of U(E(Y)) and the expected utility of the expected outcome be the linear sum of probabilities of an outcome times the utility of that outcome, or E(U(Y)) = P*U(Y_1)+(1-P)*U(Y_2), an individual is risk averse if the utility from the certain outcome (U(E(Y)) is greater than the expected utility of an expected outcome (E(U(Y)), or U(E(Y)) > E(U(Y). To motivate the relevance of this theory to natural disasters, Kahneman and Tversky (1979) demonstrated through a series of household experiments that 80% of participants preferred a certainty equivalent to probabilistic insurance[62] to cover disaster losses – what mattered to participants was knowing ex-

[62] With probabilistic insurance, there is some greater than 0 chance of a loss not being covered.

ante that losses would be covered, not what caused the loss. While an intuitive explanation of risk-aversion preference of poor households is revealed by marginal utility theory[63], considering two households, HH1 and HH2, may better illustrate this risk preference. HH_1 has expected utility just below the poverty line but faces no risk – in other words, the expected utility is just below the poverty line with certainty. HH_2 has expected utility just at the poverty line but faces risk – in other words, there is a greater than 0 probability that they suffer a (lottery) loss causing their expected utility to fall far below the poverty line. A risk-averse household prefers the certain outcome of being just below the poverty line to the uncertain outcome of variable expected utility at or well below the poverty line, even if the probability of suffering the (lottery) loss is small.

[63] Diminishing marginal utility would posit a greater marginal utility on income of lower-income households compared to higher-income households; the general resolve is that income and risk aversion are inversely related (Lipton, 1968).

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BIOGRAPHICAL SKETCH

Megan Elizabeth Silbert was born in South Carolina in 1977. Her research interests are economic development, natural disaster risk, applied econometrics and Latin American and Caribbean studies. Megan earned her Bachelor of Science in business administration degree in 1999 from the Warrington College of Business at the University of Florida. She graduated with a Master of Education degree in 2001 with her master's research focusing on the leadership and empowerment benefits of women's colleges. Upon graduation, she accepted a position at the Warrington College of Business where she served as the Associate Director for the School of Business, running the undergraduate professional development programs. She continued her education at the University of Florida by returning full-time for doctoral studies in the Food and Resource Economics department. She received a research assistantship from the department and worked as an instructor and researcher for the School of Business during doctorate study.

Megan's Ph.D. research focused on economic impacts of natural disaster risk for especially vulnerable persons and communities, specifically those on islands. Upon graduation, Megan will begin as an assistant professor of economics at Salem College in Winston-Salem, North Carolina.