ABSTRACT

Title of dissertation: INSTITUTIONS, POVERTY, AND TROPICAL CYCLONE MORTALITY

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Doctor of Philosophy, 2019

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Tropical cyclones can result in thousands of deaths when the exposed population is unprepared or ill-equipped to cope with the hazard. Evaluating the importance of institutions and socioeconomic conditions for these deaths is challenging due to the extreme variability in hazard exposure. Studies of socioeconomic risk factors that do not account for exposure will be imprecise and possibly biased, as a storm's path and intensity are important determinants of mortality and may be correlated with socioeconomic conditions. I therefore model and then control for hazard exposure by spatially interacting meteorological and socioeconomic data, allowing me to develop novel evidence of socioeconomic risk factors.

In essay 1, I construct a global dataset of over one thousand tropical cyclone events occurring between 1979 and 2016. Controlling for population exposure to strong winds and rainfall, I find that higher levels of national government effectiveness are associated with lower tropical cyclone mortality. Further, deaths are higher when exposure is concentrated over a subset of the population that is already less well off. In essay 2, I investigate whether local government capacity and poverty alleviation can reduce tropical cyclone deaths, using panel data from 78 provinces and 1,426 municipalities in the Philippines. Tropical cyclone exposure is concentrated in wealthier regions of the Philippines, but once wind exposure and rainfall are controlled for I find robust evidence of a link between local poverty rates and cyclone deaths. In essay 3, I investigate the potential for leveraging policy experiments for causal inference about the effects of development interventions on disaster mortality using an existing randomized control trial in the Philippines. This empirical example illustrates how randomization overcomes issues of multicollinearity and omitted variable bias; however, the presence of outliers in exposure and vulnerability to natural hazards interact to make average treatment effect estimates highly imprecise.

Strong evidence of an association between government effectiveness and cyclone deaths suggests that capacity constraints need to be addressed in tandem with risk-specific strategies and financial transfers. Further, evidence that local poverty rates and socioeconomic conditions matter highlights the need for equitable and inclusive approaches to mitigating the risk from tropical cyclones.

INSTITUTIONS, POVERTY, AND TROPICAL CYCLONE MORTALITY

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2019

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Acknowledgments

I am deeply grateful for the invaluable advice and guidance of my advisers, Elisabeth Gilmore and Anand Patwardhan. I thank my dissertation committee members: Anna Alberini, Christopher Foreman, and Catherine Warsnop. This work has also benefited from the advice and guidance of Brooke Anderson, Christopher Barrett, Arthur Degaetano, John Hoddinott, Richard Moss, Julie Silva, Robert Sprinkle, Larry Swatuk, and Mathieu Taschereau-Dumouchel. I am also grateful for the helpful comments and feedback of seminar and conference participants at the American Geophysical Union, the International Studies Association, Cornell University, New York University and the University of Maryland School of Public Policy. I acknowledge funding support from the University of Maryland Council of the Environment, the Anne G. Wylie Dissertation Fellowship, the University of Maryland and Clark University. This material is based upon work supported in part by the U.S. Army Research Laboratory and the U.S. Army Research Office via the Minerva Initiative under grant number W911NF-13-1-0307.

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Chapter 1: Introduction

1.1 Introduction

Tropical cyclones are frequent, deadly, and devastating. Over the past decade these powerful storms have killed over 160,000 people and caused over $213 billion in damages (Guha-Sapir, 2018). Climate change and demographic trends are expected to exacerbate risk from tropical cyclones in the future. The average intensity and rainfall of the strongest storms are likely to increase as a result of climate change (Christensen et al., 2013; Walsh et al., 2016). Trends in population growth and sea level rise will further contribute to risk in the absence of effective adaptation (Mendelsohn et al., 2012; Peduzzi et al., 2012; Walsh et al., 2016). There is also substantial uncertainty in tropical cyclone predictions, and changes are likely to vary by basin, latitude and other location specific characteristics (Kossin, 2018; Sharmila and Walsh, 2018; Sugi et al., 2017; Wang and Toumi, 2018).

Natural hazards result in humanitarian disaster only when an exposed human system fails to sufficiently adapt or cope. This dissertation investigates the institutional and socioeconomic conditions that may lead to or protect against tropical cyclone mortality. The three analytical chapters (Chapters 2, 3 and 4) span a range of scales and methods, but all are motivated by a central research question:

How do levels of institutional, economic and human development in places exposed to tropical cyclone hazard impact storm mortality?

To address this question I construct multiple new datasets that spatially interact meteorological and socioeconomic data for tropical cyclone events. This allows me to control for physical exposure at a high resolution and better isolate the socioeconomic determinants of mortality. The results lead to new insights about linkages between institutions, poverty and tropical cyclone mortality across a range of scales.

The remainder of the introduction is organized as follows. I begin by motivating the study of these broad determinants of tropical cyclone mortality. I then review the key framing concepts of vulnerability, resilience and adaptive capacity. Next, I briefly lay out my overall research design and conceptual model, followed by a summary of how this is implemented in the three analytical components of this dissertation. This is followed by a review of the literature on tropical cyclone vulnerability. I conclude the introduction with a brief statement of how this work contributes to vulnerability theory and informs public policy.

1.1.1 Motivation

Tropical cyclones are only one of the myriad shocks and stressors that threaten human wellbeing and security, many of which may be exacerbated directly or indirectly by anthropogenic climate change. According to the Fifth Assessment Report of the United Nations Framework Convention on Climate Change (UNFCCC):

> Climate change will amplify existing risks and create new risks for natu-

> ral and human systems. Risks are unevenly distributed and are generally greater for disadvantaged people and communities in countries at all levels of development." (Pachauri and Mayer, 2015, p. 13)

There are limited resources and much to contend with. Given the complex, diverse, and uncertain landscape of future hazards, one proposed pathway forward in the near term is to focus on common or general sources of vulnerability that are likely to matter for multiple sources of current and future risk. The effectiveness of institutions at the national and local level is commonly theorized to be an important limiting factor for adaptation and risk reduction (Aldrich, 2012; Blaikie et al., 2004; Ensor et al., 2015; Fankhauser and Burton, 2011; Pachauri and Mayer, 2015). Multi-dimensional poverty and inequality are also frequently cited as common root causes of vulnerability to a range of hazards. Those with less access to or command over resources, technology, social capital, human capital, and institutions - the drivers and manifestations of underdevelopment and marginalization – are likely to be least able to cope with or adapt to hazards (Adger et al., 2003; Blaikie et al., 2004; Pachauri and Mayer, 2015).

At a glance, and particularly in light of evidence that wealthier countries on average experience fewer deaths from disaster (e.g. Kahn (2005)), this might seem to imply that prioritizing economic growth is the best way forward. But there is also evidence to suggest that development efforts can have unintended consequences, and therefore lead to sub-optimal outcomes in the long run. The potential for development efforts to inadvertently exacerbate or create new vulnerabilities is a widely acknowledged problem (Adger et al., 2003; Blaikie et al., 2004; Denton et al., 2014). With sound theoretical arguments for the existence of both synergies and conflict between development and vulnerability, the compilation of empirical evidence can help us to disentangle when development and resilience are mutually reinforcing, and when they are in conflict.

This dissertation focuses on the general determinants of vulnerability to one class of hazard, tropical cyclones, and one outcome, mortality. Studying a single type of hazard allows me to credibly control for differences in event characteristics and therefore better identify the socioeconomic relationships of interest. While it also limits my ability to generalize to broad statements of system-level vulnerability or resilience, the approach and findings are buildable; identifying common causes of vulnerability to a range of hazards contributes to the knowledge base needed to target overall vulnerability reduction.

1.1.2 Key Concepts: Vulnerability, Resilience and Adaptive Capacity

1.1.2.1 Vulnerability

In the literature on global change, there is a general agreement that the term vulnerability refers to the possibility of future harm, but beyond that definitions vary widely and are continually evolving (Hinkel, 2011). The IPCC Fourth Assessment Report is frequently cited for defining vulnerability to climate change as "the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes," and further proposing that “[v]ulnerability is a function of the character, magnitude, and rate of climate change and variations to which a system is exposed, its sensitivity, and its adaptive capacity” (Parry et al., 2007, p. 21). Seven years later, the IPCC Fifth Assessment Report defines vulnerability as ”[t]he propensity or predisposition to be adversely affected,” and further specifies that ”[v]ulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt” (Agard et al., 2014). The former explicitly includes external shocks and stressors, while the latter does not. Gallopín (2006) makes a case for conceptualizing vulnerability purely as a function of the system or place in question, in which case exposure is not a component of vulnerability but instead an additional factor to be considered in tandem when assessing the risk for harm. In research practice, vulnerability tends to be defined in relation to a specific set of causes, outcomes, and/or populations (Patt et al., 2009).

Consistent with the IPCC Fifth Assessment Report, in this dissertation I treat hazard, exposure and vulnerability as distinct phenomena. I consider vulnerability to be the sensitivity and capacity of response of a place to tropical cyclone mortality, conditional on hazard and exposure. Empirically this means that hazard and exposure are treated as control variables, allowing for better identification of relationships between socioeconomic conditions and mortality.

By this definition, vulnerability may be considered a component of broader concepts including adaptive capacity and resilience (Gallopín, 2006). This research is therefore relevant to and informed by the adaptive capacity and resilience literatures. Many of the methods employed in this dissertation are applicable to exploring the determinants of alternative outcomes, particular in a resilience framework. This is a goal of my future work.

1.1.2.2 Resilience

Recent literature has adapted the concept of resilience from its ecological origins to include not only the ability of a system to return to a previous state or function following perturbation, but also to adapt or transform to a more desirable state (Cutter et al., 2008; Engle et al., 2014; Turner et al., 2003). For example, resilience in the context of climate change is defined by Engle et al. (2014) as follows:

> Resilience... [is] the potential to absorb and cope with impacts of climate shocks and extremes in the short-term, and to learn, reorganize, and redevelop, preferably to an improved state, in the longer-term. (Engle et al., 2014, p. 1296)

As a policy objective resilience has many advantages, as described by Engle et al. (2014). First, measured separately from exposure to external stressors or perturbations, it focuses on the system most within reach to local decision- and policy-makers. Second, resilience is well suited to the multiple objectives, long time-horizons, and decision-making under uncertainty inherent to development and adaptation under climate change. Third, the concept of resilience is dynamic and allows for cases where transitioning to a new state may be more desirable than preserving a current state. Linkov et al. (2014) call for a focus on overall system resilience on the grounds that uncertainties introduced by climate change are great enough that every vulnerability cannot be anticipated and addressed.

1.1.2.3 Adaptive capacity

Much like vulnerability and resilience, definitions of adaptive capacity vary based on the discipline and objectives of different researchers. The IPCC Fifth Assessment Report defines adaptive capacity in the context of climate change as "[t]he ability of systems, institutions, humans, and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences," but there are also many alternatives to this definition in the literature (Agard et al., 2014). Understanding adaptive capacity is of great interest to policy- and decision-makers; indeed, a normative argument similar to that made in the development literature for the paramount importance of capacity versus the material state of affairs (e.g. Sen (1999)) could be made in the case of adaptive capacity.

1.1.2.4 Challenges of measurement and validation

Operationalizing and building common evidence related to vulnerability, resilience and adaptive capacity is in general extremely challenging. The very breadth and complexity that make adaptive capacity and resilience so appealing to policy-makers also render them difficult to operationalize and measure. As a result, the state of the empirical evidence available to validate theories of resilience has been described in recent reviews as "in its infancy" (Asadzadeh et al., 2017) and "still at the theoretical level" (Cutter, 2016). A definition of vulnerability in relation to a specific hazard and outcome is somewhat more tractable from a measurement perspective, but still faces important limitations.

One obstacle to measuring or operationalizing the concepts of vulnerability, resilience and adaptive capacity is that they are forward-looking (Hinkel, 2011). The measures of harm by which vulnerability, resilience and adaptive capacity are often proxied are in part a consequence of and therefore lag the actual phenomena of interest. Even in the presence of an extreme event, the impacts that occur are an imperfect indicator of vulnerability or resilience (Engle et al., 2014; Hinkel, 2011). They can tell us only about vulnerability or resilience to one type and one magnitude of event, not the expected value of harm under a probability distribution of events. Compared to resilience and vulnerability, adaptive capacity is perhaps even more difficult to operationalize. While vulnerability and resilience are at least partially observable, adaptive capacity is not because it is the *ability* to respond or *availability* of responses to a decision-maker.

This limits what empirical evidence from analogue research can tell us about climate vulnerability, resilience, and adaptive capacity. This is especially true because the dynamic nature of socio-ecological systems and a changing climate mean that the past is at best an imperfect indicator of the future, particularly if we begin to cross thresholds that cause fundamental shifts in system dynamics (Adger et al., 2003; Engle et al., 2014). This is an important caution in the interpretation of all analogue work in this area, including this dissertation.

The disagreement over definitions and the context-specific and relational ways in which these concepts are often defined can further complicate the accumulation of knowledge. It is widely acknowledged that the appropriate relational definition of a concept such as vulnerability will depend on the context, and therefore *should* vary across research and programmatic efforts in different places, at different scales, and with different objectives (Cutter et al., 2008; Gallopín, 2006; Hinkel, 2011; Moran, 2010; Patt et al., 2009). Further, some argue that these concepts rely on implicit normative judgments about harm, and therefore cannot be defined with reference to local values (Hinkel, 2011). This makes comparison between studies and synthesis efforts difficult.

1.1.3 Research Design

1.1.3.1 Conceptual model

While I do not directly pose or answer questions of resilience, by defining vulnerability as distinct from hazard and exposure this research falls within a larger set of questions about what makes systems resilient to tropical cyclone risk. Further, thinking about vulnerability within a resilience framework is crucial to understanding the web of causal mechanisms by which socioeconomic conditions and cyclone deaths might become correlated.

Models and frameworks for understanding vulnerability and resilience to environmental stressors or perturbations (e.g. Cutter et al. (2008); Engle et al. (2014); Turner et al. (2003)) share a number of features: an emphasis on the dynamic nature of resilience, the importance of interaction across scales, and the place-specific nature of the phenomena. The model proposed here is broadly consistent with a range of models and frameworks in the literature, but draws most heavily on the Disaster Resilience of Place (DROP) model by Cutter et al. (2008). The DROP model begins with a snapshot of antecedent conditions, including inherent vulnerability & resilience as determined by the ongoing interaction of the social, natural, and built environment systems. When an event occurs, the total impact is a function of those antecedent conditions, the event characteristics, and coping responses. According to the model, if these impacts do not overwhelm the absorptive capacity of the community there is usually a high degree of recovery, but if they do then adaptive resilience may occur. This adaptive resilience will determine the degree and trajectory of long-term recovery, as well as impact the antecedent conditions for future events.

The conceptual framework for this research is illustrated in Figures 1.1 and 1.2. Figure 1.1 depicts a conceptual framework for resilience, and Figure 1.2 the vulnerability subset of the model that is the focus of this dissertation.

As vulnerability and resilience can only be directly observed in *response* to a specific shock or stressor, hazard and exposure are explicitly included in the model. The objective of this work is to improve our understanding of tropical cyclone vulnerability. It is distinct from efforts to indicate or develop an index to measure and compare overall levels of tropical cyclone risk (although pertinent to validating such efforts). An important distinction from these approaches is that I treat hazard and exposure as control variables in this dissertation. I am testing for relationships between tropical cyclone mortality and institutional, economic and human development characteristics *conditional* on the extent of exposure to a hazard of a specific

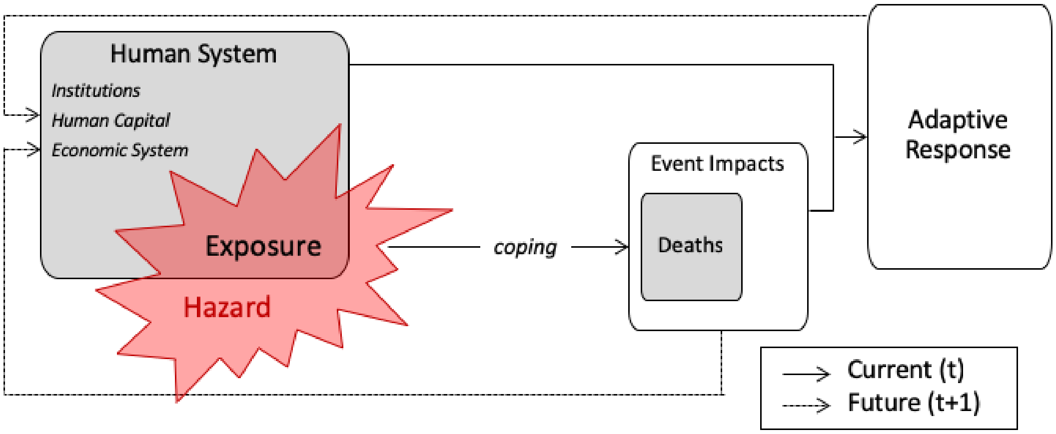

Figure 1.1: Conceptual model: tropical cyclone event resilience. The spatial interaction of the Human System and the Hazard generates Exposure. The total impacts and adaptive response to one event feed back into the antecedent conditions for future events.

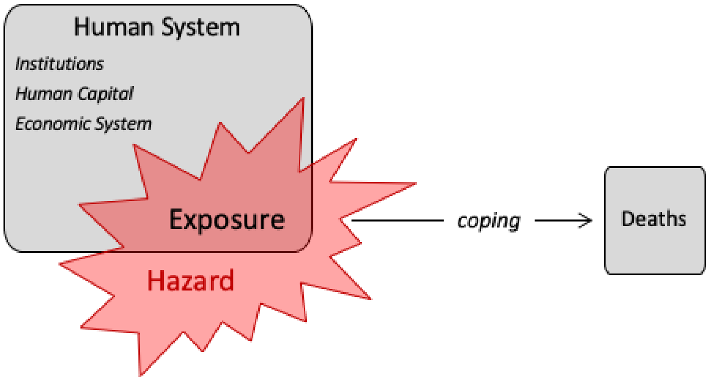

Figure 1.2: Conceptual model: vulnerability to tropical cyclone mortality. The spatial interaction of the Human System and the Hazard generates Exposure.

intensity. Given the extreme variability of tropical cyclone exposure this is necessary for precise estimates of socioeconomic relationships. Further, if exposure or intensity are correlated with socioeconomic conditions (either incidentally or causally) failure to control for storm characteristics can result in biased estimates.

In order to accurately control for the extent and intensity of hazard exposure in all analytical components of this dissertation, I model location specific wind speeds using a parametric wind speed model developed by Willoughby et al. (2006). This is implemented by adapting an existing software *stormwindmodel* by Anderson et al. (2017) for global use (available at https://github.com/liztennant/stormwindmodel). Using this tool as well as global gridded precipitation data and various spatial techniques allows me to construct hazard and exposure control variables appropriate to the scale and objectives of each analytical component.

In this model (Figures 1.1 and 1.2) coping is a moderator that is not explicitly parameterized and included in the empirical work of this dissertation. Because coping occurs in the immediate aftermath of the event, from a macro modeling perspective it can be treated as a product of the interaction between the system properties and event characteristics. For example, while the extent to which persons evacuate to cyclone shelters is clearly an important determinant of event impacts, we can reasonably treat this behavior as predetermined at event onset by the emergency systems in place, the nature of the event, and the socio-economic and cultural factors that will effect utilization of emergency systems.

1.1.3.2 Approach

In the first analytical essay of this dissertation (Chapter 2) I construct and analyze a global dataset of over one thousand tropical cyclone events occurring between 1979 and 2016. By combining disaster data from the Emergency Events Database (EM-DAT) with modeled storm winds based on the International Best Track Archive for Climate Stewardship (IBTrACS) and country-year socioeconomic data, I am able to build a new global dataset with a country-storm-event unit of analysis. The dataset includes variables that measure the country-storm specific exposure to tropical cyclones of different intensity. I estimate two sets of multivariate negative binomial regression models. The first set of models focuses on national determinants of mortality, and in particular national government effectiveness as measured by the World Governance Indicators. Next, I investigate whether cyclone mortality tends to be higher when storms impact areas of a country with weaker or less inclusive institutions.

The importance of scale is frequently emphasized in the climate vulnerability and resilience literatures; the fact that a relationship does (not) hold at one level does not imply that the same is true at other scales of analysis. Chapter 3 therefore follows a similar analytical structure to Chapter 2, but at the subnational scale in the Philippines. I use panel data models to test whether provincial and municipal poverty rates and local government financial flows are determinants of subnational tropical cyclone mortality. To my knowledge, this represents the first analysis of tropical cyclone mortality at the municipal scale.

In Chapter 4, which is also set in the Philippines, I explore an alternative analytical approach – the policy experiment – to understanding the effects of socioeconomic conditions on disaster mortality. To do so I exploit data from an existing randomized control trial (RCT) of a large community-driven development program in the Philippines. I find that randomization effectively overcomes issues of multicollinearity and omitted variable bias, but that large heterogeneities in vulnerability and exposure at the local level can lead to imbalance and compromise the precision of average treatment effect estimates. Robust data on vulnerability and exposure are needed to control for these incidental imbalances between the treatment and control groups.

Throughout this dissertation I draw from the theoretical and case study literatures to form specific hypotheses and select variables to parameterize the models. A brief review of this literature is presented in the following section. Table 1.1 summarizes the key hypotheses developed from the theory and empirical evidence as presented in these studies.

1.1.4 Tropical cyclone vulnerability

The research questions in this dissertation draw on a rich qualitative and case-study literature. In narrowly defined settings, studies are able to make convincing claims that political, social, economic, and biophysical factors can be important determinants of vulnerability. It is the goal of this analysis to systematically test hypotheses consistent with findings from this literature. These hypothesized relationships are described in the following review of the literature and summarized in Table 1.1. Table 1.1 also indicates which hypotheses are tested in each of the following analytical chapters.

Table 1.1: Summary of hypotheses

	Mechanism	Hypothesis	Ch. 2	Ch. 3	Ch. 4
Institutions	Governance	Stable, effective, and legitimate governments are better able to implement programs that promote pre-event adaptation and effective response to TCs when they occur.	x	x	x
	Social capital	The networks and access to resources afforded by social capital are useful in the sharing of information, coping, and recovery from TC events.			x
Economic	Income	A place with more average wealth or income will have more resources to invest in pre-emptive and coping responses to TC events.	x	x	
	Poverty	Individuals with insufficient incomes to meet their basic needs also lack the resources to invest in adaptation, coping, and recovery from TCs. They may also be more willing to knowingly take on risk in exchange for economic opportunity.		x	x
Human Capital	Health & Nutrition	Healthy citizens, with reliable access to food and medical care, are more mobile and able to cope with tropical cyclone events. (Some health/nutrition measures may also indicate rates of poverty and quality of institutions/ governance.)	x		
	Education	Educated citizens are more likely to have access to information about tropical cyclone risk and coping options.	x		
Cross-cutting	Exclusion	Exclusion from access to resources, political processes, or social capital can result in high TC sensitivity for marginalized groups and individuals.	x		

Micro-level evidence from several tropical cyclone affected regions indicates that households and groups with fewer productive assets and lower incomes tend to experience more severe tropical cyclone impacts (Akter and Mallick, 2013; Aldrich, 2012; Cai et al., 2016; Carter et al., 2007; Cutter et al., 2006; Faber, 2015; Hossain, 2015; Tierney, 2014). This may be because of the quality and location of housing and infrastructure, or the limited access to resources for preparedness, evacuation, and recovery (Akter and Mallick, 2013; Aldrich, 2012; Carter et al., 2007; Cutter et al., 2006; Hossain, 2015; Tierney, 2014). The vulnerability of prevalent livelihoods and economic activities, as well as availability of alternatives, also influence event impacts (Adger et al., 2005; Akter and Mallick, 2013; Carter et al., 2007; Shameem et al., 2014). The presence of strong bonding and networking social capital can protect group members, but those not in the group may actually be worse off than if the entire community had weak social capital (Adger, 2003; Aldrich, 2012; Pelling, 1999). Demographic factors such as age, health, education, and gender also appear to be important determinants of tropical cyclone impacts in some contexts, but vary somewhat by context.

1.1.4.1 Income and wealth

While tropical cyclones pose a serious risk to communities and households across the income spectrum, there is evidence that the poorer residents of a community or region are likely to suffer disproportionately high impacts from tropical cyclone events, especially in terms of injury and deaths. However, there is some variation in the patterns of differential exposure and sensitivity across studies. For example, Akter and Mallick (2013) find that the poor suffered more severe economic, physical, and structural damages from Cyclone Aila in the coastal communities studied in Bangladesh. This was at least in part because they lived in structurally weaker houses and had less access to cyclone shelters. Similarly, Hossain (2015) finds that income is associated with the structural integrity and location of homes in coastal Bangladesh, which in turn are important determinants of vulnerability. Carter et al. (2007) found that wealthier households in Honduras were actually more likely to experience loss of productive assets, but that the average percentage of household assets lost was highest in the poorest households.

Evidence of a relationship between income, exposure and sensitivity is found in the developed country context as well. Cai et al. (2016) find that median household income contributes positively to community resilience to coastal hazards in the Lower Mississippi Basin of the United States. Poverty, along with race and social inequality, is frequently cited as an important root cause of disaster from Hurricane Katrina, a storm notorious for the level of death and destruction it caused in poor and disadvantaged neighborhoods of a wealthy, democratic country (Aldrich, 2012; Cutter et al., 2006). Faber (2015) also found that the poverty rate was higher in New York City census tracts flooded by Hurricane Sandy than in dry census tracts.

1.1.4.2 Livelihoods and ecosystem services

The structure of the economy, including the vulnerability of prevalent economic activities, their diversity, and their contribution to environmental degradation, is an important determinant of impacts from tropical cyclones and other coastal disasters (Adger et al., 2005). The livelihoods in a region and amongst specific demographic, cultural and socio-economic groups can play an important role in determining the immediate impacts as well as trajectories of recovery (Adger et al., 2005; Carter et al., 2007; Shameem et al., 2014). Shameem et al. (2014) found that the productive assets, and therefore livelihoods, of fishing communities in coastal Bangladesh are particularly vulnerable to tropical cyclones, and that economic need amongst the fishing population contributes to unheeded forecasts and therefore loss of life. Carter et al. (2007) find that access to capital and labor markets after Hurricane Mitch mitigated storm impacts across income groups, but also that access to capital is higher amongst the wealthy.

In coastal communities, livelihoods and ecosystem services are often closely intertwined. Mismanagement and the subsequent degradation of coastal ecosystems therefore impact livelihoods and contribute to vulnerability to coastal disasters, including tropical cyclones (Adger et al., 2005). For example, mangrove forests can sometimes provide a protective effect against wave action (Alongi, 2008) and be a source of alternative livelihoods following disruption from a tropical cyclone event (Akter and Mallick, 2013). Yet they are currently being deforested at a rate of 1-2% per year and may be further reduced as a result of climate change (Alongi, 2008).

1.1.4.3 Demographics

Identifying the precise household and societal characteristics that exacerbate impacts from tropical cyclone events is made more difficult by the fact that economic poverty, education, health, and social and political marginalization tend to be highly correlated. There is evidence from studies of Hurricane Katrina survivors that both age and ill health contributed to negative outcomes during the storm and in the aftermath and recovery (Arcaya et al., 2014; Cutter et al., 2006). Most developing country studies of tropical cyclone impacts do not collect data on or explicitly investigate the role of health, and findings on age are not definitive. For example, in studies of rural Bangladesh Akter and Mallick (2013) do not find a statistically significant relationship between the number of children or elderly in a household and the number of fatalities or injuries sustained, and Bosher et al. (2007) do not find age to be a significant determinant of access to key resources. However, Bosher et al. (2007) do find that the respondents over fifty years of age were less likely to seek assistance post-cyclone, and many studies do not explicitly include age data.

Evidence for the effect of education on tropical cyclone impacts is mixed. Thiede and Brown (2013) find that New Orleans residents with less education were less likely and less able to evacuate during Hurricane Katrina. Hossain (2015) found that education correlated with participation in disaster training, access to weather forecasts, and receptiveness to warnings in rural Bangladesh. However, other studies do not find evidence that education is associated with impacts (e.g. Akter and Mallick (2013), also in Bangladesh), though they do not necessarily rule out such a relationship.

Gender also appears to play a role in determining tropical cyclone impacts, though because it is culturally mediated it may not be consistent across place and time. For example, Akter and Mallick (2013) found that women in rural Bangladesh were more likely to be injured in households with higher numbers of infants and elderly members, as it is typically their responsibility to see to the safety of children and the elderly. Further, traditional clothing and long hair may hinder them while doing so.

1.1.4.4 Social networks, social capital, and trust in governance

There is evidence that social capital - the resources, norms, and information available via people's connections to one another - can play an important role in tropical cyclone impacts and resilience, but also that this relationship is complex and multi-directional (e.g. Aldrich (2012); Tierney (2014)). Aldrich (2012) finds that social capital is the most important factor in explaining differences in the observed recovery of communities. Aldrich (2012) also points out, however, that social networks are not necessarily inclusive, and the disaster recovery benefits of social capital accrue primarily to group members. This can result in the exclusion or even active harm of non-group members, who are often already on the margins of society. In this way, social capital can reinforce patterns of discrimination and marginalization in society. Social capital also interacts with economic status in complex ways. Shameem et al. (2014) argue that poverty can deplete social capital, specifically because the very poor need to focus their time, energy, and resources on their livelihoods. The most desirable outcomes appear to be achieved when bonding social capital is strong and inclusive, and these groups are able to connect with high-functioning extra-local organizations and resources, such as federal government agencies and non-profits (Adger, 2003).

There is evidence that even when warnings are disseminated and coping resources available, lack of trust can inhibit coping (Mallick et al., 2011). While 87% of the population surveyed in a Bangladesh study by Mallick et al. (2011) received warning of Cyclone Aila, most discussed the warning only with family members, chose to remain in their homes, and took little or no preparatory measures. This was attributed to a lack of trust in the radio warning, as well as the distance and safety of shelters. Lack of trust between vulnerable groups and government is also cited as a factor explaining the mixed success of evacuation during Hurricane Sandy in New York City (Faber, 2015). In contrast, Veland et al. (2010) credit the successful evacuation of the indigenous island community of Warruwi in Australia prior to Tropical Cylone Monica to the successful inclusion of and coordination with local indigenous leadership and institutions.

1.1.5 Conclusions

Decision-makers are in need of well-supported typological theories of vulnerability and resilience; theories that provide “contingent generalizations about combinations or configurations of variables that constitute theoretical types” (George, 2005). In other words, policy-makers need information about the range of causal pathways available to reduce vulnerability and enhance resilience to a range of shocks and stressors, their inter-temporal dynamics, and under what circumstances different pathways are most likely to be available. The current state of the literature is largely either highly generalized or highly case specific, and thus falls short of providing theories and evidence at this level of specificity.

This dissertation is a study of the general socioeconomic conditions that contribute to tropical cyclone mortality. It directly contributes to our understanding of tropical cyclone vulnerability, at multiple scales. While the results are not directly generalizable to other hazards or general notions of vulnerability, their conditional nature actually makes their applicability (or lack thereof) more straightforward in a policy setting. Further, they are well suited to the hazard-by-hazard accumulation of knowledge on the importance of general institutional and socioeconomic conditions to a range of shocks and stressors. Tropical cyclone mortality is one piece of a larger puzzle.

Chapter 2: Socioeconomic determinants of tropical cyclone mortality: Evidence from a global dataset

2.1 Introduction

Between 1996 and 2016, tropical cyclone disasters have killed over 226,000 people across 81 countries (Guha-Sapir, 2018). By far the deadliest of these was the 2008 Cyclone Nargis in Myanmar, which triggered the worst natural disaster in the country's recorded history. Over 138,000 people died and the economic damages from the storm were estimated at $4 billion (Guha-Sapir, 2018) to over $10 billion (Fritz et al., 2009). Nargis was a powerful Category 3/4 storm at landfall, but storms of similar intensity struck several other countries that year with far fewer fatalities. Twenty-nine of the 103 tropical cyclones that occurred in 2008 correspond to a recorded disaster with loss of life in the Emergency Events Database (EM-DAT) (Guha-Sapir, 2018; Knapp et al., 2010).

What accounts for the extreme variation in the impacts of tropical cyclones? And how can we prevent mortality from future storms? In this chapter I investigate the socioeconomic determinants of tropical cyclone mortality. I test whether effective and inclusive institutions, income and other socioeconomic factors are associated with lower cyclone death tolls. Disaggregating these effects contributes to our understanding of cyclone mortality risk under different institutional and socioeconomic development scenarios.

To investigate these relationships, I construct a novel dataset of over one thousand tropical cyclone disasters in 59 countries from 1979 to 2016. Because tropical cyclone mortality results from the interaction of the physical hazard and the human system, I use spatial methods to match meteorological and socioeconomic data for each storm. Gridded population estimates are spatially matched to parametrically modeled wind profiles based on observational data from the Best Track Archive for Climate Stewardship (IBTrACS) and to rainfall data from the NOAA Climate Prediction Center's Unified Precipitation Project.

This provides multiple advantages. First, controlling for storm intensity and population exposure increases precision and controls for the possibility that cyclone exposure may be correlated with socioeconomic conditions. This improves our ability to identify relationships between socioeconomic factors and mortality. Second, I am able to study the impacts of national versus local socioeconomic conditions. Previous studies have been restricted to the national scale, which may overlook important heterogeneities within countries. Finally, because I construct hazard and exposure measures for all recorded tropical cyclones during the study period, I am able to examine the characteristics of storms that are not associated with a recorded disaster. This provides insight into the physical and socioeconomic conditions under which tropical cyclone disaster may be avoided.

I utilize this dataset to estimate the effects of socioeconomic factors on cyclone mortality for two sets of multivariate negative binomial regression models. First, I investigate the importance of national institutions and country-level development factors for cyclone fatalities from 1996 to 2016. Government effectiveness scores from the World Governance Indicators (WGI) (Kaufmann, 2010), available starting in 1996, are used to capture the relative quality of public policies and service delivery by formal institutions across countries. Next, I use subnational data to test whether death tolls are higher when storms affect areas of a country where institutions are weaker or less inclusive. Local institutional quality and inclusion are proxied using subnational infant mortality rates and spatial data on excluded ethnic groups. The subnational analysis covers a longer time period, from 1979 to 2016, and focuses on within country effects.

I find strong evidence that national government effectiveness is associated with lower mortality from tropical cyclone events. This result is highly statistically significant and robust to the inclusion of controls for income, health and education as well as alternative regression specifications. An increase of one standard deviation in government effectiveness is associated with a 50% decrease in event mortality, controlling for GDP per capita. This finding is consistent with current theory, but has not previously been shown empirically. Findings from this analysis further suggest that existing evidence of the association between GDP per capita and country-level vulnerability may overstate the importance of national income.

In my subnational analysis, I find new evidence that local socioeconomic conditions matter for tropical cyclone mortality. Specifically, death tolls are higher when infant mortality rates are elevated (compared to the national average) within the cyclone wind field. An increase in one standard deviation in the local infant mortality ratio is associated with an increase of 48% or more in event mortality. This basic result is robust to alternative definitions of exposure and regression specifications. I do not find evidence of a statistically significant relationship between fatalities and the presence of an excluded ethnic group within the storm's wind field. Consistent with recent theoretical work, these results indicate that national estimates of vulnerability may mask important subnational heterogeneities.

2.1.1 Related literature

That the poor are disproportionately vulnerable to tropical cyclones and other natural hazards has become something of a stylized fact, frequently cited throughout the development, disaster risk reduction, and climate change literatures. And in the case of tropical cyclones there is indeed evidence substantiating an association between development and mortality risk. Global studies find that tropical cyclones of similar intensity tend to have higher death tolls when they affect countries with lower GDP per capita (Hsiang and Narita, 2012; Peduzzi et al., 2005). This finding is useful for identifying at-risk countries, developing indicators and indices of vulnerability, and projecting future risk – particularly in response to climate change (Peduzzi et al., 2005).

Yet establishing an association between national income and cyclone deaths falls short of what is needed for public policy. The key studies that establish a link between development and cyclone mortality do not include multiple development factors in a single model (Hsiang and Narita, 2012; Peduzzi et al., 2005). Given the strong correlation between GDP per capita and characteristics such as governance, health and education, it is unclear whether income or some other aspect(s) of the institutional or socioeconomic environment drive the observed relationship. This evidence is therefore of limited use in substantiating proposed theoretical mechanisms that might underlie the observed income-mortality relationship.

2.1.1.1 Vulnerability theory

This chapter is motivated by a theoretical literature and case study evidence that suggest a complex causal relationship between development and vulnerability to natural hazards. Different lines of theory emphasize the importance of institutions, resources, and human or social capital – but tend to agree that vulnerability is the product of complex socio-ecological systems operating dynamically and across scales (Blaikie et al., 2004; Cutter et al., 2008; Turner et al., 2003). And while development and vulnerability to hazards are connected, they should not be conflated (Adger et al., 2003). The potential to exacerbate vulnerabilities in the pursuit of development, and in particular economic growth, is a well-documented problem (e.g. Adger et al. (2003); Blaikie et al. (2004); Denton et al. (2014)).

The potential risks posed by weak collective action and exclusion suggest that the quality and inclusiveness of institutions are likely to play an important role in reducing vulnerability to tropical cyclones and other hazards. Blaikie et al. (2004) describe how opportunity and risk tend to occur together spatially, yet the risks and benefits of opportunities often accrue unevenly according to existing power structures in society. Thus, the powerful may disproportionately benefit although the marginalized take on much of the risk: for example, when rapid urbanization leads to the growth of slums on unstable slopes or flood-prone land (Blaikie et al., 2004). Pelling (1999) finds that the strong adaptation by the political and economic elites in urban Guyana actually contributed to overall flood vulnerability, because these elites were able to co-opt and thereby reduce the effectiveness of new community organizations established to build resilience. Aldrich (2012) argues that social capital - the resources, norms, and information available via people's connections to one another - are the most important factor in explaining community-level resilience to disasters. But he also finds that social networks are not necessarily inclusive, and therefore strong social capital can result in the exclusion or even active harm of non-group members, who are often already on the margins of society.

The state plays a direct role in preparedness and response, and further influences how conducive the national environment is to collective and individual adaptation (Adger, 2003). Adger (2003) argues that economically underdeveloped countries with "well-functioning" states and civil societies have repeatedly demonstrated their capacity for adaptation to hazards. In contrast, a lack of political will and effective governance have been implicated in some of the deadliest disasters in history – including the 1970 Bhola cyclone that killed an estimated 250,000 to 500,000 people in former East Pakistan (now Bangladesh) (Hossain, 2018) and the 2008 Cyclone Nargis that killed approximately 140,000 people in Myanmar (Howe and Bang, 2017).

Further, the state is likely to be an important intermediary in multilateral climate finance transfers, such as those negotiated under the United Nations Framework Convention on Climate Change (UNFCCC) (Eakin and Lemos, 2006). The capacity of national governments to effectively channel these funds towards hazard risk reduction is an important policy question.

2.1.1.2 Gaps in the empirical literature

The existing empirical literature finds that more developed countries experience lower mortality from tropical cyclone disasters. This is based on observed statistical relationships between GDP per capita and mortality (Hsiang and Narita, 2012; Kahn, 2005; Peduzzi et al., 2012). This study confirms that GDP per capita is a useful proxy for cyclone vulnerability, but then disaggregates this effect by simultaneously testing for institutional quality and multiple aspects of development in a single model.

Existing global studies of mortality from tropical cyclones and other climate disasters are restricted to the national scale (Alberini et al., 2006; Brooks et al., 2005; Hsiang and Narita, 2012; Kahn, 2005; Peduzzi et al., 2012). As a result, these studies are unable to identify the scale at which mechanisms operate to produce vulnerability. For example, to the extent that GDP per capita is protective against tropical cyclone mortality, is this because national government resources matter, or because local institutions and individuals are, on average, wealthier in the impact zone? This analysis finds evidence that subnational development patterns matter:

mortality is higher when storm exposure is concentrated over a subset of the population that is already worse off.

Previous work has sought to compare national socioeconomic characteristics and disaster mortality rates from a range of natural hazards. Alberini et al. (2006); Brooks et al. (2005) find evidence that national development is associated with lower disaster mortality, but do not provide statistical evidence of the relative importance of different variables. Kahn (2005) finds democracy and other institutional variables to be protective against natural disaster deaths, but only when considered independently of GDP per capita. These multi-hazard disaster studies do not control for variation in physical exposure. Without measures of hazard exposure, mortality models are likely to have large standard errors and, if socioeconomic conditions are related to exposure, suffer from omitted variable bias.

In contrast, in this analysis I control for storm exposure when estimating relationships between socioeconomic factors and mortality. Failing to control for this variation would be particularly problematic if tropical cyclone climatologies are correlated with socioeconomic conditions. This correlation could be incidental, or arise from the lasting impacts of cyclones on socioeconomic development in areas of repeated exposure. For example, Hsiang and Jina (2014) find that tropical cyclones have lasting negative impacts on economic growth.

In order to construct appropriate physical exposure variables, this chapter builds on methods developed to model tropical cyclone exposure for studies on adaptation (Hsiang and Narita, 2012) and future risk of mortality from tropical cyclones (Peduzzi et al., 2012). Hsiang and Narita (2012) model annual tropical cyclone exposure by country and year to determine if countries with higher average exposure show evidence of adaptation. Peduzzi et al. (2012) take this further by spatially matching modeled winds to population data as part of a study on trends in tropical cyclone risk. I follow a similar approach to Peduzzi et al. (2005) and Peduzzi et al. (2012) to construct exposure controls, but using an alternative parametric wind speed model and adding rainfall.

Understanding the role of institutions and other socioeconomic determinants of cyclone risk is not the focus of Hsiang and Narita (2012) or Peduzzi et al. (2012). However, both studies observe a correlation between national GDP per capita and storm mortality that merits further investigation. Average income is highly correlated with other development factors, such as governance, health and education. Because these studies do not include multiple development factors in a single model, it is unclear whether income or some other facet of development drives this relationship. They are also restricted to the national scale. This analysis both disaggregates the national development-mortality relationship and includes a novel subnational analysis based on wind-field level socioeconomic variables.

2.2 The Data

Natural hazards, including tropical cyclones, result in humanitarian disaster only when an exposed human system fails to sufficiently adapt or cope. These interactions between people and storms may be highly localized. Understanding mortality from tropical cyclones therefore requires that we consider the spatial intersection of physical hazards and socioeconomic systems at a high resolution.

Tropical cyclone exposure occurs when people (or other assets) are present in the hazard area. Basic statistics on a storm's maximum wind speed or minimum central pressure are indicators of hazard intensity rather than exposure, and therefore incomplete measures of cyclone risk. Many intense storms never pass within striking distance of populated land, or weaken sufficiently to pose little threat upon landfall. When intense storms do strike land, minor differences in storm trajectory can have large implications for the number of people exposed to hazardous conditions. The speed and longevity of a storm impacts the duration of wind exposure as well as the cumulative rainfall. We are therefore interested in understanding the number of people exposed to hazardous conditions, the intensity of exposure, and also the local socioeconomic conditions of the affected population.

This requires spatial data on cyclone hazard matched to data on population, socioeconomic conditions, and mortality counts. Combining these varied data sources presents several methodological challenges. In this section I briefly describe key methods and data sources utilized to build an event-based dataset of tropical cyclone disasters that extends from 1979 to 2016. For additional details and replication please see the supplemental materials.

2.2.1 Mortality data and unit of analysis

This chapter seeks to identify the socioeconomic determinants of country-level disaster mortality. The unit of analysis is therefore the country-storm disaster event.

In other words, if a single tropical cyclone causes disasters in three countries, these are considered three separate events. Similarly, if a country experiences multiple disasters in a given year, these are considered separate events in the dataset. Our criteria for disaster follow those of the CRED/OFDA International Disaster Database, the source of our country-storm mortality data for this analysis (Guha-Sapir, 2018).[1]

Tropical cyclones precipitated over 423,000 deaths in 89 countries from 1979 to 2016, but 95% of those deaths are concentrated in just 10 countries.[2] And just two storms account for more than half of these deaths: Cyclone Gorky in Bangladesh (1991) and Cyclone Nargis in Myanmar (2008). Figure 2.1 maps total deaths by country over the 1979 to 2016 study period using data from the EM-DAT.

2.2.2 Measures of hazard intensity and exposure

Data on storms and disasters do not share a common identifier system, so it is not obvious what storm caused what disaster. Event mortality data from the EM-DAT reports disaster impacts from tropical cyclones by country-event. Tropical cyclone data are obtained from the Best Track Archive for Climate Stewardship (IBTrACS) Project, and include maximum sustained wind speed (MSWS) georeferenced at 6-hour intervals (Knapp et al., 2010). The EM-DAT disasters and IBTrACs storms were matched using a spatial algorithm that, for each disaster, looks for the closest storm in space and time. The automated match was then man-

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[1] An event may be included in EM-DAT because a state of emergency is declared or a call for international assistance issue, and/or because 10 or more people were killed, or 100 or more affected.

[2] In order from most to least tropical cyclone deaths: Bangladesh, Myanmar, the Philippines, India, Honduras, Vietnam, China, Haiti, Nicaragua and the United States.

ually reviewed for accuracy. In ambiguous cases (for example, if multiple storms could feasibly match a disaster in space and time), additional sources such as storm reports and location notes were consulted for disambiguation.

Best Track data consist of wind and pressure data geo-referenced at 6-hour intervals along the central track of the storm. In order to produce a spatial representation of storm winds, suitable for matching with gridded population and socioeconomic data, I interpolate the track data and then model the winds using a parametric tropical cyclone model. This is done using an adaptation of the R software *stormwindmodel* (Anderson et al., 2017) based on the wind speed model by Willoughby et al. (2006).[3] I then rasterize the grid winds (at a 2.5 arc-minute resolution) and map the spatial extent of the wind fields over land by country. I do this for multiple thresholds, including the tropical storm (63-118 km/hr), Saffir-Simpson Category 1 (119-153 km/hr), and Saffir-Simpson Category 2+ ($>$ 153 km/hr) force wind fields. Figure 2.3 illustrates the steps of this process for one event, the 2004 Cyclone Gafilo in Madagascar.

Once the wind hazard has been spatially delineated, we can then overlay the wind fields with population data to construct exposure variables. Subnational population estimates from the Center for International Earth Science Information Network (CIESIN) are interacted with the modeled wind fields to produce estimates of the size of populations exposed to winds of different intensities (CIESEN, 2017a,b).

Rainfall exposure is based on the CPC Global Unified Gauge-Based Analysis of

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[3] This modified version extends the functionality of *stormwindmodel* outside of the NW hemispheres and is available under an open source license at https://github.com/liztennant/stormwindmodel.

Daily Precipitation dataset, available at a 0.5 degree resolution from 1979 to present (NOAA, 2018). While rainfall data are already available in spatial form, they are not linked to specific storm events. For each country-storm event, I therefore take the maximum total rainfall (over the duration of the storm) experienced by any grid cell in the country and within a 500km buffer of the storm track.

The IBTrACS dataset begins in 1848 for some basins and has global coverage from 1945, but the underlying data quality, processing methods, and completeness of the data available have evolved dramatically over time, especially through the late 1970s (Knapp et al., 2010). This analysis is therefore limited to the satellite-era (1979+) of wind and rainfall data. Indian Ocean tropical cyclones are excluded from this analysis, in part because the best track data in IBTrACS are incomplete for this region.[4] Regional (or country) geographic controls are included in all models to control for possible differences in data collection and processing by regional meteorological organizations.

In Table 2.1 I describe the physical control variables constructed to measure hazard intensity and exposure in this analysis, as well as the sources they are drawn from (see Appendix Tables A.1 & A.2 for descriptive statistics). The cumulative population exposure from 1979 to 2016 is mapped by country in Figure 2.2.

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[4] Based on comparisons with the EM-DAT and the India Meteorological Department's Cyclone eAtlas-IMD.

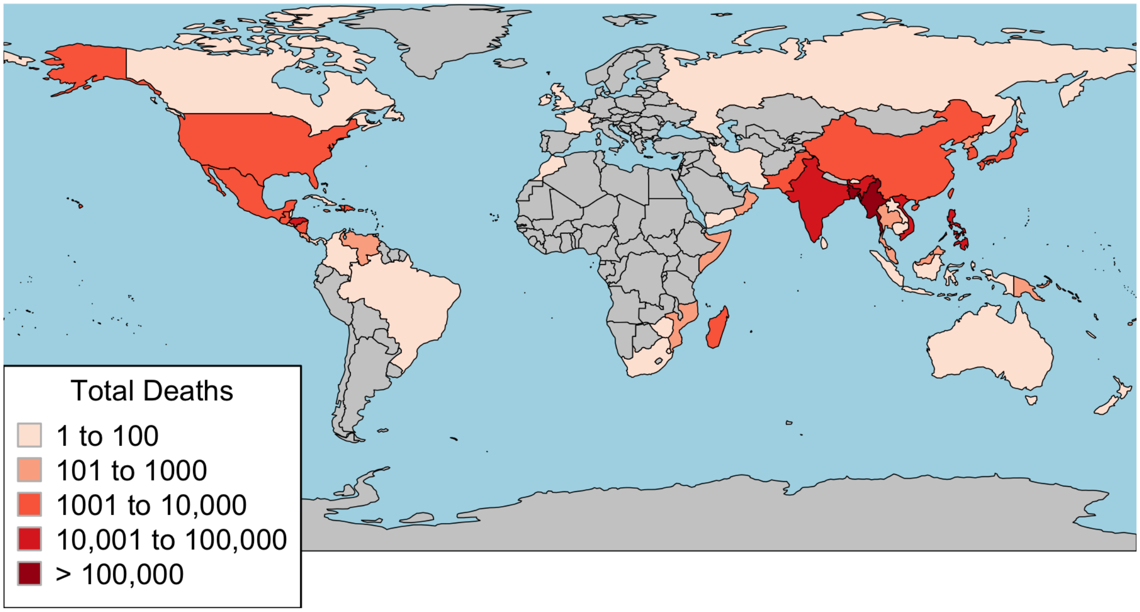


Figure 2.1: Cumulative deaths from tropical cyclone disasters, 1979 to 2016. Based on data from the EM-DAT (Guha-Sapir 2018).

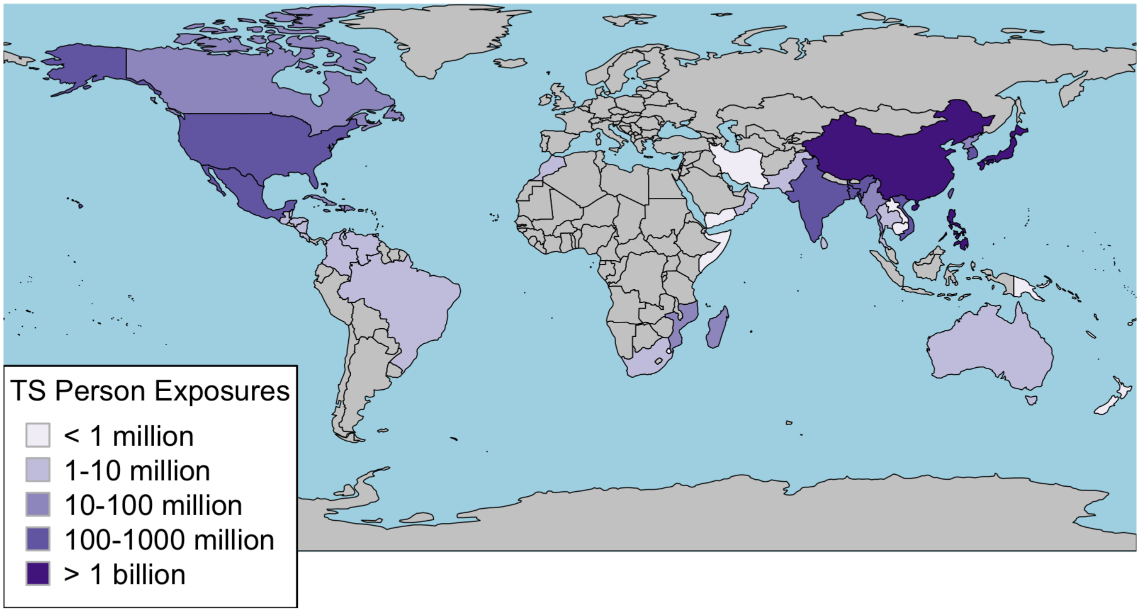
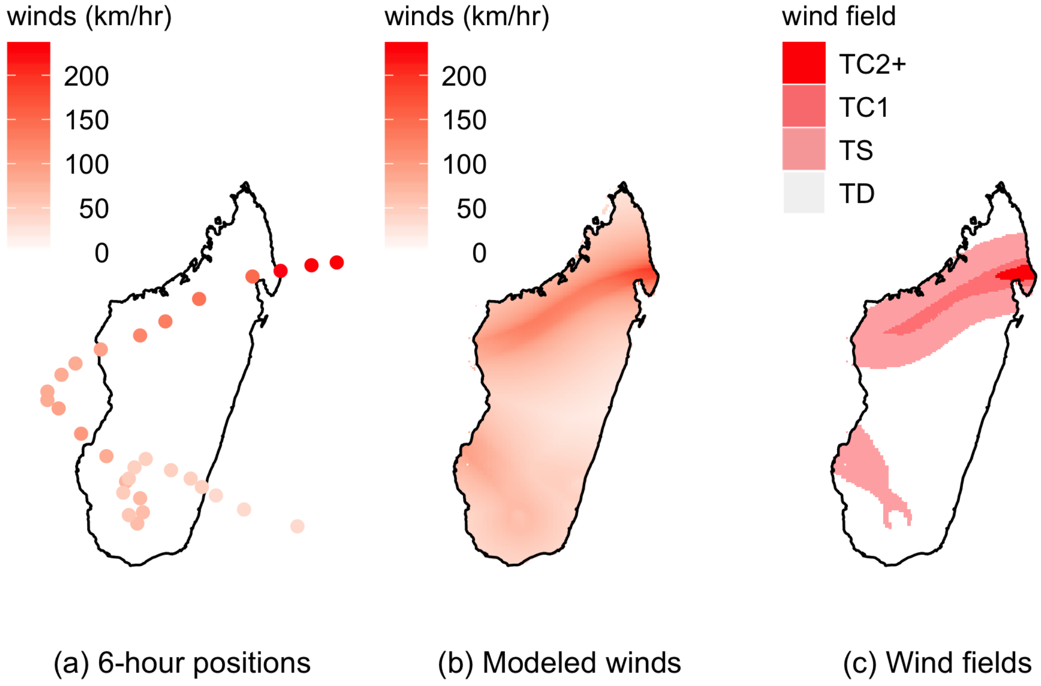


Figure 2.2: Cumulative population exposure to tropical storms and cyclones (sustained winds > 63 km/hr) from 1979 to 2016. See Table 2.1 for a description of the population exposure variables. Based on data from (CIESEN 2017a; 2017b; Knapp et al. 2010).



(a) 6-hour positions (b) Modeled winds (c) Wind fields

Figure 2.3: Modeling tropical cyclone wind fields for Cyclone Gafilo (2004) in Madagascar. I begin with (a) the 6-hourly wind speeds from the International Best Track Archive for Climate Stewardship (IBTrACS) (Knapp et al. 2010). Using a parametric wind speed model (Anderson et al. 2017 and Willoughby et al. 2006), I then estimate (b) the maximum sustained wind speed over land at a 2.5 arc-minute resolution. Finally, I define (c) the spatial extent of the TS (Tropical Storm: 63-118 km/hr), TC1 (Tropical Cyclone: 119-153 km/hr) and TC2+ (Tropical Cyclone: > 153 km/hr) wind fields.

Table 2.1: Summary of hazard intensity and exposure variables

Variable	**Description**	**Source**
Population exposed to tropical storm winds	The size of the population (in millions) in the country exposed to tropical storm conditions: sustained winds of 63-118 km/hr.	Population data from the the Center for International Earth Science Information Network (CIESIN 2017a; CIESIN 2017b). Spatial extent of wind field modeled using stormwindmodel (Anderson et al. 2017; Willoughby et al. 2006) and IBTrACS data (Knapp et al. 2010).
Population exposed to Category 1 tropical cyclone winds	The size of the population (in millions) in the country exposed to Safir-Simpson Category 1 tropical cyclone conditions: sustained winds of 119-153 km/hr.	ibid.
Population exposed to Category 2+ tropical cyclone winds	The size of the population (in millions) in the country exposed to Safir-Simpson Category 2 or higher tropical cyclone conditions: sustained winds of $>$ 153 km/hr.	ibid.
Maximum rainfall exposure (mm)	The maximum total rainfall (mm) in a populated 30 minute grid-cell, within a 500 kilometer buffer of the storm track and within the country.	CPC Global Unified Gauge-Based Analysis of Daily Precipitation dataset (NOAA 2018). Storm track buffer based on IBTrACS (Knapp et al. 2010).

2.2.3 Socioeconomic variables

Country-level socioeconomic variables are matched to tropical cyclone events based on the year and country in which they occurred. Government effectiveness scores from the World Governance Indicators (WGI) (Kaufmann, 2010) measure the quality of public policies and service delivery by formal institutions at the country level. Within countries, local institutional quality and inclusion are proxied using subnational infant mortality rates and spatial data on the political exclusion of ethnic groups. National development data on income, health and education are taken from the World Development Indicators (WDI) (WDI, 2018).

The WGI government effectiveness score is a subjective and normalized measure of governance at the country level, available biannually from 1996 to 2002 and then annually (Kaufmann, 2010). Storms in the 1996 to 2016 dataset are matched to the nearest annual governance score by date. The government effectiveness measure is designed to capture:

> [P]erceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. (Kaufmann, 2010, p. 4)

For each year, government effectiveness has approximately zero mean, unit standard deviation, and a range of roughly -2.5 to 2.5 for the global dataset (Kaufmann, 2010). Figure 2.4 maps governance scores in 2016 for countries with tropical cyclone deaths between 1979 and 2016.

Country-year panel data on income, health and education are matched to tropical cyclone events based on the country and year in which the storm occurred (see Table 2.2). The GDP per capita and infant mortality rate variables are lagged by one year. Countries affected by tropical cyclone mortality fall across the development spectrum, from Least Developed Countries to wealthy nations (see Table A.1 for descriptive statistics).

I construct two subnational variables at the wind field level. For each storm, these variables are constructed for the tropical storm ($>$ 63 km/hr) and tropical cyclone ($>$ 119 km/hr) wind field. The first is the infant mortality ratio (IM ratio), a ratio of the infant mortality rate (IMR) in the storm wind field compared to the national IMR, based on data from the Poverty Mapping Project: Global Subnational Infant Mortality Rates for the year 2000 (CIESEN, 2005). Because the resolution of subnational infant mortality data varies by country I include country controls in all models containing the infant mortality ratio variables.

The second subnational variable is the (population-weighted) percentage of the wind field that is settled by an excluded ethnic group. This is based on data from the Ethnic Power Relations (EPR) Dataset Family (Cederman et al., 2010; Vogt et al., 2015; Wucherpfennig et al., 2011). EPR provides annual data on politically relevant ethnic groups' access to state power, and classifies groups as excluded if they are powerless, discriminated or self-excluded according to the following definitions:

> While powerless means that the group is simply not represented (or

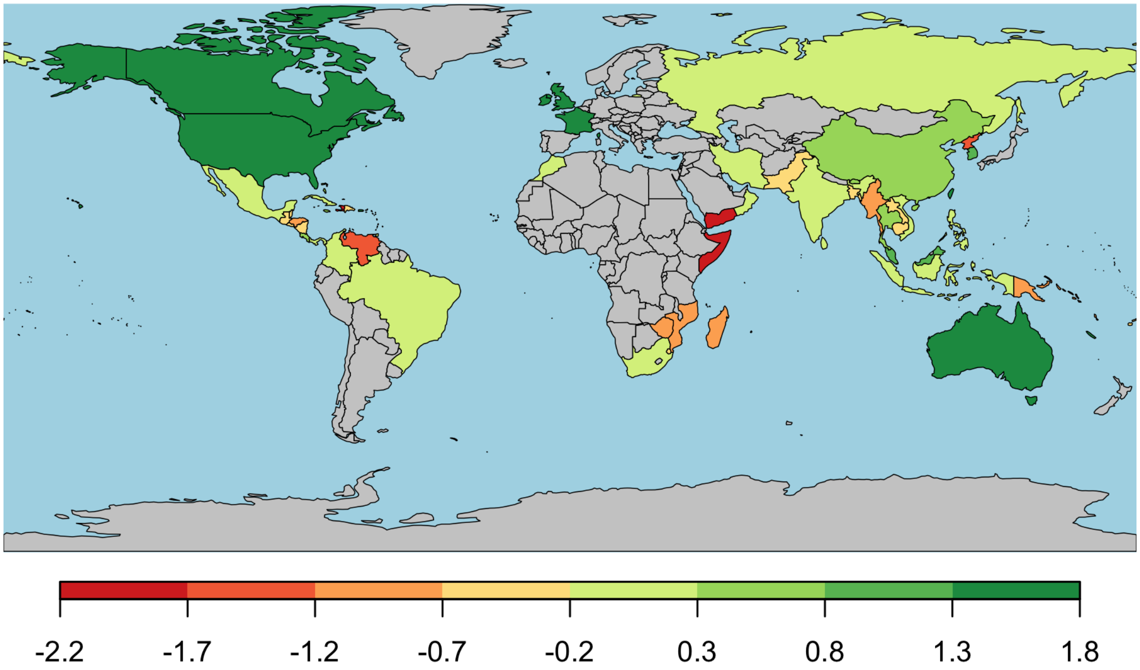


Figure 2.4: National government effectiveness scores for tropical cyclone affected countries, 2016. Countries mapped experienced tropical cyclone mortality between 1979 and 2016. Countries are shaded in grey if 2016 WGI are not available or the country has not experienced cyclone deaths during this period. Higher scores indicate more effective governance. Data from the World Governance Indicators (WGI) (Kaufmann et al. 2010).

> does not have influence) in the executive, discrimination indicates an active, intentional, and targeted discrimination by the state against group members in the domain of public politics. The special category of self-exclusion applies to groups that have excluded themselves from central state power, in the sense that they control a particular territory of the state which they have declared independent from the central government. (Vogt et al., 2015, p. 7)

In Table 2.2 I describe the key socioeconomic variables and the sources they are drawn from (see Appendix Tables A.1 & A.2 for descriptive statistics).

Table 2.2: Summary of socioeconomic variables

Variable	**Scale**	**Years**	**Description**	**Source**
Government Effectiveness	country	1996-2016*	Government effectiveness	The World Governance Indicators, the World Bank (Kaufmann, 2010)
Real GDP per capita (ln)	country	1978-2016	The natural logarithm of Real GDP per capita (constant 2010 US$)	The World Bank and Penn World Tables (World Bank, 2018; Feenstra et al., 2015)
Infant mortality rate	country	1978-2016	Mortality rate, infant (per 1,000 live births)	World Development Indicators, The World Bank (World Bank, 2018)
Education	country	1978-2016	School enrollment, primary (% net)	World Development Indicators, The World Bank (World Bank, 2018)
Infant mortality ratio	subnational	2000	Population-weighted average infant mortality rate (IMR) in wind field** / national IMR	Center for International Earth Science Information Network (CIESIN) - Columbia University (CIESEN, 2005; World Bank, 2018)
Excluded ethnic group (% of wind field**)	subnational	1978-2016	Share (population-weighted) of the wind field** settled by an excluded ethnic group	Ethnic Power Relations (EPR) Core Dataset 2018 and GeoEPR 2018 (Cederman et al., 2010; Vogt et al., 2015; Wucherpfennig et al., 2011)

Notes:

* Available biannually from 1996-2002, nearest estimate (by date) is matched to each storm.

** Variable calculated for tropical storm (63-118 km/hr) and tropical cyclone (> 119 km/hr) wind fields

2.3 Empirical Approach

Tropical cyclone deaths y for event i are modeled using a negative binomial regression model. The use of a count data model is suitable given that storm mortality is a non-negative integer, with the majority of events having few or no fatalities. Our data violate the equidispersion principle $E[y_i \mid \mathbf{x}_i] = Var[y_i \mid \mathbf{x}_i]$ required for the simpler Poisson regression model. The negative binomial regression model allows us to relax this assumption such that the variance depends on the mean and a dispersion parameter $\alpha = 1/\theta$. I use the Negbin 2 (NB2) form of the negative binomial regression model represented in equations 2.1-2.3, following Greene (2012, p. 808). The NB2 model has several useful properties compared to other negative binomial models, including that it is robust to distributional misspecification (Cameron and Trivedi, 2013). However, model standard errors may be inconsistent in cases of distributional misspecification (Hilbe, 2014). I therefore estimate robust standard errors for all negative binomial regressions presented in this analysis. One alternative would be to cluster standard errors by year and country; I compute these for comparison and find that they are very similar to the White standard errors. The NB2 model is

$$\text{Prob}(Y = y_i \mid \mathbf{x}_i) = \frac{\Gamma(\theta + y_i)}{\Gamma(y_i + 1)\Gamma(\theta)} r_i^{y_i} (1 - r_i)^{\theta}, \tag{2.1}$$

where

$$\lambda_i = \exp(\mathbf{x}_i'\boldsymbol{\beta}), \tag{2.2}$$

and

$$r_i = \lambda_i/(\theta + \lambda_i). \tag{2.3}$$

The characteristics of each country-storm-event i, represented by the vector $\mathbf{x}_i$, include socio-economic characteristics, measures of storm intensity and exposure, as well as geographic and other control variables. The parameters to estimate are: $\boldsymbol{\beta}, \theta$.

One alternative to a count data model is an ordinary least squares (OLS) regression of the natural logarithm of y on $\mathbf{x}_i$. However, because the dataset includes zero-death events and ln 0 is undefined, we must either further transform the dependent variable to ln (deaths + 1) or exclude zero death events from the analysis. Further, interpretation of the log-transformed OLS model is less useful compared to the negative binomial due to the problem of retransformation bias, that $\mathrm{E}[\ln y \mid \mathbf{x}] = \mathbf{x}_i'\boldsymbol{\beta}$ does not imply $\mathrm{E}[y \mid \mathbf{x}] = \exp(\mathbf{x}_i'\boldsymbol{\beta})$ (Cameron and Trivedi, 2013, p. 103). Therefore, while results from comparable OLS models with log transformation are provided for comparison and to test the robustness of key findings, the discussion primarily refers to the results of the negative binomial model.

2.4 Results & Discussion

I begin by presenting evidence from a country-level model that establishes a large and robust association between national government effectiveness and mortality from tropical cyclones. Next, I explore the importance of subnational development patterns for tropical cyclone risk. I find that socioeconomic conditions in the path of the storm can have a large effect on expected mortality.

The main results from the 1996-2016 national cyclone mortality analysis are presented in Table 2.3 and the 1979-2016 subnational analysis in Table 2.5. Estimates are presented as Incident Rate Ratios (IRRs) in these tables, obtained by exponentiating the estimated coefficients of the negative binomial regression models. Thus, the null hypothesis is $H_0 : IRR = 1$. If the coefficient is negative the $IRR < 1$ and if the coefficient is positive the $IRR > 1$. Interpretation is that mortality is expected to change by a factor equal to the IRR with a one-unit increase in the independent variable, holding other regressors constant.

2.4.1 National governance and development

Previously published single-variable models of tropical cyclone mortality have found GDP per capita to be negatively correlated with cyclone mortality. I recreate this finding in Table 2.3, column (2). When GDP per capita is the sole socioeconomic variable in a cross-country model of tropical cyclone mortality with physical controls, an increase of one log-unit of GDP per capita is predictive of a 75% decrease in deaths (Table 2.3, column (2)). This confirms that national GDP per capita is a useful proxy for cyclone vulnerability.

I also find that governance, infant mortality and education are predictive of cyclone mortality. Including only one socioeconomic variable at a time, each of the four national governance or development indicators tested is a highly statistically significant ($p < 0.001$) predictor of tropical cyclone event mortality, controlling for exposure (Table 2.3, columns (1-4)).

In order to disaggregate this relationship, I then test multiple aspects of development in a single model. I test combinations of government effectiveness, GDP per capita, health and education. The decrease in mortality associated with a one standard deviation increase in log-unit GDP per capita falls from 75% to 50% when we add government effectiveness to the income-only model, and loses statistical significance if we also include infant mortality and education (Table 2.3, columns (2, 5 and 6)). The effects of infant mortality and education also lose statistical significance in the joint model (Table 2.3, column (6)). In contrast, the government effectiveness coefficient remains large and statistically significant (Table 2.3, column (6)).

Table 2.3: National determinants of mortality from TC events (1996-2016): Negative binomial regression results

	IRR (1)	IRR (2)	IRR (3)	IRR (4)	IRR (5)	IRR (6)
Government Effectiveness	0.219 ***	-	-	-	0.425 ***	0.315 ***
	(0.028)	-	-	-	(0.108)	(0.107)
Ln real GDP per capita (t-1)	-	0.302 ***	-	-	0.537 *	0.624
	-	(0.042)	-	-	(0.142)	(0.248)
National infant mortality rate (t-1)	-	-	1.079 ***	-	-	0.980
	-	-	(0.006)	-	-	(0.019)
Primary school enrollment (% net)	-	-	-	0.909 ***	-	1.001
	-	-	-	(0.013)	-	(0.019)
Pop. (millions) exposed to winds 63-118 km/hr	1.008	1.004	0.996	0.992	1.009	1.017 **
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
Pop. (millions) exposed to winds 119-153 km/hr	1.197 **	1.218 **	1.229 **	1.260 ***	1.209 **	1.260 **
	(0.083)	(0.089)	(0.087)	(0.080)	(0.087)	(0.091)
Pop. (millions) exposed to winds > 153 km/hr	3.509 ***	3.437 ***	2.950 **	4.991 ***	3.658 ***	6.113 ***
	(1.188)	(1.006)	(0.980)	(2.319)	(1.089)	(2.302)
Maximum rainfall exposure (mm)	1.004 ***	1.003 ***	1.003 **	1.002 *	1.003 ***	1.002 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time (years)	0.939 **	0.962 *	0.958	0.973	0.952 *	0.961 *
	(0.021)	(0.019)	(0.025)	(0.017)	(0.020)	(0.018)
Geography	regions	regions	regions	regions	regions	regions
Observations	926	887	902	529	886	510

Notes: Negative binomial results are presented as Incident Rate Ratios (IRRs), obtained by exponentiating the estimated coefficients. Thus, we are testing the null hypothesis that $IRR = 1$. If the coefficient is negative the $IRR < 1$ and if the coefficient is positive the $IRR > 1$. Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

I find robust evidence of a large and highly statistically significant ($p < 0.001$) association between national government effectiveness and lower cyclone mortality, controlling for GDP per capita and physical exposure (see Table 2.3, column (5)). In a model with no other socioeconomic variables, a one standard deviation increase in government effectiveness is associated with a 70% decrease in mortality (Table 2.3, columns (1)). Adding GDP per capita to the model, this falls to a 50% decrease in mortality per standard deviation of government effectiveness (Table 2.3, column (5)). However, the effect of governance on mortality remains large and statistically significant with the inclusion of income, health and education variables in the model (see Table 2.3, column (6)).

The problem of multicollinearity between development factors has posed longstanding difficulties for understanding patterns of economic growth and development. Disentangling the complex causality that underlies the well-documented correlation between income and institutions is the subject of a large literature (e.g., Acemoglu et al. (2008); Boix (2011); La Porta et al. (1999); Putnam (1994)). It similarly complicates the identification of causal relationships between development and tropical cyclone mortality. Government effectiveness, GDP per capita, infant mortality, and education are all highly correlated (see Table A.3). Thus, to the extent that these factors are collinear, statistical analysis is mute on the causal source of that variation. Further, even the relatively strong evidence for an association between government effectiveness and mortality may be explained at least in part by some other, omitted variable.

Table A.5 illustrates the importance of controlling for physical exposure. I exclude the physical exposure controls in columns (1), (3) and (5) of Table A.5 (for the negative binomial and OLS models, respectively) for comparison. Including measures of exposure and intensity impacts both the size of the estimated coefficients for government effectiveness and GDP per capita, and also their statistical significance. Further, based on the Akaike information criterion (AIC), the negative binomial model that excludes the physical controls (Table A.5, column (1)) is $1.49e-42$ times as likely as the model with the physical controls (Table A.5, column (2)).

2.4.1.1 Robustness checks

The main results of this analysis are robust to various permutations of the model and the dataset. In Tables A.6 and A.7 I present OLS estimates comparable to the negative binomial results in Table 2.3. Government effectiveness has a large and statistically significant association with lower mortality in all OLS specifications tested in Tables A.6 and A.7.

Given the relative stability of government effectiveness within most countries from 1996-2016 (when the World Governance Indicators are available) I include regional but not country geographic controls in this analysis. Adding country controls, the governance coefficient loses statistical significance (see Tables A.8, A.9 and A.10). Interestingly, when we include country controls in the negative binomial model, the estimated effect of GDP per capita on mortality is very large and regains its statistical significance (Table A.8, column (6)). This is also true of the comparable OLS models (see column (6) of Tables A.9 and A.10). A within-country trend in GDP per capita also appears to be predictive of cyclone mortality in the 1979-2016 results, as discussed in the subnational analysis.

2.4.1.2 The EM-DAT: a database of disasters, not hazard exposures

Our current understanding of mortality from tropical cyclones and other hazards relies heavily on the Emergency Events Database (EM-DAT) (e.g., Alberini et al. (2006); Brooks et al. (2005); Hsiang and Narita (2012); Kahn (2005); Peduzzi et al. (2012)). It is therefore important that we consider how the database is constructed and the quality of the underlying data, which are compiled from various government and non-governmental agencies. First, there may be sources of non-classical measurement error in the data that I am unable to test or correct for. For example, it may be that countries with less government capacity and less resources are more likely to under report deaths, or that death counts from high-casualty events are more likely to suffer from measurement error. While EM-DAT's triangulation between government, United Nations (UN) and other non-governmental sources works to minimize this, they do rely on data from reporting systems which may vary in design and implementation.

Additionally, the EM-DAT is a database of disasters and not instances of hazard or potential disaster. By its own criteria it excludes events in which physical exposure did not lead to disastrous outcomes. Our hypotheses suggest that this may be due to the intervention of effective and well-endowed institutions. On the other

Table 2.4: Inclusion of exposures (> 63 km/hr sustained winds over inhabited land) in the EM-DAT from a logistic regression model

	(1)
Government Effectiveness	-0.531 **
	(0.179)
Ln real GDP per capita (t-1)	-0.341 *
	(0.152)
Time (years)	0.032 *
	(0.013)
Population exposed to winds > 63 km/hr	0.000 ***
	(0.000)
Average wind speed exposure (> 63 km/hr)	0.023 ***
	(0.003)
Maximum rainfall exposure (mm)	0.005 ***
	(0.001)
Observations	1157

Notes: Standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

hand, we might also be concerned about under-reporting by less-developed countries as a result of lower capacity or corruption. This could result in the reverse: missing observations from less-developed countries in the EM-DAT.

While I cannot fully disentangle these possible selection effects, by constructing a dataset of all country-storm exposures from 1996 to 2016 I can test if the EM-DAT is more or less likely to include tropical cyclone exposures that occur in countries with better governments and higher incomes. I estimate a logistical regression model of the probability that an exposure is included in the EM-DAT ($Y = 1$), given a vector of regressors that includes government effectiveness and real GDP per capita as well as controls for population exposure.

The results, presented in Table 2.4, indicate that tropical cyclone exposures that occur in wealthier countries with more effective governments are less likely to be included in the EM-DAT. How this might impact our point estimates in the main analysis is not obvious, but these results at least suggest that selection bias does not account for the direction of the governance-mortality estimates in the main results. Further, this result supports the hypothesis that more developed countries have a higher capacity to avert disaster when exposed to hazard. This is consistent with the findings of the main analysis.

2.4.2 Institutions and socioeconomic conditions in the cyclone wind-field

Next, I explore the importance of subnational development patterns for tropical cyclone risk. This second set of models covers a longer time period (1979 to 2016) and exploits the spatial variation of tropical cyclone exposure within countries to examine the importance of subnational factors for disaster mortality. The main results are presented in Table 2.5.

I find that death tolls are higher when infant mortality rates are elevated within the cyclone wind field. As described in Table 2.2, the infant mortality ratio (IM ratio) is an indicator of whether the infant mortality rate in the impact area is higher (IM ratio > 1) or lower (IM ratio < 1) than the national average. I first estimate a model for all events where a populated area experienced winds of tropical storm intensity or higher.[5] For this group of events I find that an increase of one standard deviation in the local IM ratio is associated with a 48% increase in event

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[5] I define tropical storm events as those with sustained winds over a populated 2.5 arc-minute grid cell that range from 63-118 km/hr, and tropical cyclones as events with sustained winds of $>$ 119 km/hr.

mortality ($p < 0.05$) (see Table 2.5, column (1)). I then split the data into tropical storms and tropical cyclones, in the latter case constructing the IM ratio for the area of more intense exposure ($>$ 119 km/hr). I find that a one standard deviation increase in the IM ratio for the tropical cyclone-strength wind field is associated with an 83% increase in mortality (see Table 2.5, column (3)).

In addition to the relative infant mortality rate, I also consider the extent to which a storm wind field overlaps with the settlement of a politically excluded ethnic group. I do not detect a statistically significant relationship between excluded settlements and cyclone mortality in Table 2.5. This may indicate that these groups, although politically excluded, still benefit from national initiatives related to cyclone preparedness, evacuation and response. Or it may be that exclusion from national government protections is compensated for by some other factor, such as strong indigenous institutions or social capital at the local level. This merits further study, especially as Kahn (2005) found ethnic fractionalization to be correlated with lower disaster mortality.

The importance of within-country variation in infant mortality shows that disaster mortality is not simply a function of national characteristics and hazard exposure. This suggests that the protective effects of national governance on cyclone vulnerability are either not inclusive or unable to overcome local vulnerabilities. This provides support for theory and case study evidence that emphasize the multi-scalar nature of vulnerability and resilience.

Table 2.5: Subnational determinants of mortality from TC events (1979-2016): Negative binomial regression results

	Winds > 63 km/hr	Winds 63-119 km/hr	Winds > 119 km/hr
	IRR (1)	IRR (2)	IRR (3)
Infant mortality ratio (wind field > 63 km/hr)	3.259 *	3.718 *	-
	(1.528)	(2.119)	-
Excluded ethnic group in (wind field > 63 km/hr)	0.753	0.689	-
	(0.463)	(0.609)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	4.690 ***
	-	-	(1.814)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	2.033
	-	-	(1.137)
National infant mortality rate (t-1)	1.003	0.992	1.029 *
	(0.011)	(0.015)	(0.014)
Ln real GDP per capita (t-1)	0.300 ***	0.338 ***	0.186 ***
	(0.065)	(0.093)	(0.054)
Pop. (millions) exposed to winds 63-118 km/hr	1.017 *	1.012	1.032 ***
	(0.007)	(0.008)	(0.010)
Pop. (millions) exposed to winds 119-153 km/hr	1.466 ***	-	1.498 ***
	(0.121)	-	(0.109)
Pop. (millions) exposed to winds > 153 km/hr	2.379 ***	-	2.845 **
	(0.617)	-	(1.020)
Maximum rainfall exposure (mm)	1.000	0.999	1.001
	(0.001)	(0.001)	(0.001)
Geography	countries	countries	countries
Observations	637	382	246

Notes: Negative binomial results are presented as Incident Rate Ratios (IRRs), obtained by exponentiating the estimated coefficients. Thus, we are testing the null hypothesis that $IRR = 1$. If the coefficient is negative the $IRR < 1$ and if the coefficient is positive the $IRR > 1$. Includes control for a linear time trend. Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.4.2.1 Robustness checks

One potential concern is that infant mortality might be elevated in certain parts of the country due to the direct or indirect impacts of tropical cyclones. I therefore rerun the negative binomial analysis excluding the years 1999 and 2000 and also for 2001-2016 (see Tables A.11 and A.12). I also estimate OLS models comparable to Table 2.5 in Tables A.13 and A.14. I find that the main results are in general robust to these changes in the dataset and regression model.

For events with population exposure to tropical storm (or higher) winds, the IM ratio coefficients are consistently positive though not always statistically significant ($p > 0.05$) (see column (1) of Tables A.11-A.14). The IM ratio for the more intense, cyclone-force wind fields remains statistically significant ($p < 0.05$) in all OLS and negative binomial models (see column (3) in Tables A.11-A.14). Further, I find that exposure is actually (on average) negatively correlated with the IM ratio variables.

2.5 Conclusions

Questions about the socioeconomic determinants of tropical cyclone mortality are made more urgent by climate change. The intensity and rainfall of the strongest tropical cyclones are likely to increase with warming seas (Christensen et al., 2013; Walsh et al., 2016). And trends in population growth and sea level rise will further contribute to risk in the absence of effective adaptation (Mendelsohn et al., 2012; Peduzzi et al., 2012; Walsh et al., 2016). The findings of this chapter indicate that adapting to current and future tropical cyclone risk requires attention to the institutional constraints that may limit progress. Country-to-country fiscal transfers and technological advances may be necessary but insufficient in countries with less effective governments.

To what extent can adaptation offset or overcome these physical risk factors? And how far can enhancing sustainable development activities – also known as 'general' or 'soft' adaptation – take us towards safe and resilient societies? To answer these questions, policy-makers are in need of an empirically grounded understanding of what aspects of institutional and socioeconomic environments matter for specific hazards, at what scales and in what contexts (e.g. Brooks et al. (2005); Denton et al. (2014); Stern and Wilbanks (2009)).

The results presented in this chapter provide new insights into the intersection of development and tropical cyclone risk. I find evidence of an association between effective governance and lower cyclone mortality, robust to controls for income and other development factors. By spatially interacting data on storm exposure and socioeconomic conditions, I find new evidence that mortality is higher when storm exposure is concentrated over a subset of the population that is already worse off.

Here I focus on national and regional determinants of tropical cyclone mortality, which allows for useful comparison across a large number of events. But are institutions uniquely important in the case of tropical cyclones, or do these findings generalize to other types of hazard? This approach could be adapted to the study of additional hazards, scales and outcomes to address various policy-relevant research questions. Used in concert with climate change models, these findings could then be used to project disaster mortality under different institutional and development scenarios. Studies extending this approach to the national or subnational scale, ideally in concert with downscaled climate models, would provide the opportunity to investigate the determinants of subnational spatial patterns in disaster mortality. Household-level research is also needed to explore the distributional and dynamic impacts of tropical cyclones and other hazards.

Chapter 3: Local governance, poverty and tropical cyclone mortality in the Philippines

3.1 Introduction

The Philippines is amongst the most tropical cyclone affected countries in the world. Over the past decade 85 storms have caused over eleven thousand fatalities in the Philippines (2007-2016) (NDRRMC, n.d.a). Yet tropical cyclones are just one of many natural hazards faced by the people of the Philippines. According to the Emergency Events Database (EM-DAT), from 1979 to 2016 the Philippines experienced disaster brought on by various forms of natural hazard including tropical cyclones (232 events), floods (133), landslides (28), earthquakes (18), volcanic activity (17) and drought (8) (Guha-Sapir, 2018). The Philippines also faces chronic poverty and underdevelopment, conflict and terrorism.

Given finite resources and the battery of potential social, economic, and environmental shocks that developing countries such as the Philippines must cope with, policy-makers need tools to identify at-risk populations and to better understand how vulnerability is produced and perpetuated. This chapter investigates the relationships between socioeconomic status, hazard exposure, and mortality from tropical cyclones in the Philippines. In particular, I ask two related research questions in this chapter. First, are poverty and local governance spatially correlated with tropical cyclone mortality in the Philippines, and if so at what scale? Second, do short-term changes in economic conditions and government capacity have a measurable impact on cyclone death tolls?

A multi-level dataset allows me to provide new evidence of the nested scales of vulnerability to tropical cyclones. To my knowledge, this is the first representative study of tropical cyclone mortality outcomes to include the municipal level, for the Philippines or any country. I demonstrate that aggregate statistics at the national and even provincial scales can obscure large heterogeneities in socioeconomically produced vulnerabilities.

Failure to control for correlations between exposure and socioeconomic conditions, across places but also over time, can result in biased estimates of the socioeconomic determinants of cyclone risk. For example, while tropical cyclones affect all regions of the Philippines, exposure has historically been highest on the islands of Luzon in the northern part of the country. Provinces and municipalities in Luzon on average have lower poverty rates and higher incomes compared to the central islands of Visayas and the southern islands of Mindanao, where cyclones are less frequent (FIES, 2018). In other words, poverty and tropical cyclone exposure are *inversely* correlated in the Philippines. I therefore include measures of hazard (winds and rainfall) and exposure (population) in all models. This corrects for potential biases and improves precision in the estimates.

Once we control for exposure, we observe that poverty rates and income are in fact positively correlated with provincial and municipal mortality from tropical cyclones, over space and time. Including location fixed effects in the model, I further find strong evidence of a link between tropical cyclone mortality and changes in municipal (but not provincial) poverty rates over time. A decrease of 1% in the municipal poverty rate is associated with a 0.37% decrease in tropical cyclone mortality. I do not find statistically significant evidence of a relationship between local government fiscal capacity and fatality rates, although there is some evidence of a correlation between provincial government expenditures and mortality. I observe a general decreasing trend in mortality over time in the Philippines (conditional on exposure), which may be due to advances in technology, disaster preparedness and response, or other macro trends.

3.2 Background and Relation to the Literature

Tropical cyclones deaths occur only when vulnerable human systems are exposed to hazardous conditions. This is commonly represented by the stylized equation:

$$Risk = Hazard \times Exposure \times Vulnerability, \tag{3.1}$$

where the risk, in our case the probability of tropical cyclone mortality, is a product of the *hazard* (the frequency and intensity or tropical cyclones), *exposure* (the assets or population in the hazard zone), and the *vulnerability* of the exposed population. While some definitions of vulnerability encompass the probability of hazard exposure, in this dissertation I consider vulnerability to be purely a function of place (e.g. Gallopín (2006)), and in particular the susceptibility of a province or municipality to tropical cyclone mortality, conditional on hazard and exposure (see Chapter 1 for additional details and discussion).

Tropical cyclones are a regular occurrence in the Philippines, with an average of 8 to 9 storms passing over the country each year (PAGASA, 2019). Yet mortality from these storms is highly variable, even at the national level (see Figure 3.1). This is in part a function of the extreme variability in the number of people exposed to winds and rainfall of different intensities during tropical cyclones in the Philippines (see Figure 3.2). Variation is even more pronounced at the local level, given the unique spatial distribution of exposures each year.

Isolating each of the three components in equation 3.1 is therefore critical to understanding the effects of institutional and socioeconomic conditions on tropical cyclone risk. Given dramatic fluctuations in $hazard \times exposure$, attempts to understand relationships between socioeconomic patterns and mortality that do not account for storm exposure and intensity will be imprecise and possibly biased. This is particularly so when data is only available for a limited time period or a subset of years, as is the case for the poverty-mortality dataset analyzed in this chapter. A key feature of this analysis is therefore that I control for population and tropical cyclone intensity at the administrative unit (province or municipal) level throughout this analysis.

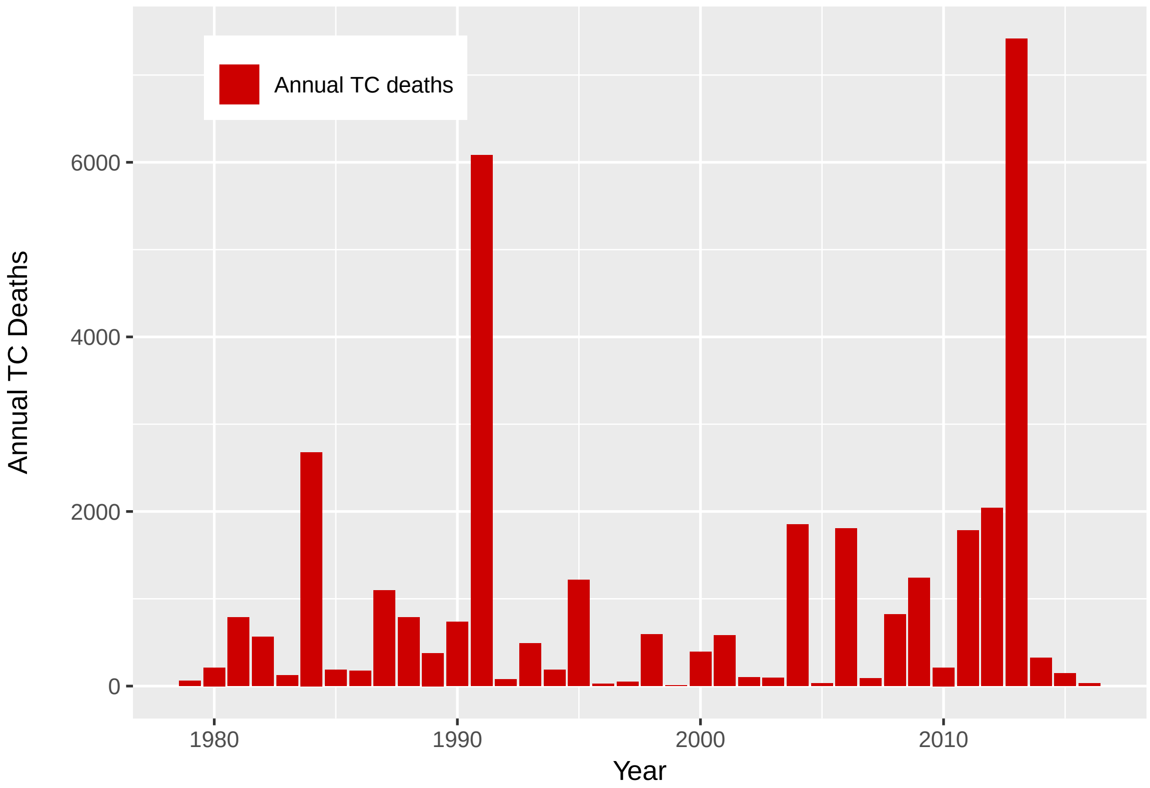

Figure 3.1: Annual deaths from tropical cyclone events in the Philippines, 1979-2016. Source data: the EM-DAT (Guha-Sapir, 2018).

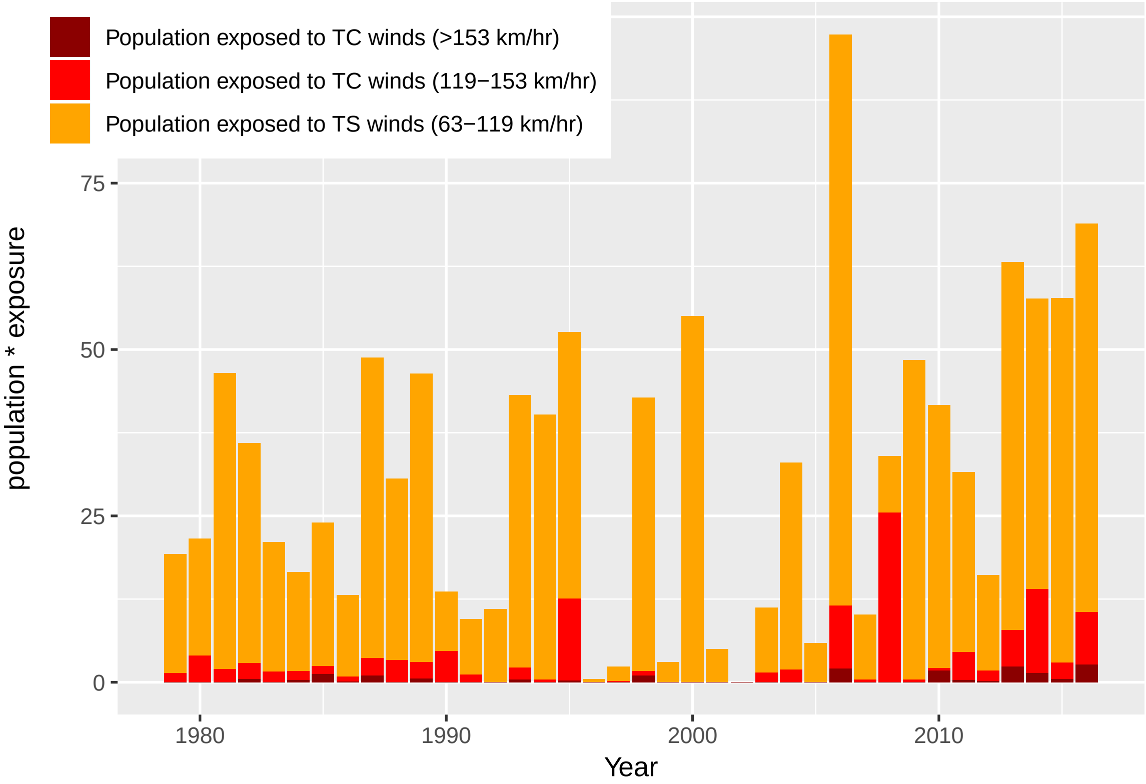

Figure 3.2: Annual population exposure to tropical cyclone events in the Philippines, 1979-2016. Source data: IBTrACS (Knapp et al. 2010) and CIESIN (2017a & 2017b).

3.2.1 Vulnerable places, or vulnerable people?

In their paper *"Poor areas, or only poor people?"* Ravallion and Wodon (1999) explore the issue of whether there is added value in targeting aid to places with a high concentration of poverty, versus simply poor households or individuals. They find evidence for strong geographic effects that cannot be attributed to easily observable household characteristics. In the case of tropical cyclone risk, the case for vulnerability of place is in many ways clearer and more obvious. We know that living in proximity to the coast, at low elevation, on unstable slopes, or without natural storm barriers are risk factors in tropical cyclone regions. But like Ravallion and Wodon (1999), we are interested in the underlying socio-economic factors that drive individuals to move to or remain in at-risk locations. Are people vulnerable because social and economic pressures cause them to occupy the most vulnerable geographies? And/or do places appear or become vulnerable when they are occupied by poor or marginalized people?

From 1970 to 2010 the population in cyclone-prone coastlines grew at more than double the rate (192 percent) of the average global population (87 percent) (Hallegatte et al., 2015). People may be drawn to these areas even when aware of the risks, attracted by economic opportunities, public services such as education and healthcare, and social networks (Hallegatte et al., 2015). It is not exclusively the poor who are attracted to the benefits of the coast, but there is some evidence that poor or socially marginalized residents are often driven to live on the most vulnerable land with the least structural protection (Blaikie et al., 2004; Ensor, 2009; Hallegatte et al., 2015; Hossain, 2015).

Poverty is frequently cited as a root cause of vulnerability in the Philippines (Bankoff, 1999; Bankoff and Hilhorst, 2009; Brower and Magno, 2011; Huigen and Jens, 2006). Bankoff (1999) argues that the history of disasters in the Philippines has enabled growth in the inequality of wealth and power in the country. Because the poor and marginalized are least able to cope with and recover from exposure to natural hazards, over multiple cycles of disaster they become increasingly vulnerable (Bankoff, 1999). Bankoff and Hilhorst (2009) argue that these root vulnerabilities are (perhaps inadvertently) exacerbated by the centralized nature of disaster management in the Philippines and the government's tendency to treat disaster as an abberation from 'normal' conditions. This implies the goal of returning to pre-disaster conditions, which unfortunately often means a state of underdevelopment and inequality (Bankoff and Hilhorst, 2009).

The idea of addressing disaster vulnerability via its socioeconomic roots has over time gained traction in the Philippines, and is now formally codified in the Disaster Risk Reduction and Management Act (DRRMA) signed into law in 2010 (Brower and Magno, 2011). The DRRMA also substantively integrates local governments and civil society into the national architecture for DRRMA (Brower and Magno, 2011). However, disaster risk reduction and management remains highly centralized under the Office of Civil Defense, with the military frequently involved in operations (Brower and Magno, 2011). It is therefore unclear how active and meaningful a role different levels of local government play in disaster risk reduction in the Philippines.

3.2.2 Existing empirical evidence

Recent global studies find that less-developed countries with weaker institutions tend to have higher death tolls from tropical cyclones (Hsiang and Narita (2012); Peduzzi et al. (2012); Chapter 2). Evidence from a global dataset (see Chapter 2) further suggests that local socioeconomic conditions are important for explaining the variation in cyclone mortality within countries. Yet representative studies of tropical cyclone vulnerability at the subnational level are scarce, with the exception of a few regional and state/province level studies such as Anttila-Hughes and Hsiang (2013); Pugatch (2019); Yonson et al. (2018). None of these studies include a municipal scale of analysis.

In a study of the socio-economic impacts of typhoons in the Philippines, Anttila-Hughes and Hsiang (2013) find evidence of large and enduring storm impacts on all-cause female infant mortality rates. This observed increase in infant deaths is largest amongst the poorest households and labeled by the authors 'economic deaths' based on evidence that they are mediated by the economic impacts of the storm (Anttila-Hughes and Hsiang, 2013). Their findings suggest that short-term casualty data, such as the statistics used in this analysis, may underestimate the full effects of tropical cyclone disasters on mortality by an order of magnitude or more.

In a recently published study, Yonson et al. (2018) investigate a similar set of research questions to those laid out in this chapter: how social vulnerability, hazard and exposure contribute to fatalities from tropical cyclones in the Philippines. The authors use province level data (2005-2010) to test for the effects of socioeconomic factors including income, poverty, and province-level governance on tropical cyclone fatalities, controlling for hazard intensity and exposure. Yonson et al. (2018) find "strong evidence that socioeconomic development and good local governance reduces disaster fatalities" based on results from an unbalanced random-effects regression model. While not their preferred specification, they also present fixed effects models for comparison in which they do not detect statistically significant effects of poverty, income or governance on tropical cyclone fatalities. Yonson et al. (2018) control for hazard in their model, but do not find a statistically significant relationship between wind speed and fatalities, and their estimated coefficient on rainfall is small in magnitude. They therefore argue that "fatalities are not mainly results of the destructive characteristics of tropical cyclones, but more so of exposure and vulnerability" (Yonson et al., 2018).

3.3 Model

Understanding the scale and correlates of disaster risk may have value for policy targeting and corroborate theories and case study evidence on the long-term root causes of disaster vulnerability. Yet it is insufficient for understanding how gains in institutional capacity and socioeconomic development are likely to impact risk. I therefore employ panel data methods to test for the effects of local socioeconomic conditions and local government financial flows on mortality, controlling for hazard exposure.

There is strong theoretical and empirical evidence for unobserved heterogeneity across the provinces and municipalities of the Philippines. Differences in the historical and geographic characteristics of localities are likely to impact both their long-term development trajectories as well as vulnerability to tropical cyclones. Empirically, I find strong evidence of unobserved heterogeneity using the Lagrangian Multiplier test for individual effects. I also find that the strict exogeneity assumption for random effects is violated (see Results). My preferred specification is therefore the fixed effects regression model.

I model tropical cyclone mortality y for province (or municipality) i and in time period t using the following linear fixed effects regression model,

$$ln(y_{it}+1) = \alpha_i + \mathbf{v}'_{it}\boldsymbol{\beta}_1 + \mathbf{h}'_{it}\boldsymbol{\beta}_2 + \text{year}_t\beta_3 + \varepsilon_{it} \tag{3.2}$$

where α_i is the place fixed effect, $\mathbf{v}_{it}$ is a vector of local institutional and poverty regressors, and $\mathbf{h}_{it}$ represents the control variables for local hazard (wind and rainfall) intensity. I allow for a linear time trend $year_t$ to account for improvement in national disaster preparedness and response, technology and other macro trends. As poverty rates are decreasing over time for most provinces and municipalities, the poverty variable might otherwise pick up improvements in national disaster management or technology. However, this also risks absorbing causal variation in poverty into the time variable. I present an alternative set of specifications excluding $year_t$ for comparison. I also present an alternative specification with year dummies in the appendices.

The log transformation of a dependent variable plus one allows us to utilize a linear model with a dependent variable, tropical cyclone deaths, that is non-negative and includes zero values. In some cases, this type of 'count data' can also be modeled using Poisson or negative binomial models. However, a Poisson model would be inconsistent in this case due to overdispersion in the data: $E[y_i \mid \mathbf{x}_i] << Var[y_i \mid \mathbf{x}_i]$ (Greene, 2012). The negative binomial model relaxes the equidispersion principle, but available methods either do not offer a true fixed effect or tend to underestimate standard errors (Allison and Waterman, 2002). Further, I find negative binomial panel data methods to be computationally untenable for many specifications (particularly at the municipal level) due to the large number of local government units (Allison, 2009).

The analysis of fixed effects in this paper provides novel evidence of how improvements (or deterioration) in a locality's socioeconomic conditions and fiscal capacity can impact mortality from a tropical cyclone. Standard errors are clustered by administrative unit to allow for variation in treatment effects by locality (Abadie et al., 2017), following methods developed by Pustejovsky and Tipton (2018) and implemented in the R package *clubSandwich*.

A limitation of the fixed effects approach is that we are losing all of the between-unit variation in our data, which can render the estimates inefficient. This is a common problem with the fixed effects model, which can result in the underestimation of coefficients (Angrist and Pischke, 2009). In order to exploit the between variation in the dataset, I next estimate a random effects and pooled OLS model. While I find evidence that these estimates are inconsistent (see Results), they still provide a useful analysis of correlations in the dataset and serve as an 'upper bound' on the independent variable effects.

Parameterizing these models requires spatially and temporally matching observations from socio-economic, disaster mortality, and physical storm data sources. In the following section I describe both the underlying data sources as well as the methods used to combine them into an integrated dataset.

3.4 The Data

I construct and analyze a new dataset that captures the pre-event socioeconomic conditions, intensity of exposure, and death tolls from tropical cyclones in the Philippines, disaggregated at the province (2005-2016) and municipal scales (2007-2016). Descriptive statistics are presented in Tables 3.3 and 3.4.

3.4.1 Hazard exposure

Over the 1979 to 2016 period, the Philippines have been exposed to more tropical storms and cyclones than any other country (based on data and tools from Anderson et al. (2017); Knapp et al. (2010); Willoughby et al. (2006)). While all regions of the Philippines are periodically exposed to tropical cyclones, exposure is highly variable in intensity and frequency over space and time (see Figure 3.2). Further, exposure has historically been higher in the more affluent, northern regions of the country. In order to control for bias and reduce imprecision introduced by tropical cyclone exposure, I therefore construct time-variant province and municipal exposure metrics. These variables include the intensity of wind and rainfall, and are summarized in Table 3.1.

Wind speeds are modeled using a parametric wind speed model developed by Willoughby et al. (2006) and implemented using a modified version of the *stormwindmodel* software in R (available at github.com/liztennant/stormwindmodel) (Anderson et al., 2017). I begin with a 15 arc-minute modeling of all storms recorded by the Best Track Archive for Climate Stewardship (IBTrACS) Project from 1979 to 2016 globally. Storms that generate sustained winds of 18 km/hr over the Philippines in this model are then modeled at a 2.5 arc-minute (5km at the equator) resolution. These raster wind fields are then overlain with municipal and provincial boundaries to estimate a maximum sustained wind speed variable. The annual maximum wind speed for an administrative unit is the strongest sustained wind speed experienced by that province or municipality for any storm occurring in that year.

The maximum total rainfall is also computed for each storm and province, based on data from the CPC Global Unified Gauge-Based Analysis of Daily Precipitation dataset, available at a 0.5 degree (35 km) resolution from 1979 to present (NOAA, 2018). A raster of total rainfall within the dates of each storm is first computed, then overlain with province shapefiles to extract the maximum value of any intersecting grid cell. Rainfall is not calculated at the municipal level, given the insufficient resolution of the raster data.

Table 3.1: Summary of hazard exposure variables

Variable	**Description**	**Source**
Max sustained wind speed (km/hr)	Maximum sustained wind speed in kilometers per hour, by administrative unit.	Spatial extent of wind field modeled using stormwindmodel (Anderson et al. 2017; Willoughby et al. 2006) and IBTrACS data (Knapp et al. 2010).
Maximum total rainfall (cm)	The maximum cumulative rainfall (cm) over all days of the event, by province. Resolution insufficient for estimates at the municipality level.	CPC Global Unified Gauge-Based Analysis of Daily Precipitation dataset (NOAA 2018). Storm track buffer based on IBTrACS (Knapp et al. 2010).

3.4.2 Mortality

Mortality data disaggregated at the province and municipal levels is compiled from statistics and casualty reports published by the Philippines' National Disaster Risk Reduction and Management Council (NDRRMC) and its predecessor, the National Disaster Coordinating Council (NDCC). These documents were obtained from NDRRMC directly or retrieved from the Reliefweb website (reliefweb.int). While province-level summary mortality statistics are compiled by NDRRMC, municipal deaths were tabulated based on the permanent residence of victims as listed in NDRRMC casualty reports. The NDRRMC reports are compiled based on inputs from several of the council's member agencies, including the Department of Social Welfare and Development (DSWD).

According to NDRRMC records, a total of 13,108 deaths were attributed to tropical cyclones occurring between 2005 and 2016. Of these, 12,653 deaths occurred in the 78 provinces included in this analysis. The National Capital Region, including Metropolitan Manila, is not a part of any province and therefore excluded from this analysis. Three additional provinces were excluded were due to missing data or administrative changes that render them incomparable over the study period.

NDRRMC casualty reports include a data field that sometimes contains remarks on the cause or circumstances of the death. The field is often missing, particularly for the most heavily impacted locales and the strongest storms. A remark of some kind is included for only 34% (3,752) of deaths tabulated for 2007 to 2015. When remarks are included they do not follow a consistent coding scheme and are therefore not well suited to quantitative analysis. For example, entries such as "trauma" and "hit by a falling tree" could describe very different or very similar events.

While clearly not representative, these data a provide a useful exploratory look at a range of causes and circumstances of tropical cyclone mortality. The word cloud in Figure 3.3 tabulates the frequency of the 100 words most frequently used to describe the cause or circumstances of death. 'Drowning' or 'drowned' stand out as a common cause of death, which may result from a range of circumstances including storm surge, rain fed flooding, boating accidents, river crossings and more. Landslides and being 'hit' by various flying debris, falling trees and collapsed structures are also common.

3.4.3 Institutional and socioeconomic conditions

Annual socioeconomic data at the province and municipal levels is compiled to test the effects of local government financial flows and poverty on tropical cyclone mortality. Details of the key socioeconomic variables in this analysis are summarized in Table 3.2.

The Family Income and Expenditure Survey (FIES) is the primary source of sub-national income data in the Philippines. This household survey is conducted every three years, and province-level poverty and income data published from the 2006, 2009, 2012 and 2015 surveys was obtained from the Philippines Statistical Authority (PSA) for this analysis (FIES, 2018). At the municipal level, the FIES

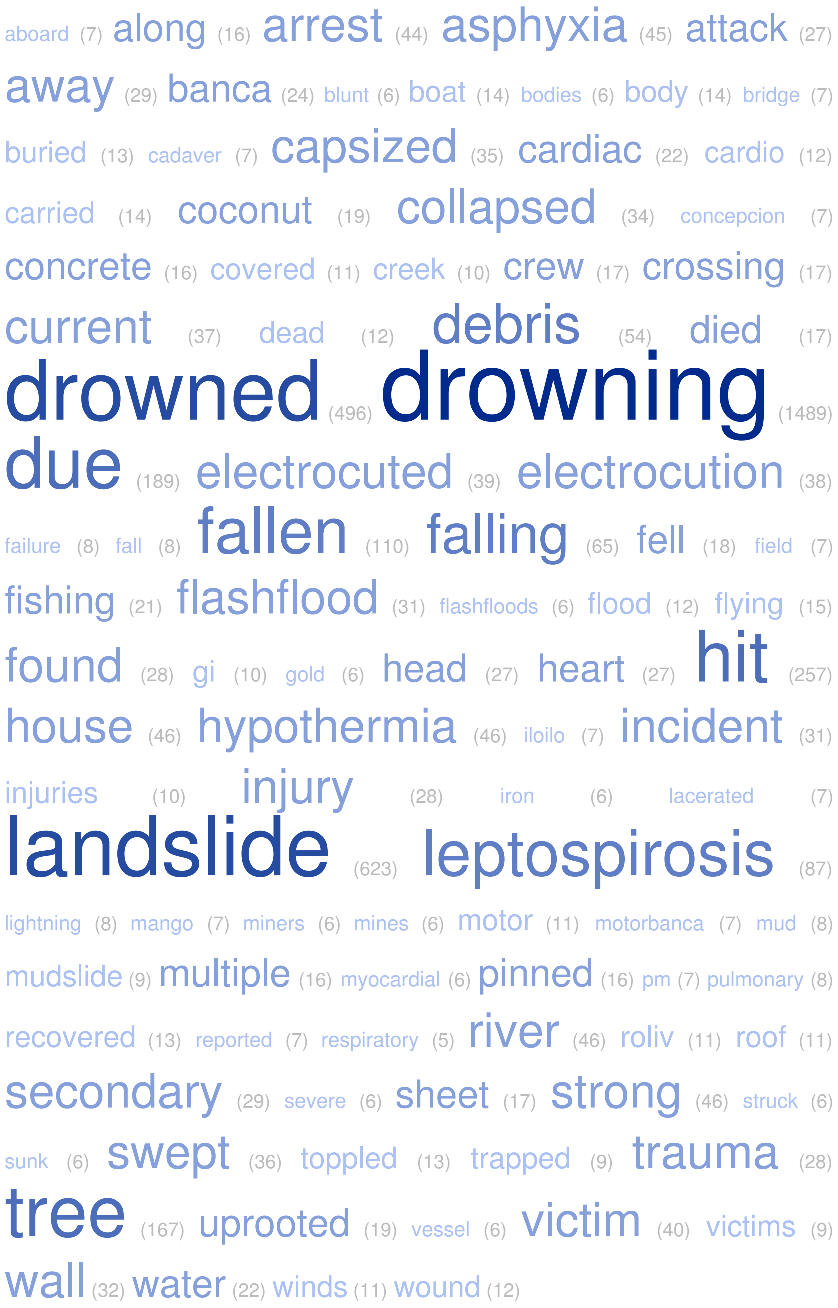

Figure 3.3: Tabulation of the 100 most commonly used words used to describe the cause or circumstances of tropical cyclone death, from NDRRMC tropical cyclone casualty reports, 2007 to 2015. Word cloud generated using the TagCrowd.com online tool.

data are combined with census data from the same year to provide high quality estimates of local poverty rates using a technique known as Small Area Estimation (Elbers et al., 2003). These small area poverty estimates are published by the Philippines Statistics Authority drawing on projects by the PSA, World Bank and other partners (PSA, 2016). Poverty in these estimates is defined in accordance with the Social Reform and Poverty Alleviation Act (Republic Act 8425): "families and individuals whose income fall below the poverty threshold and who cannot afford to provide for their minimum basic needs in a sustained manner." (PSA, 2016). Income data is not available at the municipal level, and is not available at the province scale for the year 2015.

The constraint of three-year poverty estimates is an important limitation in this analysis, as it limits the panel to 3 or 4 (for municipalities and provinces, respectively) time periods. Particularly in the municipal results, where we have a large number of observations but limited time periods, this may result in inconsistent estimates of α_i. However, historical mortality records are limited and, to my knowledge, sub-nationally representative poverty data is simply not systematically collected on an annual basis for the Philippines. The Annual Poverty Indicators Survey (APIS) that has recently been implemented (from 2013) is designed to be representative only at the national level.

A subjective indicator of government effectiveness, similar to the government effectiveness measure used in the country-level analysis in Chapter 2, is not available subnationally for the Philippines. One alternative proxy for government effectiveness is a local government unit's fiscal capacity, including its ability to raise locally generated revenues and manage expenditures. Both provinces and municipalities have the authority to levy taxes and fees (mainly on properties and businesses). Local government expenditure may go towards a range of social services including health, education and economic development. Data on the financial flows of provinces and municipalities are compiled from Local Government Unit (LGU) fiscal reports published by the Bureau of Local Government Finance in the Philippines (BLGF, 2018). I adjust financial flows for inflation using the World Bank's Consumer Price Index for the Philippines (World Bank, 2019). I measure local revenue per capita as my primary fiscal capacity measure, but also construct a measure of the share of revenue that is locally generated as an alternative proxy, following Yonson et al. (2018). I also test whether total expenditure by local government units is linked to tropical cyclone mortality.

Table 3.2: Summary of socioeconomic variables

Variable	**Scale**	**Years**	**Description**	**Source**
poverty rate	province	2006, 2009, 2012, 2015	The percentage of the population below the poverty line, at the province level.	Family Income and Expenditure Survey (FIES), Philippine Statistics Authority
income	province	2006, 2009, 2012	Average family income in Philippine pesos	Family Income and Expenditure Survey (FIES), Philippine Statistics Authority
poverty rate	municipality	2006, 2009, 2012	Small area estimates of the percentage of the population below the poverty line, at the municipal level.	Philippine Statistics Authority; NSCB/World Bank/AusAID Project on the Generation of the 2006 and 2009 City and Municipal Level Poverty Estimates.
ln local revenue	province; municipality	2005-2015	Total of local sources of government revenue, per capita (Philippine pesos)	Bureau of Local Government Finance, Department of Finance, Republic of the Philippines
ln local expenditure	province; municipality	2005-2015	Total expenditure by the local government unit, per capita (Philippine pesos)	Bureau of Local Government Finance, Department of Finance, Republic of the Philippines
local share revenue	province; municipality	2005-2015	Share of total revenue from local sources	Bureau of Local Government Finance, Department of Finance, Republic of the Philippines

Table 3.3: Descriptive statistics for Provinces in the Philippines, 2004-2016

variable	**min**	**max**	**median**	**mean**	**std.dev**
deaths	0.00	5400	0.00	12.2	175
province poverty rate	1.80	73.8	32.8	32.9	15.2
province income (pesos)	76200	376000	158000	164000	51500
local revenue per capita	1.00	1060	144	183	149
local expenditure per capita	1.00	3860	905	1070	537
local share revenue	0.00	219	0.13	0.80	8.41
Wind speed (km/hr)	0.70	53.8	13.3	15.2	11.0
Wind speed squared (sq-km/hr)	0.49	2900	176	351	449
Total rainfall (cm)	3.14	155	19.3	24.7	18.6

3.5 Results & Discussion

The dataset indicates that over the study period annual tropical cyclone deaths were in fact slightly lower in poorer provinces and municipalities (see Tables B.1 and B.2). However, once we control for a strong negative correlation between poverty and exposure, evidence of a positive correlation between poverty and cyclone deaths emerges. At the municipal level, I also find evidence from a fixed effects model that local variation in poverty rates has an impact on cyclone fatalities. The comparable model does not yield statistically significant results at the provincial scale. The balance of the evidence does not support a statistically significant relationship between local government fiscal capacity and fatalities, although we do observe a negative correlation between provincial government expenditure and cyclone deaths.

3.5.1 Poverty

The results of the fixed effects models are presented in Tables 3.5 and 3.7. I find robust and statistically significant evidence of an association between munici-

Table 3.4: Descriptive statistics for Municipalities in the Philippines, 2004-2015

variable	**min**	**max**	**median**	**mean**	**std.dev**
deaths	0.00	1380	0.00	0.50	15.3
municipal poverty rate	0.66	84.8	33.2	33.1	1.00
local revenue per capita	1.00	49000	201	310	640
local expenditure per capita	1.00	24300	1630	2020	1500
local share revenue	0.00	1.00	0.10	0.13	0.12
Wind speed (km/hr)	0.59	55.4	14.5	15.6	10.4
Wind speed squared (sq-km/hr)	0.35	3070	211	351	421

pal poverty rates and tropical cyclone mortality. A 1% increase in a municipality's poverty rate is associated with approximately a 0.37% increase in tropical cyclone fatalities ($p < 0.001$) (Table 3.7 (1)). This is only slightly attenuated and remains highly statistically significant if we control for provincial poverty incidence and income (Table 3.7 (2)). While fluctuations in poverty are likely to be correlated with trends in income and other measures of socioeconomic development which I do not control for, these results represent new evidence that short-term changes in socioeconomic conditions can measurably impact disaster mortality at the local level.

At the province level, the poverty coefficient is positive but not statistically significant (Table 3.5 (4)). Higher income, for which data is available at the province but not municipal level, is associated with lower tropical cyclone deaths; however, this result is not statistically significant if we include the linear time trend (Tables 3.5 (5)). Further, province level poverty rates and income are not statistically significant determinants of municipal deaths in a model that also contains municipal poverty measures (Tables 3.7 (2)), suggesting that the time-variant relationship between poverty and mortality is highly localized.

In comparable pooled OLS models, tropical cyclone deaths were higher in provinces and municipalities with a higher incidence of poverty or income during the study years (see Tables 3.6 and 3.7). These effects are large and statistically significant ($p < 0.05$). A 1% increase in the poverty rate is associated with a 0.88% or 0.47% increase in deaths at the provincial and municipal levels, respectively (see Tables 3.6 (1) and 3.7 (3)). In the province model, a 1% increase in income is associated with an 0.67% decrease in mortality (Tables 3.6 (2)). However, poverty and income are highly correlated; when included in the same model both coefficients lose statistical significance. Results of the random effects specification are similar in magnitude and statistical significance to the pooled model (Tables 3.6 and 3.7).

However, there is strong evidence that the random effects and pooled OLS specifications violate key assumptions necessary for causal inference. Intuitively, we would expect there to be some unobserved heterogeneity between administrative units, and further it seems implausible that the individual effects α_i are uncorrelated with the independent variables (i.e. poverty, governance) for all past, current and future time periods. This is confirmed by results of the Breusch-Pagan Lagrange Multiplier and Hausman test statistics, which (strongly) reject the null hypotheses that the pooled and random effects estimates are consistent for specifications presented in Tables 3.6 - 3.13.

Table 3.5: Fixed Effects: Annual deaths from tropical cyclones by province, Philippines (2007, 2010, 2013, 2016)

	FE	FE	FE	FE	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)
province poverty rate (t-1)	0.014	-	-0.008	0.007	-	-0.010
	(0.008)	-	(0.012)	(0.008)	-	(0.012)
ln province income (pesos) (t-1)	-	-1.102 *	-1.188 **	-	-1.266	-1.460
	-	(0.433)	(0.389)	-	(0.808)	(0.779)
Total rainfall (cm)	0.011	0.010	0.010	0.012	0.009	0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Wind speed (km/hr)	0.057 **	0.077 **	0.078 **	0.064 **	0.076 **	0.077 **
	(0.017)	(0.021)	(0.021)	(0.018)	(0.022)	(0.022)
ln population	-1.058 *	0.162	0.140	-0.318	0.021	-0.082
	(0.489)	(0.795)	(0.793)	(0.232)	(0.706)	(0.688)
year	-	-	-	-0.050 **	0.017	0.027
	-	-	-	(0.014)	(0.059)	(0.059)
n	78	78	78	78	78	78
T	4	3	3	4	3	3
N	312	234	234	312	234	234
R-squared	0.258	0.333	0.334	0.28	0.333	0.335

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.6: Random Effects and Pooled OLS: Annual deaths from tropical cyclones by province, Philippines (2007, 2010, 2013, 2016)

	RE	RE	RE	Pooled	Pooled	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
province poverty rate (t-1)	0.009	-	0.002	0.009	-	0.002
	(0.005)	-	(0.009)	(0.005)	-	(0.009)
ln province income (pesos) (t-1)	-	-0.681 *	-0.618	-	-0.674 *	-0.606
	-	(0.313)	(0.356)	-	(0.312)	(0.356)
Total rainfall (cm)	-0.003	-0.005	-0.005	-0.003	-0.006	-0.005
	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Wind speed (km/hr)	0.044 ***	0.052 ***	0.052 **	0.043 ***	0.052 ***	0.052 ***
	(0.011)	(0.014)	(0.014)	(0.011)	(0.014)	(0.014)
ln population	0.247 **	0.336 ***	0.338 **	0.246 **	0.335 ***	0.337 **
	(0.070)	(0.089)	(0.093)	(0.070)	(0.088)	(0.093)
year	-0.034 ***	0.040	0.037	-0.034 ***	0.040	0.037
	(0.010)	(0.029)	(0.032)	(0.009)	(0.029)	(0.032)
n	78	78	78	78	78	78
T	4	3	3	4	3	3
N	312	234	234	312	234	234
R-squared	0.238	0.282	0.283	0.239	0.282	0.283

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.7: Annual deaths from tropical cyclones by municipality, Philippines (2007, 2010, 2013)

	FE	FE	RE	RE	RE	Pooled	Pooled	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
municipal poverty rate (t-1)	0.004 ***	0.003 ***	0.005 ***	0.003 ***	0.001 **	0.005 ***	0.003 ***	0.001 **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
province poverty rate (t-1)	-	-0.000	-	0.004 ***	0.001	-	0.004 ***	0.001
	-	(0.001)	-	(0.001)	(0.001)	-	(0.001)	(0.001)
ln province income (pesos) (t-1)	-	-0.103	-	0.120 ***	-0.116	-	0.134 ***	-0.116
	-	(0.087)	-	(0.033)	(0.086)	-	(0.033)	(0.086)
Wind speed (km/hr)	0.026 ***	0.026 ***	0.015 ***	0.016 ***	0.026 ***	0.015 ***	0.015 ***	0.026 ***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
ln population	0.061	0.049	0.078 ***	0.083 ***	0.052 ***	0.076 ***	0.081 ***	0.052 ***
	(0.043)	(0.045)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
year	-0.024 ***	-0.018 **	-0.003	-0.010 ***	-0.019 ***	-0.002	-0.010 ***	-0.019 ***
	(0.003)	(0.006)	(0.002)	(0.003)	(0.006)	(0.002)	(0.003)	(0.006)
Observations	-	-	-	-	-	-	-	-
Log-Likelihood	-	-	-	-	-	-	-	-

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.5.2 Local government capacity and expenditure

I next test for a relationship between tropical cyclone mortality and provincial and municipal fiscal capacity proxied by locally generated revenues. I do not find statistically significant evidence of a relationship between tropical cyclone mortality and fiscal capacity in the province or municipal fixed effects models (Table 3.8), either for local revenue per capita (*local revenue per capita*) or the share of total income raised locally (*local share revenue*). This is also the case for the provincial random effects and pooled models. However, evidence from the municipal random effects and pooled models is more ambiguous; estimated coefficients are negative for all three specifications testing *local revenue per capita*, but only one of the three is statistically significant ($p < 0.05$) (see Tables 3.12 and 3.13).

Overall, we do not see clear evidence of a link between tropical cyclone mortality and fiscal capacity at the provincial or regional level. This may be because capacity to levy taxes and fees is not sufficiently correlated with the particular attributes of governance necessary for reducing vulnerability to disaster mortality. Features such as public trust in government and civic engagement are not well captured by financial flows. Further, to the extent that general administrative capacity is required for both revenue collection and the types of planning and public works necessary for disaster risk reduction, there may be other limiting factors such as lack of disaster-specific knowledge and authority. This would be consistent with the centralized governance of disaster management in the Philippines, or with the active role that non-governmental organizations (NGOs) play in this space (Bankoff and

Hilhorst, 2009; Brower and Magno, 2011).

The fixed effects models show no statistically significant association between province or municipal government expenditure and tropical cyclone mortality (Table 3.8 (2)). In contrast, the pooled and random effects models do show an association between local expenditure and deaths; a 1% increase in local expenditure is associated with an increase in deaths of approximately 0.34% (in both the random and pooled model, Tables 3.9 (2) and 3.10 (2)). However, once again the Lagrange Multiplier and Hausman test statistics indicate that the random effects and pooled estimates are inconsistent.

Table 3.8: Fixed Effects Model: Annual deaths from tropical cyclones by province, Philippines (2005-2016)

	(1)	(2)	(3)	(4)
ln local revenue per capita (t-1)	0.020	-	-	0.045
	(0.079)	-	-	(0.083)
ln local expenditure per capita (t-1)	-	-0.265	-	-0.287
	-	(0.302)	-	(0.311)
local share revenue (t-1)	-	-	-0.001	-0.000
	-	-	(0.001)	(0.002)
Total rainfall (cm)	0.021 ***	0.021 ***	0.021 ***	0.021 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Wind speed (km/hr)	0.044 ***	0.044 ***	0.044 ***	0.044 ***
	(0.006)	(0.006)	(0.006)	(0.006)
ln population	-0.003	-0.330	-0.018	-0.329
	(0.179)	(0.407)	(0.167)	(0.421)
year	-0.030 **	-0.021	-0.028 **	-0.025 *
	(0.008)	(0.010)	(0.007)	(0.010)
n	73	73	73	73
T	12	12	12	12
N	876	876	876	876
R-squared	0.217	0.219	0.217	0.22

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.9: Random Effects Model: Annual deaths from tropical cyclones by province, Philippines (2005-2016)

	(1)	(2)	(3)	(4)
ln local revenue per capita (t-1)	-0.008	-	-	0.009
	(0.038)	-	-	(0.037)
ln local expenditure per capita (t-1)	-	-0.337	-	-0.341
	-	(0.184)	-	(0.188)
local share revenue (t-1)	-	-	-0.001	-0.000
	-	-	(0.001)	(0.001)
Total rainfall (cm)	0.013 ***	0.013 ***	0.013 ***	0.013 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Wind speed (km/hr)	0.036 ***	0.036 ***	0.036 ***	0.036 ***
	(0.004)	(0.004)	(0.004)	(0.004)
ln population	0.300 ***	0.154	0.301 ***	0.153
	(0.048)	(0.091)	(0.048)	(0.092)
year	-0.027 ***	-0.023 **	-0.027 ***	-0.024 **
	(0.007)	(0.008)	(0.008)	(0.007)
n	73	73	73	73
T	12	12	12	12
N	876	876	876	876
R-squared	0.238	0.243	0.238	0.243

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.10: Pooled Model: Annual deaths from tropical cyclones by province, Philippines (2005-2016)

	(1)	(2)	(3)	(4)
ln local revenue per capita (t-1)	-0.002	-	-	0.014
	(0.037)	-	-	(0.035)
ln local expenditure per capita (t-1)	-	-0.340	-	-0.344
	-	(0.172)	-	(0.175)
local share revenue (t-1)	-	-	-0.001	-0.000
	-	-	(0.001)	(0.001)
Total rainfall (cm)	0.011 **	0.012 ***	0.011 **	0.012 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Wind speed (km/hr)	0.035 ***	0.035 ***	0.035 ***	0.035 ***
	(0.004)	(0.004)	(0.004)	(0.004)
ln population	0.298 ***	0.151	0.298 ***	0.150
	(0.046)	(0.085)	(0.047)	(0.086)
year	-0.026 ***	-0.022 **	-0.026 ***	-0.023 **
	(0.007)	(0.008)	(0.008)	(0.007)
n	73	73	73	73
T	12	12	12	12
N	876	876	876	876
R-squared	0.253	0.259	0.253	0.259

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.11: Fixed Effects Model: Annual deaths from tropical cyclones by municipality, Philippines (2007-2015)

	(1)	(2)	(3)	(4)
ln local revenue per capita (t-1)	0.011	-	-	0.007
	(0.006)	-	-	(0.007)
ln local expenditure per capita (t-1)	-	0.003	-	-0.002
	-	(0.017)	-	(0.017)
local share revenue (t-1)	-	-	0.100	0.065
	-	-	(0.066)	(0.074)
Wind speed (km/hr)	0.011 ***	0.011 ***	0.011 ***	0.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)
ln population	0.022	0.019	0.014	0.017
	(0.021)	(0.028)	(0.022)	(0.029)
year	-0.005 ***	-0.005 ***	-0.005 ***	-0.005 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	-	-	-	-
Log-Likelihood	-	-	-	-

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.12: Random Effects Model: Annual deaths from tropical cyclones by municipality, Philippines (2007-2015)

	(1)	(2)	(3)	(4)	(5)
ln local revenue per capita (t-1)	-0.005	-	-	-0.010 **	-0.007
	(0.003)	-	-	(0.003)	(0.004)
ln local expenditure per capita (t-1)	-	0.008	-	0.010	0.027 *
	-	(0.011)	-	(0.011)	(0.011)
local share revenue (t-1)	-	-	-0.008	0.060	0.057
	-	-	(0.033)	(0.045)	(0.045)
Wind speed (km/hr)	0.009 ***	0.009 ***	0.009 ***	0.009 ***	0.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
coastal	0.017 *	0.017 *	0.016 *	0.019 *	0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
ln population	0.057 ***	0.059 ***	0.056 ***	0.059 ***	0.062 ***
	(0.004)	(0.007)	(0.005)	(0.007)	(0.007)
year	-0.003 ***	-0.003 ***	-0.003 ***	-0.003 ***	-0.005 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	-	-	-	-	-
Log-Likelihood	-	-	-	-	-

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.13: Pooled Model: Annual deaths from tropical cyclones by municipality, Philippines (2007-2015)

	(1)	(2)	(3)	(4)	(5)
ln local revenue per capita (t-1)	-0.005	-	-	-0.010 **	-0.007
	(0.003)	-	-	(0.003)	(0.004)
ln local expenditure per capita (t-1)	-	0.008	-	0.010	0.027 *
	-	(0.011)	-	(0.011)	(0.011)
local share revenue (t-1)	-	-	-0.007	0.059	0.057
	-	-	(0.033)	(0.046)	(0.045)
Wind speed (km/hr)	0.009 ***	0.009 ***	0.009 ***	0.009 ***	0.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
coastal	0.016 *	0.016 *	0.015 *	0.018 *	0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
ln population	0.057 ***	0.059 ***	0.056 ***	0.059 ***	0.062 ***
	(0.004)	(0.007)	(0.005)	(0.007)	(0.007)
year	-0.003 **	-0.003 ***	-0.003 ***	-0.003 **	-0.005 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	-	-	-	-	-
Log-Likelihood	-	-	-	-	-

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.5.3 Physical controls

Yonson et al. (2018) find that socioeconomic factors have a larger impact on fatalities than storm characteristics, and do not find evidence of an association between wind speed and fatalities. In contrast, in this analysis estimated coefficients for wind are large and highly statistically significant in all specifications. Rainfall is also statistically significant in most specifications, and notably in the absence of wind the magnitude and statistical significance of rainfall generally increases, as wind and rainfall are correlated (see Tables B.1 and B.2). Consistent with theory and the bulk of the empirical literature on tropical cyclone vulnerability, resilience and adaptive capacity (e.g. Anttila-Hughes and Hsiang (2013); Hsiang and Narita (2012); Peduzzi et al. (2012); Pugatch (2019)), this suggests that wind speed is an important control for the destructive potential of a storm.

3.5.4 Robustness of results

I explore multiple sources of potential sensitivity for these results, including the years of analysis and the choice of a linear time trend versus year dummy variables. The observed relationship between municipal poverty rates and cyclone mortality is robust to multiple alternative specifications and analytical choices. Other results appear to be somewhat more sensitive. These alternative specifications are presented in the chapter appendix.

Poverty data are only available every three years with a total of 3 (4) measurements available for municipalities (provinces), which substantially reduces the years and therefore number of storms included in this portion of the analysis. As an alternative to the annual panel model, I construct a dataset with three year periods (so poverty in 2006 is compared to storm exposure and mortality in 2007-2009). The results at the municipal scale are in general robust to this alternative construction of the dataset, although some poverty estimates are reduced in magnitude and statistical significance. A 1% increase in a municipality's poverty rate is associated with approximately a 0.32% increase in tropical cyclone fatalities in the three-year model, compared to 0.37% in the annual model (Table B.5 (1)). In contrast, the associations observed between tropical cyclone mortality and provincial poverty and income in the pooled and OLS model are in most cases not found to be statistically significant under this alternative construction of the dataset (see Tables B.3, B.4 and B.5).

The main model specifications include year as a continuous variable, to allow for improvements in technology, national (or international) capacity for disaster risk reduction, and other macro trends. I find that there *is* evidence of a time trend in the Philippines during the study period; deaths appear to be decreasing over time, controlling for hazard exposure and local socioeconomic conditions. This relies on the assumption that the time trend is approximately linear, while the more typical practice of including year dummies can account for shocks as well as trends. However, in this particular case the concern is that time dummies are likely to absorb the large swings in average annual hazard intensity and exposure. The municipal results testing the relationship between poverty and tropical cyclones are robust to this decision (see Table B.8), but once again the province-level poverty results are more sensitive and a number of specifications lose statistical significance under the alternative time specifications (see Tables B.6, B.7).

In the case of local financial flows, some subtle differences do appear when we use year dummies versus a linear time trend. For example, the province-level fixed effects model with year dummies supports a statistically significant relationship between per capita expenditure and cyclone deaths. A 1% increase in provincial expenditure is associated with a 0.40% decrease in mortality (Table B.9 (2)). The comparable coefficient in the specification with a continuous year variable is also negative in sign, but is smaller in magnitude and not statistically significant (Table 3.8 (2)).

3.6 Conclusions

In this chapter I present results from a nested-scale, panel data analysis of tropical cyclone vulnerability in the Philippines. I control for hazard exposure at the provincial and municipal levels using high-resolution parametrically modeled wind speeds and population data. This allows me to correct for observed correlations between socioeconomic conditions and exposure, and to more precisely estimate the relationships of interest. To the best of my knowledge, this is the first nationally representative analysis of cyclone mortality at the municipal scale for the Philippines or any country.

I present novel evidence of a relationship between the share of people living in poverty at the municipal level and tropical cyclone mortality risk. Using a municipal fixed effects model, I find that an increase of 1% in the poverty rate is associated with a 0.37% decrease in tropical cyclone mortality. This result controls for tropical cyclone hazard and exposure, and is highly statistically significant and robust to a range of analytical choices. This does not necessarily indicate that poverty is the only or dominant causal mechanism underlying this result, as poverty rates tend to be highly correlated with income and other socioeconomic variables. However, these results do provide robust evidence that short-term fluctuations in local socioeconomic conditions are associated with changes in the mortality risk from tropical cyclones. At the provincial level there is some evidence of correlation between poverty rates and tropical cyclone deaths, but overall the evidence is weaker and more sensitive than at the municipal scale. This indicates that poverty-driven vulnerability to cyclone risk in the Philippines is highly localized. From a policy perspective, this further suggests that income gains - perhaps especially at the bottom of the distribution - may have short-term payoffs for disaster risk reduction at the local level.

In contrast, the balance of the evidence does not indicate a statistically significant relationship between local fiscal capacity and tropical cyclone mortality rates. There is some evidence that per capita expenditure by provincial governments is at least correlated with lower cyclone mortality, but without sufficient evidence to support a causal relationship.

One explanation for these results may be that local government fiscal capacity is not sufficiently correlated with the types of capacity needed for disaster risk reduction. Alternatively, it may be that general administrative abilities are not currently the binding constraint on local governments' efficacy in disaster risk management. In a country with historically centralized governance of disasters like the Philippines it is credible that, in addition to general administrative capacity, local governments are in need of specific knowledge, skills and accountability to promote effective engagement in this sphere. Locally representative data on qualities such as trust in governance, civic engagement, and disaster-specific knowledge and capacity are not readily available for the Philippines. In the following chapter we explore natural experiments as an alternative means of investigating the governance hypothesis in the absence of such data.

Chapter 4: Policy experiments and tropical cyclone mortality: an example from the Philippines

4.1 Introduction

The elimination of poverty and disaster risk reduction are critical public policy objectives with the shared goal of human well-being. Given finite resources, strategies are needed that can mutually target these twin objectives and avoid working at cross-purposes. This is particularly important given the challenges posed by climate change, including shifts in extreme weather events. In this chapter I explore how leveraging existing policy experiments can increase our understanding of the impacts of development interventions on disaster risk. Using a randomized community-driven development program in the Philippines as an example, I illustrate the strong assumptions and data requirements necessary to draw causal inference from this analytical approach.

While poverty and under-development are widely believed to be important risk factors for disaster mortality, empirical evidence of how development interventions are likely to impact mortality risk from environmental hazards is scarce. Is poverty a dominant root cause of disasters and, if so, will disaster risk reduction follow autonomously on the heels of inclusive economic development? Or is a focus on certain types of economic development driving changes that are maladaptive in the long-run, particularly under climate change?

The existing empirical literature on this topic is dominated by case studies and quantitative analyses of observational data. Case studies provide important evidence of a complex causal landscape but can be difficult to generalize from. Quantitative analyses based on observational data are useful for identifying patterns and associations, but causal inference is more difficult. Many of the conditions thought to be important for resistance and resilience to climate shocks are highly correlated in time and place, and therefore difficult to disentangle. The likelihood of multi-directional causality between socioeconomic conditions and disasters further complicates the interpretation of observed correlations in space and time. One approach for overcoming the problems of omitted variable bias and multicollinearity is to design a randomized control trial (RCT), in which the intervention of interest is randomly assigned to a subset of the population.

In this chapter I explore the potential of exploiting existing policy experiments such as randomized control trials (RCTs) to develop causal inference about the effects of development interventions on disaster mortality. Randomized control trials are designed to provide unbiased estimates of average treatment effects (ATEs); but the precision of the estimates relies on the balance of other causal variables across the treatment and control groups (Deaton and Cartwright, 2016). Randomization does not guarantee this balance, particularly in the case of small sample sizes and/or where there is substantial heterogeneity in causal variables (Angrist and Pischke, 2009; Deaton and Cartwright, 2016; Suzuki and VanderWeele, 2018). In this chapter I examine whether a random sample of communities is likely to have a balanced distribution of causal factors contributing to cyclone mortality. I argue that the large heterogeneities in community-level tropical cyclone vulnerability and exposure are in fact likely to result in incidental imbalance between randomly selected treatment and control groups, particularly if sample sizes are small. This may lead to imprecise estimates of average treatment effects in a simple differences model. I use an example case from the Philippines to empirically test and illustrate this point.

The Philippines is exposed to more tropical cyclones than any other country in the world (modeled winds based on data and methods by Anderson et al. (2017); Knapp et al. (2010); Willoughby et al. (2006). Many of these are deadly and destructive; over the past decade 85 deadly storms have killed over eleven thousand people in the Philippines (2007-2016) (NDRRMC, n.d.a). This frequent exposure to tropical cyclones highlights the importance of developing strategies to reduce socioeconomic vulnerability to storms in the Philippines. It also makes the Philippines an ideal study area, as it is one of very few countries where individual localities are regularly exposed to tropical cyclones, which is necessary to observe trends in vulnerability over time.

In this chapter, I consider the case of a randomized community-driven development intervention in the Philippines. The intervention studied is the second phase (2011-2015) of the Kapit-bisig Laban sa Kahirapan, translated "Linking Arms Against Poverty," Comprehensive and Integrated Delivery of Social Services (Kalahi-CIDSS or KC). As part of an Innovation for Poverty Action (IPA) impact evaluation sponsored by the Millenium Challenge Corporation (MCC), a portion of the program slots were randomized at the municipal level, affording a unique opportunity to test for causal effects of the program. Disaster risk reduction was not a primary goal of KC during the study period, but theory suggests that each of the program goals - reducing poverty, improving local governance, and empowering communities – may be important to the root drivers of disaster mortality risk. Evidence from the IPA impact evaluation further provides some insight into actual program impacts in each of these areas.

Using the Kalahi-CIDSS case I illustrate how the prevalence of outliers in vulnerability and exposure in the Philippines can result in imbalances of the causal factors influencing tropical cyclone mortality across treatment and control groups, even when randomly selected. Techniques to correct for these imbalances are found to be useful, but limited by data availability. For example, I demonstrate how controlling for wind hazard ameliorates the incidental imbalance in exposure between the treatment and control groups; but also that it is insufficient. I test a difference-in-differences approach to control for incidental imbalance in community-level vulnerability, but the limited duration of available mortality records constrains my ability to observe trends in pre-treatment vulnerability in the treatment and control municipalities. This is particularly problematic given the passage of Super Typhoon Yolanda over the Philippines during the KC treatment period, as there is no event of comparable intensity during the pre-treatment period. High resolution data on storm surge and flooding is needed to better control for time-variant, incidental imbalances in exposure to tropical cyclones. Testing and correcting for imbalances in place-specific vulnerabilities could be addressed via the compilation of local mortality records over longer periods of time or by improving local data collection on known, observable causes of vulnerability.

4.2 Background and Motivation

The weight of the evidence from case studies and quantitative empirical work on tropical cyclone risk supports a correlation between socioeconomic development and vulnerability (see Chapters 1 and 2 for a review of the literature). The causal processes that produce this association are less clear, as the evidence is consistent with multiple theoretical mechanisms. The poor may be more vulnerable because of their poverty; because their houses are poorly built, their health is more fragile, or their coping resources fewer. Long-standing inequalities in wealth and power are also frequently cited in the co-production of poverty and vulnerability to environmental hazards (e.g. Bankoff (1999); Blaikie et al. (2004). Patterns of vulnerability might also be a legacy of the disruption and devastation wrought by tropical cyclones themselves (e.g. Anttila-Hughes and Hsiang (2013); Hsiang and Jina (2014)). This spatial overlap of underdevelopment and cyclone vulnerability raises concerns that those most in need of adaptive measures will lack the resources, institutions and social capital to effectively implement solutions (Denton et al., 2014; Gupta et al., 2010).

What gains can be made through development? Current evidence falls short of demonstrating that economic development activity, particularly following traditional models, will necessarily lead to less vulnerability. In fact, particularly as the frequency and intensity of natural hazards shift under global climate change, there is concern that development-as-usual may lead to increased disaster risk, or 'maladaptation.'

One proposed solution is to harness the synergies between development and vulnerability reduction and safeguard against maladaptation by purposefully integrating development, climate adaptation, and disaster risk reduction. This is sometimes referred to as 'soft' or 'general' adaptation, or the 'mainstreaming' of adaptation into development. It may start with the 'climate-proofing' of existing development efforts, with the eventual goal of deeper integration of these spheres into institutional structures and long-term plans (Ayers et al., 2014). Building adaptive capacity, and particularly institutional development, may be necessary in the short-term as a foundation for specific adaptation efforts in the future (Fankhauser and Burton, 2011). Ensor et al. (2015) emphasize the critical role of effective and inclusive institutions as necessary conditions for just adaptation.

Others are more skeptical of the 'mainstreaming' approach, concerned that the top-down, managerialist nature of development agencies is problematic and symptomatic of the very underlying power imbalances that result in vulnerabilities. Adger et al. (2003) argues that the mainstreaming of adaptation into existing agencies or the creation of new top-down structures for adaptation is insufficient. Pelling (1999) illustrates how entrenched power relationships can complicate vulnerability reduction efforts. He describes how political and economic elites in urban Guyana co-opted and thereby reduced the effectiveness of new community organizations established to build resilience, effectively increasing overall flood vulnerability.

4.2.1 The benefits and limitations of randomization

Randomized control trials (RCTs) and natural experiments are often employed to measure the effects of policies or interventions on outcomes of interest. By randomizing assignment to treatment and control groups in RCTs researchers are able to ameliorate the problems of multicollinearity and omitted variable bias, which make it so difficult to infer causality in observational studies. This allows researchers to isolate the average treatment effect of a policy or intervention in a specific context. When well designed and executed, the strong internal validity of an RCT can be particularly useful in establishing 'proof-of-concept'; demonstrating that a treatment can have a particular effect, at least for some populations and in some circumstances (Angrist and Pischke, 2009; Deaton and Cartwright, 2016; Suzuki and VanderWeele, 2018). Whether the effects identified via an RCT are likely to hold across different places and contexts – referred to as the external validity of the results – relies on strong assumptions and is often more controversial (e.g. Deaton and Cartwright (2016); Imbens (2018); Suzuki and VanderWeele (2018)).

In this chapter I focus on the first order internal validity of the experimental approach for studying the impacts of a community-driven development program on tropical cyclone mortality. Given the paucity of empirical evidence in this area, providing 'proof-of-concept' evidence for the impacts of a development program on tropical cyclone mortality would be a useful contribution, even if the external validity of the results is limited.

A basic model for estimating average treatment effects is represented in equation 4.1 following Deaton and Cartwright (2016):

$$\bar{Y}^1 - \bar{Y}^0 = \bar{\beta}^1 + \sum_{j=1}^{J}(\bar{x}^1_{ij} - \bar{x}^0_{ij}) = \bar{\beta}^1 + (\bar{S}^1 - \bar{S}^0), \tag{4.1}$$

where $\bar{Y}^1$ and $\bar{Y}^0$ represent the average outcomes for the treatment and control groups, respectively; $\bar{\beta}^1$ is the average treatment effect; and the x's represent all causal variables (other than treatment) that impact storm mortality, and may be observable or unobservable.

The difference in outcomes between the treatment and control groups in equation 4.1 is equal to the average treatment effect *plus* an error term that is the net effect of all other factors that are not perfectly balanced between the treatment and control groups. Under perfect randomization this error term is zero in expectation, but in a single trial or experiment it will be equal to zero only if the net effects of all non-treatment variables are perfectly balanced between the treatment and control group (Deaton and Cartwright, 2016). Randomizing treatment therefore does not guarantee balance in the treatment and control groups (e.g. Angrist and Pischke (2009); Cartwright (2007); Deaton and Cartwright (2016); Heckman (2008); Suzuki and VanderWeele (2018)).

The likelihood of incidental imbalances in causal factors depends upon the specific phenomenon and system under study, and there is some debate as to how serious a threat imbalance is likely to pose for the precision of ATE estimates in

RCTs (Angrist and Pischke, 2009; Deaton and Cartwright, 2016; Imbens, 2018; Suzuki and VanderWeele, 2018). As noted by Suzuki and VanderWeele (2018), further research is needed to determine in what settings and for what processes causal factors are likely to be more or less homogenous. This has implications not only for balance, but also for the external validity of results and their applicability to individuals. Large sample sizes may reduce the likelihood of imbalance in causal factors between treatment and control groups; however, resource constraints often limit sample sizes in the case of RCTs designed to evaluate development interventions. Further, what an appropriate sample size threshold might be requires assumptions about the distribution of unobserved causal variables (e.g. Deaton and Cartwright (2016); Suzuki and VanderWeele (2018)).

I argue in this chapter that the threat of incidental imbalance is high and not easily corrected for in the case of tropical cyclone mortality. In the Philippines, we have direct and indirect evidence of large heterogeneities in causal factors for tropical cyclone mortality across municipalities and over time. For example, higher wind speeds are associated with increased mortality risk, and the data show high variance in wind exposure over place and time. The prevalence of large outliers in mortality records at the municipal level can be taken as indirect evidence that variance in vulnerability and/or exposure over space and time is high. This suggests that randomization into treatment and control groups is in fact unlikely to ensure the balance in causal factors necessary for the uncritical comparison of mean outcomes. Given the likelihood of imbalance, it is particularly concerning that we cannot easily anticipate and observe many of the important causal factors at play. This means that we cannot fully test and correct for imbalance between the treatment and control groups, at least with currently available data.

There are a number of techniques designed to address the risk of incidental imbalance in randomized control trials. Ex ante, in cases where important causal variables are known and easily observable, researchers may design RCTs such that treatment and control groups are well balanced on these characteristics (Angrist and Pischke, 2009). Ex post, additional causal factors can be included as control variables to improve precision (Angrist and Pischke, 2009; Deaton and Cartwright, 2016). However, these techniques cannot account for potential imbalances that are unknown and/or unobservable (Deaton and Cartwright, 2016). Difference-in-difference techniques, which do not require balance in causal factors but instead rely on the assumption of parallel trends between the treatment and control groups, are an alternative option. In particular, difference-in-differences may be preferred if we believe that there are likely to be persistent differences in levels of baseline vulnerability between the treatment and control groups.

While the KC study design includes ex ante matching on a limited set of socioeconomic characteristics, it was not designed to match baseline tropical cyclone vulnerabilities. Even if we were to design an experiment specifically to measure the impact of a treatment on tropical cyclone outcomes, our ability to improve balance using matching techniques would be limited. It is impossible to perfectly observe differences in baseline vulnerability (Engle et al., 2014; Hinkel, 2011) and exposure is not known in advance. I do explore the ex post approach of controlling for potential imbalances in this exercise, using variables such as proximity to the coast and tropical cyclone exposure. I also employ a difference-in-differences approach that compares pre- and post-treatment cyclone mortality rates in the treatment and control groups. Yet there remain known causal factors that are unobserved and time-variant in this dataset, such as exposure to storm surge and flooding. I discuss how this compromises our ability to identify and correct for imbalances between the treatment and control groups, using the illustrative example of an outlier case.

4.2.2 The Kalahi-CIDSS project

Policy interventions for disaster risk reduction may directly target specific vulnerabilities, for example by constructing tropical cyclone shelters or developing evacuation plans. Alternatively, interventions may seek to build the broad base of capacities that people and communities need to be resilient to a range of shocks and stressors (i.e. livelihoods, human capital, and effective institutions). Although it does not explicitly target disaster risk, we hypothesize that programs like the Kalahi-CIDSS project may reduce disaster risk via this latter mechanism; specifically, by alleviating poverty and building local institutional capacity and civic engagement.

The Kalahi-CIDSS program is a large-scale multi-phase community driven development initiative implemented by the national government of the Philippines. The second phase of the KC program (2011 to 2015) was funded by a US $120 million grant by the Millenium Challenge Corporation (MCC) and a US $59 million loan from the World Bank (WB). A portion of KC funding slots in this phase was randomized for evaluation purposes. An impact evaluation funded by the MCC was designed and carried out by Innovations for Poverty Action (IPA), as described by Beatty et al. (2014), Beatty et al. (2015) and Beatty et al. (2018). Unless otherwise specified, in this paper I am in referring to this randomized subset of the phase two KC MCC project.

In addition to the training and capacity-building components, the KC program, the program also invested in poverty reduction sub-projects. Participating treatment municipalities were allotted an average of about US $11,250 per barangay (village) to fund these sub-projects. Local government units contributed at least a 30% match to KC project funds, either with cash or in-kind contributions (Beatty et al., 2018). For comparison, GDP per capita in 2012 was approximately US $2,350 (WDI, 2018) and the expected return on investment used for power calculations in the baseline report was an 8% change in income (Beatty et al., 2014). In other words, these were sizable investments theorized to have large impacts on poverty.

The goals of the KC MCC program were (1) poverty reduction; (2) improved participation in local governance; and (3) community empowerment:

> **Empower local communities** by developing capacities of community members and instituting community-based mechanisms that will allow the people to decide on issues affecting their own development. Vulnerable groups such as women, Indigenous Peoples, farmers, fisherfolk, and communities in conflict are given priority by including them in the decision-making process, especially on matters pertaining to allocation and use of resources.

> **Improve local governance**, (both at the barangay and municipal levels), by revitalizing mechanisms that encourage community consultation, transparency and, accountability, especially on processes around local development planning and the use of limited resources to address community-identified local priorities, following the principles of good governance as mandated by the Local Government Code or LGC (Republic Act 7160).
>
> **Reduce poverty** by providing funds for projects that the community itself identifies, designs, and implements, based on priority needs identified by the communities themselves. It is assumed that with empowered communities and improved local governance, development projects implemented by communities will be relevant, successful and sustainable.
>
> *Philippines' Department of Social Welfare and Development (2012)*, as reproduced in Beatty et al. (2018).

Each of these three areas have been theorized in the literature as important determinants of adaptive capacity and vulnerability to tropical cyclones and other natural hazards. In addition, many of the sponsored sub-projects included roads, flood management, and other infrastructure that might moderate the impacts or aftermath of a typhoon. Although KC was not specifically designed to target disaster risk reduction, DSWD reports have described how several KC MCC sub-projects protected communities during the devastating Typhoon Yolanda in 2013. Vignettes such as "Last-minute construction saves community from Typhoon Yolanda" and

"Village folks built sea wall that saved them from 'Yolanda'" describe KC sponsored projects holding back dangerous flash floods and storm surge (Sison et al., n.d.).

Yet the overall impact of such projects on risk and vulnerability across place and time are uncertain. As described by Blaikie et al. (2004) there is a 'paradox of flood control,' whereby infrastructure may afford protection for some while exacerbating impacts for others. In the village where a sea wall was constructed, it only protected approximately 25% of the village and homes beyond its reach were flooded or washed away (Sison et al., n.d.). And even amongst the success stories there remained a specter of catastrophic failure:

> Still, even with the care and their efforts, they felt fear, because they knew how strong the currents could get. Julie Pasaral, 43, a Kalahi-CIDSS volunteer, admitted, "Nung una, natakot kami na umapaw ang tubig mula sa dike dahil sa bagyo, pero sa awa ng Diyos, hindi naman (At first, we were afraid that the rivers would overflow during the typhoon, but with God's mercy, they did not)." (Sison et al., n.d.)

These vignettes further emphasize ways in which volunteer networks and leaders cultivated via the KC process were leveraged in the aftermath of Yolanda. But in the absence of a counterfactual, it is difficult to judge whether the sub-projects themselves or networks and capacity built during the implementation process demonstrably impacted tropical cyclone risk in recipient communities.

4.2.2.1 Randomization of eligibility and treatment

Program eligibility, random assignment, and adherence for KC projects are described in detail in Beatty et al. (2014). As determined by the DSWD, the KC program targeted municipalities in 48 of the Philippines' poorest provinces. The number of municipalities that received KC in each of these provinces was capped at 50 percent minus 1, with priority granted to municipalities with a poverty incidence exceeding 70 percent. Only in provinces with remaining slots were municipalities with 34 to 69 percent poverty incidence that had not previously received KC funding eligible to be included in the evaluation sample. As a result, randomization only occurred in 26 of the 48 target municipalities and is representative of poor, but not the poorest, provinces and municipalities in the Philippines.

In the 26 provinces with municipalities eligible for participation in the evaluation portion of KC, public lottery events were held to randomize treatment (see Beatty et al. (2014) for a detailed description). Municipalities that did not indicate interest and send a representative to the lottery event were excluded, and from the remaining 290 municipalities 99 matched pairs (198 municipalities) were selected as the target evaluation sample. Pairs were matched based on province, poverty incidence, population, land area, and number of barangays.

4.2.2.2 Program design and implementation

The KC program includes community training at the municipal and barangay (village) levels, which consisted of guidance in the design, selection and implementation of poverty-related development projects. This occurred via a five-stage process known as the Community Empowerment Activity Cycle (CEAC), described in detail by Beatty et al. (2018). Municipalities are given block grants which are awarded to sub-projects proposed, selected, and implemented by the barangays. While all barangays in treatment municipalities are invited to participate in training and propose sub-projects, they were not guaranteed an award. By the 2015 third-round survey 70% of barangays in treatment municipalities had completed at least one sub-project (Beatty et al., 2018, p. 24). The evaluation team categorized the awarded sub-projects into five broad categories: infrastructure, education or health, water and electricity, water protection, and support (see Beatty et al. (2018) for a detailed description). The most common sub-types were "roads, flood prevention measures, school buildings, and access trails and footpaths" (Beatty et al., 2018).

The timeline of program implementation and data collection is described in detail by Beatty et al. (2014) and Beatty et al. (2018). The public lottery events for selection into the treatment or control group were held in May and June of 2011, and the social preparation phase began in June of 2012. The IPA evaluation team implemented household and barangay surveys, key informant interviews, focus groups, as well as observations of structured community activities and barangay assemblies. Survey data collection occurred in three rounds, referred to as the baseline (April – July 2012), interim (February – June 2014) and final or third-round (July – October 2015) surveys.

4.2.2.3 Findings from the impact evaluation

The IPA impact evaluation by Beatty et al. (2018) finds evidence of increased service provision, including reduced travel time and transportation costs, increased school enrollment and lower student-teacher ratios, and reduced time and financial costs to collecting water. Agricultural productivity was negatively impacted, likely due to the displacement of agricultural land with roads or other infrastructure. The evaluation does not find statistically significant gains in longer-term socioeconomic indicators, such as household assets, consumption, home values or labor force participation at the time of the 2015 final survey.

The KC evaluation team tested several hypotheses related to the program's institutional effects (Beatty et al., 2018). They find that the program resulted in sub-projects that matched well with ex ante preferences, and that the treatment group had increased knowledge and awareness of local governance from the baseline to the final survey. They do not find that KC had a statistically significant effect on participation, information sharing and inclusiveness between the baseline and final surveys. However, at interim a statistically significant increase in participation was detected. The survey found a small but statistically significant decrease in confidence and self-efficacy.

IPA also investigated whether KC empowered community members to take part in local decision-making processes (Beatty et al., 2018). They found that KC increased participation in community organizations, but did not find that it increased interaction between peers. This might in part be due to high baseline levels of bonding social ties: on average, survey respondents know 71% of other barangay residents and were related to 23% of other households (Beatty et al., 2018).

Following the passage of Typhoon Yolanda in 2013 the IPA team modified their interim evaluation plan to test whether "KC helps people better deal with hardship" using a hardship index in the household survey module (see Beatty et al. (2015) for a detailed description). For those who experienced financial hardship as a result of a natural disaster, this measures "the number of different types of people who gave the household financial and/or moral support, if the person/people offering support reside in the barangay, and whether they received financial and or in-kind support." They find a large and statistically significant increase in all three of these variables in the interim survey, but not in the final survey round.

The limited observed impacts of the KC project on its stated goals of poverty reduction, community empowerment and improving local governance, as found by the IPA impact evaluation highlight the limited efficacy of the program to achieve aims consistent with disaster risk reduction. In particular, if we believe income poverty to be a dominant causal mechanism the IPA evaluation suggests that measurable gains were not achieved during our time frame for analysis.

4.3 Models

For the example case I estimate and compare three models of the Kalahi-CIDSS program treatment effect on tropical cyclone mortality. A negative binomial

(NB2) regression model is estimated for all three variants because the outcome variable, tropical cyclone deaths, takes only non-negative integer values and we have overdispersion in the data. A drawback of the negative binomial model is that interpretation of the interaction effect in equation (4.4) is not straightforward. Corresponding linear models are also presented in the appendices for comparison.

I begin with a basic treatment effect model, which is sometimes appropriate in cases of randomization because program assignment is plausibly independent from other variables which may impact the outcome. However, as discussed in the background section of this chapter, randomization alone does not guarantee that the treatment and control groups are well balanced in terms of causal variables. The KC treatment and control municipalities are matched and therefore well balanced in terms of province, poverty incidence, population, land area and number of barangays - all of which may feasibly affect tropical cyclone risk. The study design did not include matching on variables specific to tropical cyclone vulnerability (for example, populations in low-lying coastal areas or flood plains). The conditional mean of tropical cyclone deaths μ_i is

$$ln(\mu_i) = \beta_1 + \beta_2 T_i + \varepsilon_i, \tag{4.2}$$

where T_i for municipality i is the treatment dummy ($T_i = 1$ for the treatment group and $T_i = 0$ for the control).

However, tropical cyclone mortality has unique properties as an outcome variable. The trajectory of tropical cyclones is exogenous to the analytical setting but not evenly distributed; some places are more likely to experience more frequent or more intense tropical cyclones than others. The selection of treatment and control pairs from the same province helps to balance wind exposure somewhat, but as discussed in Chapter 3, tropical cyclones are also extremely variable and their effects can be highly localized. We should therefore be cautious about assuming there is no incidental imbalance in hazard exposure in the post-treatment period. Excluding an important covariate such as exposure from the model is likely to result in large standard errors and imprecise estimates (Angrist and Pischke, 2009).

I examine the balance of the treatment and control groups for four years prior to treatment on available outcome and hazard exposure metrics. The descriptive statistics presented in Table 4.1 suggest that the treatment and control groups are well-balanced in terms of their recent and historical (1979-2006) wind exposure. Further, the treatment and control groups include a similar (72% and 75%, respectively) number of coastal municipalities. Comparison based on the Table 4.4 metrics does not reveal any statistically significant differences between the treatment and control groups. However, given the extreme variability in tropical cyclone exposure patterns over time, balance in the pre-treatment period does not necessarily imply balance in the post-treatment. In equation (4.3) I therefore include a *hazard* covariate in the model. If the KC program had not explicitly matched treatment and control municipalities based on population this might also be included as a proxy for exposure. The second model for the conditional mean of tropical cyclone deaths μ_i is

$$ln(\mu_i) = \beta_1 + \beta_2 T_i + \beta_3 hazard_i + \varepsilon_i, \tag{4.3}$$

Even given reasonable evidence of balance on observables and controlling for wind hazard exposure, equations (4.2) and (4.3) are only valid if the treatment and control groups are also balanced in terms of unobserved features of vulnerability and exposure to tropical cyclones. In Table 4.1 we observe that pre-treatment tropical cyclone casualties were slightly higher in the treatment (44) versus control (33) group, which could indicate an imbalance in baseline vulnerability. Therefore, in addition to including a hazard control variable in equation (4.3), I estimate a negative binomial difference-in-differences model for comparison. The model for the conditional mean of tropical cyclone deaths μ_{it} for municipality i in time t is

$$ln(\mu_{it}) = \beta_1 + \beta_2 T_i + \beta_3 hazard_i + \beta_4 A_t + \delta T_i \times A_t + \varepsilon_i, \tag{4.4}$$

where A_t for municipality i indicates before ($A_t = 0$) and after ($A_t = 1$) the start of the KC project. This allows for different baseline vulnerability in the treatment and control groups. However, it still relies on the assumption that, in the absence of the KC program, the trend in tropical cyclone deaths for the treatment and control groups would be the same (conditional on hazard exposure). A parallel trends analysis (see Figure 4.1) of cyclone mortality in the pre-treatment period does not indicate strong support for this assumption. Further, we know that mortality in previous years is an imperfect proxy for vulnerability to the types of events experienced in the after treatment period. This limits our ability to test the validity

Table 4.1: Balance of pre-treatment hazard exposure characteristics

				wind speed (km/hr)			
group	n	coastal	deaths	mean	sd	max	sum
Control, Before	99	74	33	2.62	4.33	37.33	15547.10
Treatment, Before	99	71	44	2.58	4.27	38.30	15335.83

Note: Summary statistics are for all province-storm events occurring in the four years prior to the start of the KC project.

of assumptions that models 4.2 - 4.4 rely upon.

Estimates for the negative binomial regression results are presented as Incident Rate Ratios (IRRs) in the results tables, obtained by exponentiating the estimated coefficients of the negative binomial regression models. Thus, the null hypothesis is $H0 : IRR = 1$. If the coefficient is negative the $IRR < 1$ and if the coefficient is positive the $IRR > 1$. Interpretation is that mortality is expected to change by a factor equal to the IRR with a one-unit increase in the independent variable, holding other regressors constant.

4.4 The Data

Data on tropical cyclone mortality, KC treatment status, and tropical cyclone wind exposure is compiled at the storm level for all 198 treatment and control municipalities in the randomized KC evaluation. The data are grouped by storm dates into pre- and post-treatment. For the main analysis, the post-treatment period includes tropical cyclone events that occurred between December 1st 2012 (by which time the social preparation phase had been completed by all municipalities) and November 30th 2014. This end date was chosen based on the ramp-up of the third phase of KC in 2015, during which a similar project was delivered to treatment and control municipalities (see Beatty et al. (2018) for details). Further, estimates of KC program impact were higher for several key metrics in the interim (2014) versus final (2015) survey. The pre-treatment phase in the main analysis includes storms occurring between June 1st 2008 and May 31st 2012, just prior to the start of the KC social preparation phase. The longer pre-treatment phase is intended to balance the stronger and more frequent exposure to tropical cyclones in the post-treatment period (see Table 4.4).

The data sources and methods used to compile the outcome variable, tropical cyclone mortality, and exposure control variables are identical to those used in the Chapter 3 analysis. The variables, including tropical cyclone deaths, wind speed, and KC treatment status, are summarized in Table 4.2. See Chapter 3 for a full description of the dataset methodology.

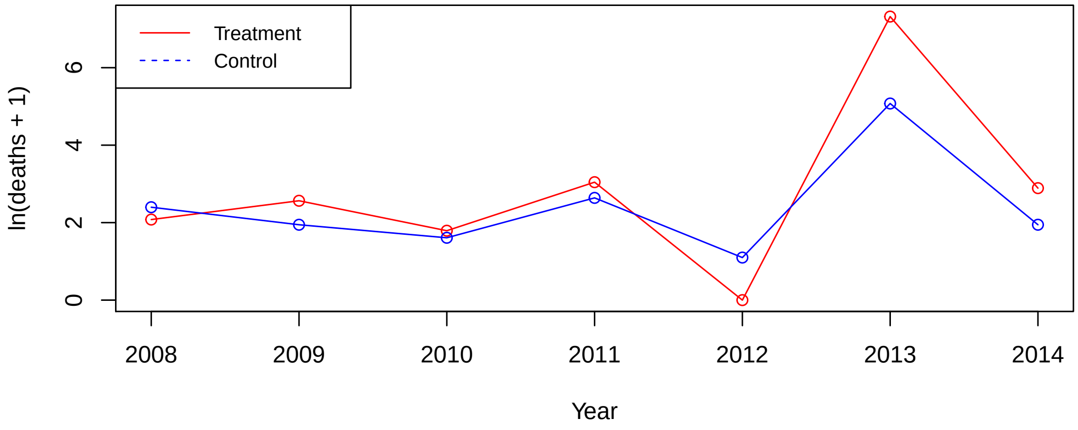

Figure 4.1: Parallel trends plot. Total tropical cyclone deaths per year for treatment and control groups, 2008-2014.

Table 4.2: Summary of variables

Variable	**Description**	**Source**
Deaths	Deaths from tropical cyclones, by municipality	National Disaster Risk Reduction and Management Council (NDRRMC, 2018)
Treatment	Binary variable for KC treatment (T = 1) and control (T = 0) assignment, by municipality	Obtained from Innovation for Poverty Action (2018)
After	Binary variable for before (A = 0) and after (A = 1) the start of KC treatment	Obtained from Innovation for Poverty Action (2018)
Max sustained wind speed (km/hr)	Maximum sustained wind speed in kilometers per hour, by municipality	Wind fields modeled using stormwindmodel (Anderson et al. 2017; Willoughby et al. 2006) and IBTrACS data (Knapp et al. 2010).
Sum of historical winds (km/hr)	Sum of maximum sustained wind speeds for all storms, 1979-2016, by municipality	Wind fields modeled using stormwindmodel (Anderson et al. 2017; Willoughby et al. 2006) and IBTrACS data (Knapp et al. 2010).

4.5 Results & Discussion

The results of this analysis provide a useful illustration of the issues of balance that can compromise the precision of ATE estimates, even under randomization. They also highlight broader difficulties of causal inference related to vulnerability from extreme events. I unpack the results to demonstrate how the singular nature of tropical cyclones, although plausibly exogenous in terms of trajectory, is likely to result in exposure imbalances across treatment and control groups. Large heterogeneities in local vulnerability further exacerbate problems of balance. Both vulnerability and exposure are difficult to adequately observe and therefore test and correct for. To illustrate these issues, I work through the three models represented in equations 4.2 - 4.4. None of the estimated models indicate that the KC program reduced tropical cyclone mortality in treatment municipalities. It is unclear whether this is due to issues of balance and imprecision in the estimates, insufficient gains in the KC project objectives during the study period, or because these general development gains did not translate into reduced tropical cyclone risk.

Estimation of the most basic post-intervention treatment model (equation 4.2) presented in Table 4.3 (1) indicates that KC treatment is associated with a statistically significant, nine-fold *increase* in tropical cyclone deaths. By controlling for wind speed as we estimate equation (4.3) this effect is attenuated down to a three-fold, still statistically significant increase in tropical cyclone deaths (Table 4.3 (2)). In the difference-in-differences model (equation 4.4) the $treatment \times after$ effect is positive but not statistically significant (Table 4.3 (3)). We next examine how precise we can reasonably assume these estimates to be. I conclude that under current data limitations it is not defensible to draw conclusions about the causal impact of the KC program on disaster effectiveness from any of these models (4.2 - 4.4).

In Table 4.4 I extend the earlier pre-treatment balance analysis to compare the deaths and exposure in the pre- and post-treatment periods. The dramatic increase in deaths in the treatment group immediately stands out: 1,525 deaths occurred in the treatment group in the second (post-intervention) time period, compared to 167 deaths in the control group and only 77 deaths total (treatment + control) in the baseline period. We also note that the mean and maximum wind speed, while well-balanced between the treatment and control groups, is much higher in the second period compared to baseline. These dramatic differences in the before and after maximum wind speeds are largely due to Super Typhoon Yolanda.

In November of 2013, the Philippines was impacted by Super Typhoon Yolanda (also known as Haiyan), one of the strongest landfalling tropical cyclones ever recorded. According to NDRRMC reports and statistics, the storm killed an estimated 6,386 people, with 1,375 of those recorded casualties occurring in the Kalahi-CIDSS treatment municipality of Tanauan, Leyte. In Carigara, Leyte, the control municipality paired with Tanauan, there were 14 casualties during Typhoon Yolanda. A deeper dive into this KC matched pair provides a useful illustration of how the presence of outliers can compromise the balance necessary for precise estimates of average treatment effects when using data from a randomized control trial.

Table 4.3: Kalahi-CIDSS: Negative binomial regression results

	IRR (1)	IRR (2)	IRR (3)
treatment	9.132 *	3.120 *	1.777
	(8.846)	(1.643)	(0.674)
after	-	-	0.550
	-	-	(0.275)
Wind speed squared (sq-km/hr)	-	1.003 ***	1.002 ***
	-	(0.001)	(0.001)
treatment:after	-	-	1.818
	-	-	(1.206)
Observations	198	198	396
Log-Likelihood	-261.7	-226.5	-379.3

Notes: Negative binomial results are presented as Incident Rate Ratios (IRRs), obtained by exponentiating the estimated coefficients. Thus, we are testing the null hypothesis that $IRR = 1$. If the coefficient is negative the $IRR < 1$ and if the coefficient is positive the $IRR > 1$. Robust standard errors are reported in parentheses. Statistical significance is indicated by * p < 0.05, ** p < 0.01, *** p < 0.001.

4.5.1 Comparing hazard and exposure

Maximum sustained wind speeds are a commonly used control variable for hazard intensity in the tropical cyclone vulnerability literature (e.g. Anttila-Hughes and Hsiang (2013); Hsiang and Narita (2012); Mendelsohn et al. (2012); Peduzzi et al. (2012); Pugatch (2019)). According to the modeled wind speeds, Tanauan did experience stronger maximum sustained winds (174 km/hr) than Cariga (146 km/hr), as well as stronger wind gusts (259 km/hr vs. 217 km/hr). Yet five other municipalities in the sample were exposed to stronger winds than Tanauan; all of which experienced casualties, but none on the scale of Tanauan. Tanauan also experienced higher rainfall than Cariga, but many municipalities in the sample were exposed to much higher rainfall totals.

Table 4.4: Balance of pre- and post-treatment hazard exposure characteristics

				wind speed (km/hr)			
group	n	coastal	deaths	mean	sd	max	sum
Control, Before	99	74	33	2.62	4.33	37.33	15547.10
Treatment, Before	99	71	44	2.58	4.27	38.30	15335.83
Control, After	99	74	167	3.24	5.89	54.47	12821.26
Treatment, After	99	71	1525	3.24	5.93	53.58	12839.72

Note: Summary statistics are for all province-storm events occurring in the four years prior to the start of the KC project.

What our model does not capture is coastal storm surge. These data were not available, and it is therefore unclear how including them explicitly in the model would impact the results. However, the Tanauan - Cariga case suggests that this may be important. A first order cause of the enormous loss of life in Tanauan, Leyte was the presence of a large number of people in an area inundated by an estimated 5.2-5.8 meters of storm surge (Soria et al., 2016). In contrast, while official estimates of storm surge in Cariga were not available, review of modeled storm surge maps by Takagi et al. (2017) as well as anecdotal reports indicate that it was likely minimal (DILG, n.d.). In inland Tanauan, the primary causes of death were related to the strong winds (Yi et al., 2015); but fatalities were concentrated in the 17 coastal barangays of Tanauan, and in these areas 683 municipal death certificates obtained by Yi et al. (2015) (94.7% of those examined) indicated death by drowning. This is consistent with the importance of storm surge hazard for understanding mortality.

> [I]t was in Tanauan, Leyte where ignoring early warnings and orders to evacuate had terrible and tragic consequences. People who earlier refused to leave their homes realized too late that they were no longer

> safe and called for help. The local rescue team responded but by then the typhoon was at the height of its fury and the team's vehicle was swept away by the storm surge. Several rescuers did not survive. (NDRRMC, n.d.b, p. 41)

Why did so many coastal residents of Tanauan remain in the hazard zone rather than evacuate? At least 19 hours prior to landfall, the Philippine Atmospheric, Geophysical and Astronomical Services Administration issued a storm surge warning: "against storm surges which may reach up to 7-meter wave height" in addition to ratcheting up the Public Storm Warning Signal from a No. 2 (>60 to 100 kph winds) to a No. 3 (>100 to 185 kph) (NDRRMC, 2013a,b). The extent to which this warning was fully disseminated and how those who received the warning reacted to it is less clear. Exploratory survey efforts and anecdotal reports suggest a complex story in which some residents underestimated the severity of the storm or speed of inundation, did not fully understand the warnings (for example, of what was meant by 'storm-surge'), or lacked knowledge or trust in the evacuation process (IRIDeS, 2014; Leelawat et al., 2015; Yi et al., 2015).

4.5.2 Assessing baseline vulnerability

During the pre-treatment period there were no casualties in Tanauan and one death in Cariga; the before period does a poor job of telling us about Tanauan's pre-treatment vulnerability to a tropical cyclone like Yolanda because no such exposure occurred. In fact, the nearest historical precedent to Typhoon Yolanda occurred in 1897, when a tropical cyclone of similar (though still different) trajectory caused large storm surges in Eastern Leyte including Tanauan (Soria et al., 2016). This suggests that our study design is not able to sufficiently test for incidental imbalances in baseline vulnerability, particularly to extreme events. The inadequate observation of vulnerability also means that it is difficult to credibly assess whether the counterfactual trends in vulnerability are comparable in the treatment and control groups, as necessary for causal inference under a difference-in-differences model.

4.6 Conclusions

In this chapter I explore whether leveraging data from existing policy experiments is an effective strategy for developing causal inference about the impact of development interventions on tropical cyclone mortality. Because treatment is randomly assigned in experimental data sets, this approach addresses the problems of multicollinearity and omitted variable bias that currently limit causal arguments about tropical cyclone mortality based on observational analyses. However, using an illustrative example from the Philippines, I demonstrate that causal variables for tropical cyclone mortality are likely to be imbalanced between treatment and control groups due to large heterogeneities in vulnerability and/or exposure. This problem is exacerbated by the small sample sizes typical of RCTs of community-level policy interventions. Therefore not all policy experiments will be suitable for producing valid causal inference, as we find in the KC example. To test and control for such imbalances will require robust longitudinal data on hazard exposure and vulnerability.

Randomly selected treatment and control groups matched only on socioeconomic characteristics during the designed phase should not be assumed to be well balanced in terms of their baseline vulnerability and exposure to tropical cyclone hazard. Vulnerability is highly heterogeneous across communities, and difficult to measure because it is unobservable except under stress. Therefore, using pre-treatment mortality as a proxy to test for balance in baseline vulnerability, or to control for imbalance as part of a difference-in-differences model, is likely be insufficient. This is particularly problematic if tropical cyclone exposures vary markedly between the pre- and post-treatment periods. For example, the deadly and destructive Super Typhoon Yolanda occurred during the post-treatment period of the KC example with no analogue event in the pre-treatment period. The town of Tanauan suffered the vast majority of casualties from Yolanda in our sample, but had no casualties in the pre-treatment period. Tanauan had previously suffered massive casualties from a tropical cyclone of similar character in 1897. In light of the long return periods for high-intensity tropical cyclone events, this is likely to be a frequent limitation of this analytical approach.

Exposure to tropical cyclones is not only heterogeneous across places, but also over time. Further, exposure during the treatment phase of an experiment is unknown ex ante, and therefore cannot be balanced using matching methods. Controlling for exposure ex post can ameliorate this problem, particularly *if* we believe that vulnerability profiles are similar in the treatment and control groups and *when* we have data on comparable exposures over time. I demonstrate that controlling for wind exposure can assist in correcting for an exposure imbalance and improve precision when estimating relationships between socioeconomic vulnerability and tropical cyclone deaths. However, it is also clear that wind speed is not a complete proxy for tropical cyclone hazard, and that data on storm surge in particular would strengthen our conditional independence assumption.

Data from randomized control trials and natural experiments represent a promising opportunity for developing causal inference about the effects of development programs on tropical cyclone mortality. However, better data on vulnerability and exposure are needed to do this well. Proceeding without sufficient data to evaluate and correct for potential balance issues may result in imprecise and misleading estimates of program impact. A strong strategy would address gaps in both exposure and vulnerability data. Additional exposure variables, for which systematic data is not currently available, should include storm surge and flooding. Where historical records are limited, recent improvements in modeling may offer a promising solution for reconstructing historical exposures to storm surge and flooding (e.g. Lapidez et al. (2015)). Data on known sources of vulnerability, such as the size of populations living in low-lying coastal areas, flood planes and on unstable slopes, may help to identify high-risk localities. The compilation of mortality records over longer time periods would also be useful for capturing vulnerability to a larger distribution of exposures. These historical records may exist within communities, and might be collected alongside implementation of other RCT elements with modest additional effort.

Chapter 5: Conclusions

Knowledge of the general determinants of mortality from tropical cyclones can inform risk reduction policies and, in combination with research on a range of other hazards and outcomes, contribute to more general theories of vulnerability and resilience. Yet tropical cyclone vulnerability research faces several challenges. Tropical cyclones are singular in their trajectory, speed, intensity and duration. Harm is therefore a sparse proxy for vulnerability; we have only snapshots of how systems respond to a unique set of conditions at a specific point in time. Issues of multicollinearity and omitted variable bias further complicate attempts at causal inference. And vulnerability is multi-scalar; the existence of a relationship at one scale does not necessarily imply that it holds at different levels of aggregation.

With these complexities in mind, this dissertation seeks to forward our understanding of tropical cyclone vulnerability at multiple scales and using a range of analytical techniques. I construct new datasets that spatially interact meteorological and socioeconomic data for over one thousand tropical cyclones globally and over one-hundred storms in the Philippines. This affords a precision that allows me to test for multiple socioeconomic variables in a single model and begin to disaggregate the linkages between development and tropical cyclone mortality. This work spans multiple and sometimes nested scales; to my knowledge Chapter 3 is the first nationally representative longitudinal study of tropical cyclone vulnerability at the municipal level.

The results from these analyses advance the state of the evidence on tropical cyclone vulnerability theory in several areas that have direct relevance to open policy questions.

- I find evidence that national government effectiveness is associated with lower mortality from tropical cyclone events. This effect is large, statistically significant, and robust to controls for income, health and education. This is consistent with theoretical arguments that national institutions are a limiting factor in the implementation of disaster risk reduction. From a policy perspective, this suggests that achieving optimal outcomes in disaster risk reduction will require attention to institutional capacity constraints.
- Multiple lines of evidence also indicate that the protections afforded by national institutions are not uniformly inclusive. In the Philippines municipal poverty rates are a strong predictor of local variation in tropical cyclone mortality, even as we observe a trend of decreasing mortality conditional on hazard exposure at the national level during the study period. This is corroborated by global evidence that mortality is elevated when storms hit areas of a country that are already less well off. This indicates that targeting based on national or event state- or province-level aggregates of poverty and other proxies of vulnerability may be insufficient. Combining local data on socioeconomic risk

factors with models of hazard and exposure risk is a promising way forward.

- In light of evidence for a localized connection between poverty and tropical cyclone mortality, a natural next step is to test whether existing development interventions are actually mitigating disaster risk. In the final chapter I illustrate how exploiting existing policy experiments can overcome the multicollinearity and omitted variable bias that limit causal inference in observational studies. However, I also find that credible comparisons of vulnerability across groups and over time can be difficult in the case of rare events such as tropical cyclones. I demonstrate how controlling for hazard intensity via wind speed and comparison with previous mortality rates can ameliorate this problem, but may still be insufficient. The development of high resolution storm surge models and the compilation of mortality records for longer periods of time would be important steps forward. Given the large number of existing published studies of randomized control trials and natural experiments in the literature, this is a potentially critical body of evidence that might be fruitfully re-examined under the lens of tropical cyclone vulnerability.

While the results of this dissertation provide new insights on the institutional and socioeconomic determinants of tropical cyclone risk, but they also have some important limitations.

- First, I demonstrate that including wind speed and rainfall improve the unbiasedness and precision of the estimates. However, a model or dataset on the height and spatial extent of storm surge was not available. While storm surge and wind speed are correlated, this may be a source of bias and imprecision in my estimates and findings.

- Second, the multicollinearity of development factors means that observational analysis cannot fully overcome the threat of omitted variable bias, particularly as theory suggests that tropical cyclone vulnerability and resilience are endogenous processes. Exploiting existing policy experiments such as randomized control trials overcomes this, but presents an alternative set of challenges.

- Finally, the outcome variable in this analysis is tropical cyclone deaths, as measured by disaster statistics from the EM-DAT and NDRRMC in the Philippines (Guha-Sapir, 2018; NDRRMC, n.d.a). These are compiled in the immediate aftermath of storms and may underestimate the longer-term death tolls associated with tropical cyclones. These additional deaths may be mediated by institutionally driven factors (i.e. the provision of medical care) and individual economic hardship (Anttila-Hughes and Hsiang, 2013; Kishore et al., 2018).

In my future work I hope to continue to explore solutions to these and other challenges. Estimating dynamic models from longitudinal household surveys may provide new insights into causal mechanisms. Integrating all-cause mortality data and other well-being outcomes may provide a fuller picture of vulnerability and take us closer to measuring resilience. I further intend to extend this approach to build knowledge of vulnerability to additional types of hazard.

Appendix A: Supplemental Tables for Chapter 2

Table A.1: Descriptive statistics for national analysis dataset (1996-2016)

variable	min	max	median	mean	std.dev
Deaths	0.00	14600.00	5.00	70.38	583.63
Government Effectiveness	-2.27	1.99	0.09	0.24	0.90
Real GDP per capita	459.43	53399.36	8428.91	16131.49	15063.05
National infant mortality rate	1.70	137.70	18.10	20.81	17.65
Primary school enrollment (% net)	55.58	99.94	94.91	93.15	6.21
Pop. (millions) exposed to winds 63-118 km/hr	0.00	92.68	0.37	6.09	13.14
Pop. (millions) exposed to winds 119-153 km/hr	0.00	25.51	0.00	0.35	1.45
Pop. (millions) exposed to winds $>$ 153 km/hr	0.00	3.15	0.00	0.04	0.22
Maximum rainfall exposure (mm)	0.00	1550.66	206.75	233.43	186.96

Note: Please see Tables 2.1 and 2.2 for a more detailed description of the variables and their sources.

Table A.2: Descriptive statistics for subnational analysis dataset (1979-2016)

variable	min	max	median	mean	std.dev
Deaths	0.00	14600.00	8.50	85.72	592.58
Infant mortality ratio (wind field $>$ 63 km/hr)	0.29	1.86	1.00	0.99	0.21
Infant mortality ratio (wind field $>$ 119 km/hr)	0.30	1.83	1.00	1.02	0.22
Excluded ethnic group in (wind field $>$ 63 km/hr)	0.00	1.00	0.00	0.13	0.25
Excluded ethnic group in (wind field $>$ 119 km/hr)	0.00	1.00	0.00	0.08	0.23
National infant mortality rate	1.80	171.10	18.80	24.45	22.08
Real GDP per capita	344.16	53399.36	9107.74	15930.67	14728.27
Pop. (millions) exposed to winds 63-118 km/hr	0.00	92.68	2.25	8.15	13.90
Pop. (millions) exposed to winds 119-153 km/hr	0.00	25.51	0.00	0.48	1.60
Pop. (millions) exposed to winds $>$ 153 km/hr	0.00	3.19	0.00	0.06	0.27
Maximum rainfall exposure (mm)	0.00	1550.66	230.86	264.41	171.88

Note: Please see Tables 2.1 and 2.2 for a more detailed description of the variables and their sources.

Table A.3: Pairwise correlations in national dataset (1996-2016)

	Deaths	Governance	RealGDPpc	IMR	Education	ExpTS	ExpTC1	ExpTC2	MaxRain
	Deaths	Government Effective-ness	Real GDP per capita	National infant mortality rate	Primary school enrollment (% net)	Pop. (millions) exposed to winds 63-118 km/hr	Pop. (millions) exposed to winds 119-153 km/hr	Pop. (millions) exposed to winds > 153 km/hr	Maximum rainfall exposure (mm)
Deaths	1.000	-0.064	-0.072	0.067	-0.013	0.004	0.062	0.142	0.090
Governance	-0.064	1.000	0.895	-0.687	0.431	0.209	0.122	0.017	0.185
RealGDPpc	-0.072	0.895	1.000	-0.653	0.394	0.170	0.092	0.034	0.104
IMR	0.067	-0.687	-0.653	1.000	-0.758	-0.198	-0.096	-0.040	-0.074
Education	-0.013	0.431	0.394	-0.758	1.000	0.176	0.048	0.012	0.000
ExpTS	0.004	0.209	0.170	-0.198	0.176	1.000	0.345	0.055	0.208
ExpTC1	0.062	0.122	0.092	-0.096	0.048	0.345	1.000	0.245	0.196
ExpTC2	0.142	0.017	0.034	-0.040	0.012	0.055	0.245	1.000	0.072
MaxRain	0.090	0.185	0.104	-0.074	0.000	0.208	0.196	0.072	1.000

Table A.4: Pairwise correlations in subnational dataset (1979-2016)

	Deaths	IMRratioTS	ExcludedTS	IMR	RealGDPpc	ExpTS	ExpTC1	ExpTC2	MaxRain
	Deaths	Infant mortality ratio (wind field > 63 km/hr)	Excluded ethnic group in (wind field > 63 km/hr)	National infant mortality rate	Real GDP per capita	Pop. (millions) exposed to winds 63-118 km/hr	Pop. (millions) exposed to winds 119-153 km/hr	Pop. (millions) exposed to winds > 153 km/hr	Maximum rainfall exposure (mm)
Deaths	1.000	0.003	-0.006	0.065	-0.091	0.004	0.063	0.140	0.068
IMRratioTS	0.003	1.000	0.289	0.021	0.147	-0.453	-0.039	0.030	0.133
ExcludedTS	-0.006	0.289	1.000	-0.178	0.294	-0.149	-0.020	0.092	0.082
IMR	0.065	0.021	-0.178	1.000	-0.650	-0.167	-0.081	-0.009	-0.050
RealGDPpc	-0.091	0.147	0.294	-0.650	1.000	0.110	0.073	0.023	0.056
ExpTS	0.004	-0.453	-0.149	-0.167	0.110	1.000	0.312	0.015	0.127
ExpTC1	0.063	-0.039	-0.020	-0.081	0.073	0.312	1.000	0.224	0.157
ExpTC2	0.140	0.030	0.092	-0.009	0.023	0.015	0.224	1.000	0.008
MaxRain	0.068	0.133	0.082	-0.050	0.056	0.127	0.157	0.008	1.000

Table A.5: Exposure controls for testing national determinants of mortality from TC Events (1996-2016)

	Negative Binomial		OLS		OLS	
	deaths		ln (deaths + 1)		ln (deaths)	
	IRR (1)	IRR (2)	(3)	(4)	(5)	(6)
Government Effectiveness	0.718	0.425 ***	-0.327 *	-0.388 **	-0.431 **	-0.565 ***
	(0.217)	(0.108)	(0.130)	(0.130)	(0.156)	(0.156)
Ln real GDP per capita (t-1)	0.358 **	0.537 *	-0.284 *	-0.345 **	-0.264 *	-0.302 *
	(0.137)	(0.142)	(0.115)	(0.114)	(0.132)	(0.130)
Pop. (millions) exposed to winds 63-118 km/hr	-	1.009	-	0.012 **	-	0.009 *
	-	(0.006)	-	(0.004)	-	(0.004)
Pop. (millions) exposed to winds 119-153 km/hr	-	1.209 **	-	0.114 ***	-	0.102 ***
	-	(0.087)	-	(0.026)	-	(0.024)
Pop. (millions) exposed to winds > 153 km/hr	-	3.658 ***	-	0.731	-	0.942 *
	-	(1.089)	-	(0.428)	-	(0.401)
Maximum rainfall exposure (mm)	-	1.003 ***	-	0.002 ***	-	0.002 ***
	-	(0.001)	-	(0.000)	-	(0.000)
Time (years)	0.961	0.952 *	-0.035 ***	-0.036 ***	-0.025 *	-0.028 **
	(0.032)	(0.020)	(0.010)	(0.009)	(0.011)	(0.010)
Geography	regions	regions	regions	regions	regions	regions
Observations	886	886	886	886	687	687

Notes: Events with zero deaths are omitted from models (5) and (6). Negative binomial results are presented as Incident Rate Rations (IRRs), obtained by exponentiating the estimated coefficients. Thus, we are testing the null hypothesis that IRR = 1. If the coefficient is negative the IRR < 1 and if the coefficient is positive the IRR > 1. Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.6: Robustness: National determinants of mortality from TC events (1996-2016), OLS regressions of log (deaths + 1)

	(1)	(2)	(3)	(4)	(5)	(6)
Government Effectiveness	-0.689 ***	-	-	-	-0.388 **	-0.485 ***
	(0.060)	-	-	-	(0.130)	(0.140)
Ln real GDP per capita (t-1)	-	-0.640 ***	-	-	-0.345 **	-0.267
	-	(0.052)	-	-	(0.114)	(0.166)
National infant mortality rate (t-1)	-	-	0.036 ***	-	-	-0.004
	-	-	(0.004)	-	-	(0.009)
Primary school enrollment (% net)	-	-	-	-0.052 ***	-	-0.004
	-	-	-	(0.010)	-	(0.013)
Pop. (millions) exposed to winds 63-118 km/hr	0.011 **	0.012 ***	0.009 *	0.002	0.012 **	0.010 *
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Pop. (millions) exposed to winds 119-153 km/hr	0.114 ***	0.115 ***	0.108 ***	0.119 ***	0.114 ***	0.120 ***
	(0.025)	(0.027)	(0.029)	(0.032)	(0.026)	(0.028)
Pop. (millions) exposed to winds > 153 km/hr	0.612	0.729	0.687	1.150 *	0.731	1.484 **
	(0.356)	(0.438)	(0.383)	(0.493)	(0.428)	(0.567)
Maximum rainfall exposure (mm)	0.002 ***	0.002 ***	0.002 ***	0.001 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	-0.043 ***	-0.030 **	-0.021 *	-0.026 *	-0.036 ***	-0.030 **
	(0.009)	(0.009)	(0.009)	(0.011)	(0.009)	(0.011)
Geography	regions	regions	regions	regions	regions	regions
Observations	926	887	902	529	886	510

Notes: Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.7: Robustness: National determinants of mortality from TC events (1996-2016), OLS regressions of ln (deaths)

	(1)	(2)	(3)	(4)	(5)	(6)
Government Effectiveness	-0.865 ***	-	-	-	-0.565 ***	-0.590 **
	(0.074)	-	-	-	(0.156)	(0.183)
Ln real GDP per capita (t-1)	-	-0.701 ***	-	-	-0.302 *	-0.372
	-	(0.063)	-	-	(0.130)	(0.197)
National infant mortality rate (t-1)	-	-	0.035 ***	-	-	-0.008
	-	-	(0.005)	-	-	(0.010)
Primary school enrollment (% net)	-	-	-	-0.035 **	-	0.017
	-	-	-	(0.011)	-	(0.016)
Pop. (millions) exposed to winds 63-118 km/hr	0.008 *	0.008 *	0.003	-0.004	0.009 *	0.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Pop. (millions) exposed to winds 119-153 km/hr	0.102 ***	0.103 ***	0.099 ***	0.137 ***	0.102 ***	0.132 ***
	(0.024)	(0.024)	(0.026)	(0.028)	(0.024)	(0.027)
Pop. (millions) exposed to winds > 153 km/hr	0.689	0.963 *	0.846 *	0.909	0.942 *	1.251 *
	(0.375)	(0.396)	(0.346)	(0.530)	(0.401)	(0.614)
Maximum rainfall exposure (mm)	0.002 ***	0.002 ***	0.002 ***	0.001 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	-0.033 **	-0.020 *	-0.013	-0.023	-0.028 **	-0.030 *
	(0.010)	(0.010)	(0.011)	(0.013)	(0.010)	(0.013)
Geography	regions	regions	regions	regions	regions	regions
Observations	708	687	690	408	687	397

Notes: Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.8: Robustness: National determinants of mortality from TC events (1996-2016), negative binomial regression models with country fixed effects

	IRR (1)	IRR (2)	IRR (3)	IRR (4)	IRR (5)	IRR (6)
Government Effectiveness	0.541	-	-	-	1.192	0.701
	(0.211)	-	-	-	(0.515)	(0.406)
Ln real GDP per capita (t-1)	-	0.123 ***	-	-	0.116 ***	0.042 **
	-	(0.056)	-	-	(0.059)	(0.042)
National infant mortality rate (t-1)	-	-	1.031 *	-	-	0.969
	-	-	(0.014)	-	-	(0.034)
Primary school enrollment (% net)	-	-	-	1.021	-	1.015
	-	-	-	(0.025)	-	(0.037)
Pop. (millions) exposed to winds 63-118 km/hr	1.013 *	1.010 *	1.011 *	1.015 *	1.010 *	1.014 *
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Pop. (millions) exposed to winds > 119 km/hr	1.450 ***	1.493 ***	1.487 ***	1.614 ***	1.492 ***	1.709 ***
	(0.093)	(0.093)	(0.090)	(0.098)	(0.093)	(0.114)
Maximum rainfall exposure (mm)	1.003 ***	1.003 ***	1.003 ***	1.002 ***	1.003 ***	1.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	0.954 **	1.017	0.973	0.967	1.017	1.010
	(0.015)	(0.018)	(0.020)	(0.018)	(0.019)	(0.028)
Geography	country	country	country	country	country	country
Observations	926	887	902	529	886	510

Notes: Negative binomial results are presented as Incident Rate Ratios (IRRs), obtained by exponentiating the estimated coefficients. Thus, we are testing the null hypothesis that $\text{IRR} = 1$. If the coefficient is negative the $\text{IRR} < 1$ and if the coefficient is positive the $\text{IRR} > 1$. Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.9: Robustness: National determinants of mortality from TC events (1996-2016), OLS regressions of log (deaths + 1) with country fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Government Effectiveness	-0.624 *	-	-	-	-0.221	-0.484
	(0.242)	-	-	-	(0.269)	(0.375)
Ln real GDP per capita (t-1)	-	-1.475 ***	-	-	-1.386 ***	-1.733 *
	-	(0.336)	-	-	(0.349)	(0.800)
National infant mortality rate (t-1)	-	-	0.012	-	-	-0.032
	-	-	(0.011)	-	-	(0.023)
Primary school enrollment (% net)	-	-	-	-0.009	-	-0.020
	-	-	-	(0.020)	-	(0.025)
Pop. (millions) exposed to winds 63-118 km/hr	0.018 ***	0.017 ***	0.017 ***	0.016 **	0.017 ***	0.016 **
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Pop. (millions) exposed to winds 119-153 km/hr	0.116 ***	0.120 ***	0.118 ***	0.134 ***	0.119 ***	0.129 ***
	(0.025)	(0.027)	(0.027)	(0.031)	(0.027)	(0.030)
Pop. (millions) exposed to winds > 153 km/hr	0.651	0.649	0.647	1.168 *	0.653	1.431 *
	(0.347)	(0.407)	(0.356)	(0.456)	(0.407)	(0.619)
Maximum rainfall exposure (mm)	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	-0.047 ***	-0.008	-0.041 ***	-0.039 ***	-0.008	-0.015
	(0.009)	(0.012)	(0.011)	(0.011)	(0.012)	(0.017)
Geography	countries	countries	countries	countries	countries	countries
Observations	926	887	902	529	886	510

Notes: Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.10: Robustness: National determinants of mortality from TC events (1996-2016), OLS regressions of ln (deaths) with country fixed effects

	(1)	(2)	(3)	(4)	(5)
Government Effectiveness	-0.598	-	-	-	-0.263
	(0.319)	-	-	-	(0.339)
Ln real GDP per capita (t-1)	-	-1.026 **	-	-	-0.926 *
	-	(0.370)	-	-	(0.388)
National infant mortality rate (t-1)	-	-	0.006	-	-
	-	-	(0.011)	-	-
Primary school enrollment (% net)	-	-	-	0.039	-
	-	-	-	(0.022)	-
Pop. (millions) exposed to winds 63-118 km/hr	0.013 **	0.012 **	0.012 **	0.012 *	0.012 **
	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)
Pop. (millions) exposed to winds 119-153 km/hr	0.106 ***	0.112 ***	0.112 ***	0.143 ***	0.111 ***
	(0.024)	(0.025)	(0.025)	(0.031)	(0.025)
Pop. (millions) exposed to winds > 153 km/hr	0.849 *	0.927 *	0.857 *	1.015 *	0.930 *
	(0.355)	(0.408)	(0.362)	(0.489)	(0.410)
Maximum rainfall exposure (mm)	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	-0.038 ***	-0.011	-0.038 **	-0.047 ***	-0.012
	(0.011)	(0.015)	(0.013)	(0.014)	(0.015)
Geography	countries	countries	countries	countries	countries
Observations	708	687	690	408	687

Notes: Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.11: Robustness: Subnational determinants of mortality from TC events (1979-2016, excluding 1999-2000) negative binomial (NB2) regression results

	Winds > 63 km/hr	Winds 63-119 km/hr	Winds > 119 km/hr
	IRR (1)	IRR (2)	IRR (3)
Infant mortality ratio (wind field > 63 km/hr)	3.240 *	3.563 *	-
	(1.591)	(2.130)	-
Excluded ethnic group in (wind field > 63 km/hr)	0.802	0.730	-
	(0.495)	(0.652)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	4.630 ***
	-	-	(1.806)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	2.165
	-	-	(1.264)
National infant mortality rate (t-1)	1.003	0.992	1.031 *
	(0.011)	(0.015)	(0.014)
Ln real GDP per capita (t-1)	0.292 ***	0.324 ***	0.192 ***
	(0.063)	(0.088)	(0.056)
Pop. (millions) exposed to winds 63-118 km/hr	1.016 *	1.014	1.032 ***
	(0.007)	(0.009)	(0.010)
Pop. (millions) exposed to winds 119-153 km/hr	1.454 ***	-	1.482 ***
	(0.121)	-	(0.106)
Pop. (millions) exposed to winds > 153 km/hr	2.397 ***	-	2.882 **
	(0.634)	-	(1.069)
Maximum rainfall exposure (mm)	1.000	0.999	1.001
	(0.001)	(0.001)	(0.001)
Geography	countries	countries	countries
Observations	608	363	236

Notes: Negative binomial results are presented as Incident Rate Rations (IRRs), obtained by exponentiating the estimated coefficients. Thus, we are testing the null hypothesis that IRR = 1. If the coefficient is negative the IRR < 1 and if the coefficient is positive the IRR > 1. Includes control for a linear time trend. Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.12: Robustness: Subnational determinants of mortality from TC events (2001-2016) negative binomial (NB2) regression results

	Winds > 63 km/hr	Winds 63-119 km/hr	Winds > 119 km/hr
	IRR (1)	IRR (2)	IRR (3)
Infant mortality ratio (wind field > 63 km/hr)	2.619	1.692	-
	(1.872)	(1.369)	-
Excluded ethnic group in (wind field > 63 km/hr)	1.582	2.028	-
	(1.157)	(1.947)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	15.250 ***
	-	-	(11.324)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	1.867
	-	-	(1.347)
National infant mortality rate (t-1)	0.954	0.940 *	0.996
	(0.027)	(0.027)	(0.047)
Ln real GDP per capita (t-1)	0.035 ***	0.023 ***	0.031 **
	(0.026)	(0.019)	(0.040)
Pop. (millions) exposed to winds 63-118 km/hr	1.019 *	1.023	1.018
	(0.009)	(0.012)	(0.010)
Pop. (millions) exposed to winds 119-153 km/hr	1.405 ***	-	1.329 ***
	(0.097)	-	(0.083)
Pop. (millions) exposed to winds > 153 km/hr	3.148 *	-	3.374 *
	(1.441)	-	(1.759)
Maximum rainfall exposure (mm)	1.001	1.002	1.001
	(0.001)	(0.001)	(0.001)
Geography	countries	countries	countries
Observations	347	222	120

Notes: Negative binomial results are presented as Incident Rate Rations (IRRs), obtained by exponentiating the estimated coefficients. Thus, we are testing the null hypothesis that $IRR = 1$. If the coefficient is negative the $IRR < 1$ and if the coefficient is positive the $IRR > 1$. Includes control for a linear time trend. Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.13: Robustness: Subnational determinants of mortality from TC events (1979-2016), OLS regression of ln (deaths + 1)

	Winds > 63 km/hr	Winds 63-119 km/hr	Winds > 119 km/hr
	(1)	(2)	(3)
Infant mortality ratio (wind field > 63 km/hr)	0.639	0.439	-
	(0.372)	(0.430)	-
Excluded ethnic group in (wind field > 63 km/hr)	-0.329	-0.084	-
	(0.287)	(0.401)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.238 **
	-	-	(0.465)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	-0.358
	-	-	(0.435)
National infant mortality rate (t-1)	0.013	0.016	0.013
	(0.007)	(0.009)	(0.012)
Ln real GDP per capita (t-1)	-1.153 ***	-1.274 ***	-1.473 ***
	(0.188)	(0.246)	(0.316)
Pop. (millions) exposed to winds 63-118 km/hr	0.034 ***	0.030 ***	0.034 ***
	(0.006)	(0.008)	(0.008)
Pop. (millions) exposed to winds 119-153 km/hr	0.136 ***	-	0.131 **
	(0.040)	-	(0.040)
Pop. (millions) exposed to winds > 153 km/hr	1.037 ***	-	0.961 *
	(0.257)	-	(0.371)
Maximum rainfall exposure (mm)	0.002 ***	0.001 *	0.002 ***
	(0.000)	(0.001)	(0.001)
Geography	countries	countries	countries
Observations	637	382	246

Notes: Robust standard errors are reported in parentheses. Includes control for a linear time trend. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.14: Robustness: Subnational determinants of mortality from TC events (1979-2016), OLS regression of ln (deaths)

	Winds > 63 km/hr (1)	Winds 63-119 km/hr (2)	Winds > 119 km/hr (3)
Infant mortality ratio (wind field > 63 km/hr)	0.186	0.025	-
	(0.361)	(0.410)	-
Excluded ethnic group in (wind field > 63 km/hr)	-0.239	0.030	-
	(0.321)	(0.454)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.191 *
	-	-	(0.484)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	-0.156
	-	-	(0.458)
National infant mortality rate (t-1)	0.009	0.005	0.019
	(0.007)	(0.009)	(0.012)
Ln real GDP per capita (t-1)	-0.734 ***	-0.719 **	-1.193 ***
	(0.194)	(0.246)	(0.312)
Pop. (millions) exposed to winds 63-118 km/hr	0.027 ***	0.017 *	0.037 ***
	(0.006)	(0.007)	(0.008)
Pop. (millions) exposed to winds 119-153 km/hr	0.136 ***	-	0.132 **
	(0.038)	-	(0.042)
Pop. (millions) exposed to winds > 153 km/hr	0.993 ***	-	0.908 *
	(0.268)	-	(0.394)
Maximum rainfall exposure (mm)	0.002 ***	0.001	0.002 ***
	(0.000)	(0.001)	(0.001)
Geography	countries	countries	countries
Observations	558	328	222

Notes: Zero death events are excluded as ln (0) is undefined. Robust standard errors are reported in parentheses. Includes control for a linear time trend. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix B: Supplemental Tables for Chapter 3

Table B.1: Pairwise correlations in province dataset (2004-2016)

	deaths	poverty	income	localrev	sharelocal	expenditure	wind	wind_sq
	deaths	province poverty rate	province income (pesos)	local revenue per capita	local share revenue	local expenditure per capita	Wind speed (km/hr)	Wind speed squared (sq-km/hr)
deaths	1.000	-0.020	0.080	0.012	-0.012	-0.047	0.141	0.139
poverty	-0.020	1.000	-0.762	-0.416	0.138	0.145	-0.236	-0.184
income	0.080	-0.762	1.000	0.494	-0.147	-0.099	0.120	0.056
localrev	0.012	-0.416	0.494	1.000	0.017	0.217	0.204	0.163
sharelocal	-0.012	0.138	-0.147	0.017	1.000	-0.019	-0.070	-0.055
expenditure	-0.047	0.145	-0.099	0.217	-0.019	1.000	0.102	0.087
wind	0.141	-0.236	0.120	0.204	-0.070	0.102	1.000	0.953
wind_sq	0.139	-0.184	0.056	0.163	-0.055	0.087	0.953	1.000

Table B.2: Pairwise correlations in municipal dataset (2004-2016)

	deaths	poverty	localrev	sharelocal	expenditure	wind	wind_sq
	deaths	municipal poverty rate	local revenue per capita	local share revenue	local expenditure per capita	Wind speed (km/hr)	Wind speed squared (sq-km/hr)
deaths	1.000	-0.010	0.000	0.012	-0.012	0.067	0.089
poverty	-0.010	1.000	-0.285	-0.494	0.084	-0.458	-0.359
localrev	0.000	-0.285	1.000	0.573	0.169	0.068	0.046
sharelocal	0.012	-0.494	0.573	1.000	-0.151	0.102	0.066
expenditure	-0.012	0.084	0.169	-0.151	1.000	0.094	0.074
wind	0.067	-0.458	0.068	0.102	0.094	1.000	0.950
wind_sq	0.089	-0.359	0.046	0.066	0.074	0.950	1.000

Table B.3: Fixed Effects: Annual deaths from tropical cyclones by province, Philippines (2007-2009, 2010-2012, 2013-2015)

	FE	FE	FE	FE	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)
province poverty rate (t-1)	-0.009	-	-0.012	-0.008	-	-0.009
	(0.015)	-	(0.015)	(0.015)	-	(0.015)
ln province income (pesos) (t-1)	-	-0.500	-0.576	-	0.052	-0.103
	-	(0.464)	(0.449)	-	(0.837)	(0.819)
Total rainfall (cm)	0.024 ***	0.023 ***	0.023 ***	0.024 ***	0.024 ***	0.024 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Wind speed (km/hr)	0.062 ***	0.063 ***	0.063 ***	0.065 ***	0.065 ***	0.065 ***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
ln population	0.255	0.948	0.851	1.259	1.395	1.243
	(1.226)	(1.222)	(1.234)	(1.177)	(1.125)	(1.167)
year	-	-	-	-0.145	-0.155	-0.127
	-	-	-	(0.095)	(0.178)	(0.175)
n	76	76	76	76	76	76
T	3	3	3	3	3	3
N	228	228	228	228	228	228
R-squared	0.282	0.285	0.288	0.29	0.289	0.291

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.4: Random Effects and Pooled OLS: Annual deaths from tropical cyclones by province, Philippines (2007-2009, 2010-2012, 2013-2015)

	RE	RE	RE	Pooled	Pooled	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
province poverty rate (t-1)	0.009	-	0.013	0.009	-	0.016
	(0.007)	-	(0.009)	(0.007)	-	(0.010)
ln province income (pesos) (t-1)	-	-0.280	0.249	-	-0.169	0.506
	-	(0.437)	(0.595)	-	(0.432)	(0.630)
Total rainfall (cm)	0.013 **	0.012 **	0.013 **	0.011 *	0.010 *	0.011 *
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Wind speed (km/hr)	0.053 ***	0.052 ***	0.053 ***	0.052 ***	0.050 ***	0.052 ***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
ln population	0.658 ***	0.634 ***	0.654 ***	0.647 ***	0.615 ***	0.639 ***
	(0.102)	(0.097)	(0.100)	(0.100)	(0.096)	(0.097)
year	-0.096	-0.050	-0.134	-0.097	-0.068	-0.174
	(0.084)	(0.110)	(0.129)	(0.084)	(0.109)	(0.132)
n	76	76	76	76	76	76
T	3	3	3	3	3	3
N	228	228	228	228	228	228
R-squared	0.322	0.318	0.324	0.344	0.339	0.347

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.5: Annual deaths from tropical cyclones by municipality, Philippines (2007-2009, 2010-2012, 2013-2015)

	FE	FE	RE	RE	RE	Pooled	Pooled	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
municipal poverty rate (t-1)	0.003 *	0.003	0.002 **	0.002 **	0.001	0.002 **	0.002 **	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
province poverty rate (t-1)	-	-0.002	-	0.002	-0.000	-	0.002	-0.000
	-	(0.002)	-	(0.001)	(0.002)	-	(0.001)	(0.002)
ln province income (pesos) (t-1)	-	-0.182	-	0.130	-0.181	-	0.139 *	-0.181
	-	(0.120)	-	(0.066)	(0.120)	-	(0.066)	(0.120)
Wind speed (km/hr)	0.017 ***	0.017 ***	0.017 ***	0.016 ***	0.018 ***	0.017 ***	0.016 ***	0.018 ***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
ln population	0.093	0.060	0.148 ***	0.149 ***	0.145 ***	0.148 ***	0.149 ***	0.145 ***
	(0.089)	(0.091)	(0.012)	(0.013)	(0.015)	(0.012)	(0.013)	(0.015)
year	-0.013	0.017	-0.015	-0.035 *	0.010	-0.015	-0.037 *	0.010
	(0.010)	(0.023)	(0.010)	(0.015)	(0.024)	(0.010)	(0.015)	(0.024)
Observations	-	-	-	-	-	-	-	-
Log-Likelihood	-	-	-	-	-	-	-	-

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.6: Fixed Effects with year dummies: Annual deaths from tropical cyclones by province, Philippines (2007, 2010, 2013, 2016)

	FE	FE	FE
	(1)	(2)	(3)
province poverty rate (t-1)	0.006	-	-0.005
	(0.008)	-	(0.013)
ln province income (pesos) (t-1)	-	-1.002	-1.098
	-	(0.783)	(0.765)
Total rainfall (cm)	0.004	0.002	0.002
	(0.006)	(0.007)	(0.007)
Wind speed (km/hr)	0.059 **	0.074 **	0.074 **
	(0.017)	(0.021)	(0.020)
ln population	-0.379	-0.154	-0.202
	(0.208)	(0.639)	(0.627)
Y_2010	-0.560 ***	-0.448 *	-0.430 *
	(0.119)	(0.183)	(0.188)
Y_2013	-0.049	0.102	0.130
	(0.152)	(0.347)	(0.346)
Y_2016	-0.602 ***	-	-
	(0.125)	-	-
n	78	78	78
T	4	3	3
N	312	234	234
R-squared	0.347	0.394	0.394

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.7: Random Effects and Pooled OLS with year dummies: Annual deaths from tropical cyclones by province, Philippines (2007, 2010, 2013, 2016)

	RE	RE	RE	Pooled	Pooled	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
province poverty rate (t-1)	0.006	-	0.003	0.006	-	0.003
	(0.005)	-	(0.009)	(0.005)	-	(0.009)
ln province income (pesos) (t-1)	-	-0.578	-0.440	-	-0.550	-0.405
	-	(0.299)	(0.370)	-	(0.292)	(0.369)
Total rainfall (cm)	-0.007	-0.009	-0.008	-0.008	-0.009	-0.009
	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Wind speed (km/hr)	0.042 ***	0.053 ***	0.053 ***	0.041 ***	0.052 ***	0.052 ***
	(0.011)	(0.013)	(0.014)	(0.010)	(0.013)	(0.013)
ln population	0.230 **	0.328 ***	0.332 **	0.229 **	0.325 ***	0.330 ***
	(0.065)	(0.085)	(0.089)	(0.064)	(0.084)	(0.088)
Y_2010	-0.527 ***	-0.470 ***	-0.496 ***	-0.525 ***	-0.472 ***	-0.500 ***
	(0.112)	(0.108)	(0.137)	(0.111)	(0.108)	(0.137)
Y_2013	0.149	0.221	0.174	0.158	0.222	0.173
	(0.151)	(0.174)	(0.192)	(0.152)	(0.174)	(0.191)
Y_2016	-0.559 ***	-	-	-0.556 ***	-	-
	(0.100)	-	-	(0.099)	-	-
n	78	78	78	78	78	78
T	4	3	3	4	3	3
N	312	234	234	312	234	234
R-squared	0.319	0.343	0.343	0.319	0.341	0.342

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.8: Annual deaths from tropical cyclones by municipality with year dummies, Philippines (2007, 2010, 2013)

	FE	FE	RE	RE	RE	Pooled	Pooled	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
municipal poverty rate (t-1)	0.004 ***	0.004 ***	0.005 ***	0.003 ***	0.001 **	0.005 ***	0.003 ***	0.001 **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
province poverty rate (t-1)	-	0.001	-	0.005 ***	0.002	-	0.005 ***	0.002
	-	(0.001)	-	(0.001)	(0.001)	-	(0.001)	(0.001)
ln province income (pesos) (t-1)	-	-0.032	-	0.158 ***	-0.053	-	0.169 ***	-0.053
	-	(0.088)	-	(0.035)	(0.087)	-	(0.035)	(0.087)
Wind speed (km/hr)	0.025 ***	0.025 ***	0.015 ***	0.016 ***	0.026 ***	0.015 ***	0.015 ***	0.026 ***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
ln population	0.069	0.070	0.078 ***	0.083 ***	0.052 ***	0.076 ***	0.081 ***	0.052 ***
	(0.044)	(0.046)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Y_2010	-0.114 ***	-0.107 ***	-0.067 ***	-0.101 ***	-0.105 ***	-0.063 ***	-0.100 ***	-0.105 ***
	(0.012)	(0.020)	(0.009)	(0.013)	(0.019)	(0.009)	(0.013)	(0.019)
Y_2013	-0.141 ***	-0.130 ***	-0.018	-0.073 ***	-0.132 ***	-0.009	-0.069 ***	-0.132 ***
	(0.016)	(0.034)	(0.010)	(0.017)	(0.033)	(0.010)	(0.016)	(0.033)
Observations	-	-	-	-	-	-	-	-
Log-Likelihood	-	-	-	-	-	-	-	-

Notes: Statistical significance is indicated by * p < 0.05, ** p < 0.01, *** p < 0.001.

Table B.9: Fixed Effects Model with year dummies: Annual deaths from tropical cyclones by province, Philippines (2005-2016)

	(1)	(2)	(3)
ln local revenue per capita (t-1)	-0.015	-	-
	(0.071)	-	-
ln local expenditure per capita (t-1)	-	-0.398	-
	-	(0.272)	-
local share revenue (t-1)	-	-	-0.001
	-	-	(0.002)
Total rainfall (cm)	0.016 ***	0.016 ***	0.016 ***
	(0.003)	(0.003)	(0.003)
Wind speed (km/hr)	0.042 ***	0.042 ***	0.042 ***
	(0.006)	(0.006)	(0.006)
ln population	-0.053	-0.519	-0.047
	(0.185)	(0.378)	(0.173)
Y_2006	0.343 *	0.345 *	0.342 *
	(0.133)	(0.133)	(0.132)
Y_2007	0.221 *	0.258 **	0.227 *
	(0.089)	(0.096)	(0.094)
Y_2008	0.087	0.150	0.085
	(0.129)	(0.143)	(0.128)
Y_2009	0.427 **	0.509 **	0.423 **
	(0.144)	(0.156)	(0.141)
Y_2010	-0.273 **	-0.218 *	-0.280 **
	(0.090)	(0.096)	(0.082)
Y_2011	0.627 ***	0.699 ***	0.618 ***
	(0.175)	(0.190)	(0.169)
Y_2012	0.477 ***	0.561 ***	0.468 ***
	(0.131)	(0.129)	(0.122)
Y_2013	0.192	0.285	0.180
	(0.145)	(0.159)	(0.144)
Y_2014	0.167	0.264	0.156
	(0.123)	(0.135)	(0.113)
Y_2015	-0.131	-0.046	-0.142
	(0.105)	(0.122)	(0.092)
Y_2016	-0.339 **	-0.225	-0.353 ***
	(0.102)	(0.123)	(0.082)
n	73	73	73
T	12	12	12
N	876	876	876
R-squared	0.287	0.292	0.287

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.10: Random Effects Model with year dummies: Annual deaths from tropical cyclones by province, Philippines (2005-2016)

	(1)	(2)	(3)
ln local revenue per capita (t-1)	-0.006	-	-
	(0.036)	-	-
ln local expenditure per capita (t-1)	-	-0.374 *	-
	-	(0.167)	-
local share revenue (t-1)	-	-	-0.001
	-	-	(0.001)
Total rainfall (cm)	0.010 **	0.011 **	0.010 **
	(0.003)	(0.003)	(0.003)
Wind speed (km/hr)	0.036 ***	0.036 ***	0.035 ***
	(0.004)	(0.004)	(0.004)
ln population	0.294 ***	0.131	0.294 ***
	(0.045)	(0.083)	(0.045)
Y_2006	0.451 ***	0.438 ***	0.452 ***
	(0.126)	(0.126)	(0.126)
Y_2007	0.236 **	0.258 **	0.243 **
	(0.086)	(0.089)	(0.091)
Y_2008	0.177	0.212	0.177
	(0.126)	(0.130)	(0.126)
Y_2009	0.542 ***	0.586 ***	0.542 ***
	(0.134)	(0.133)	(0.134)
Y_2010	-0.258 **	-0.231 **	-0.259 **
	(0.077)	(0.081)	(0.078)
Y_2011	0.688 ***	0.722 ***	0.686 ***
	(0.166)	(0.170)	(0.167)
Y_2012	0.531 ***	0.570 ***	0.528 ***
	(0.137)	(0.136)	(0.136)
Y_2013	0.270	0.313 *	0.267
	(0.146)	(0.146)	(0.146)
Y_2014	0.220	0.264 *	0.217
	(0.121)	(0.120)	(0.121)
Y_2015	-0.077	-0.050	-0.080
	(0.082)	(0.090)	(0.085)
Y_2016	-0.342 ***	-0.284 **	-0.346 ***
	(0.073)	(0.085)	(0.075)
n	73	73	73
T	12	12	12
N	876	876	876
R-squared	0.309	0.316	0.309

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.11: Pooled Model with year dummies: Annual deaths from tropical cyclones by province, Philippines (2005-2016)

	(1)	(2)	(3)
ln local revenue per capita (t-1)	0.004	-	-
	(0.035)	-	-
ln local expenditure per capita (t-1)	-	-0.363 *	-
	-	(0.156)	-
local share revenue (t-1)	-	-	-0.001
	-	-	(0.001)
Total rainfall (cm)	0.009 **	0.009 **	0.009 **
	(0.003)	(0.003)	(0.003)
Wind speed (km/hr)	0.034 ***	0.035 ***	0.034 ***
	(0.004)	(0.004)	(0.004)
ln population	0.292 ***	0.135	0.293 ***
	(0.044)	(0.078)	(0.044)
Y_2006	0.474 ***	0.459 ***	0.474 ***
	(0.126)	(0.126)	(0.127)
Y_2007	0.241 **	0.262 **	0.251 **
	(0.086)	(0.088)	(0.090)
Y_2008	0.198	0.230	0.199
	(0.126)	(0.129)	(0.126)
Y_2009	0.570 ***	0.610 ***	0.571 ***
	(0.134)	(0.133)	(0.134)
Y_2010	-0.251 **	-0.223 **	-0.250 **
	(0.075)	(0.079)	(0.077)
Y_2011	0.705 ***	0.739 ***	0.707 ***
	(0.167)	(0.169)	(0.167)
Y_2012	0.547 ***	0.587 ***	0.549 ***
	(0.140)	(0.138)	(0.138)
Y_2013	0.291	0.335 *	0.294
	(0.149)	(0.148)	(0.148)
Y_2014	0.237	0.282 *	0.239
	(0.123)	(0.121)	(0.123)
Y_2015	-0.059	-0.030	-0.056
	(0.081)	(0.088)	(0.084)
Y_2016	-0.335 ***	-0.273 **	-0.332 ***
	(0.071)	(0.082)	(0.073)
n	73	73	73
T	12	12	12
N	876	876	876
R-squared	0.325	0.332	0.325

Notes: Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.12: Fixed Effects Model with year dummies: Annual deaths from tropical cyclones by municipality, Philippines (2007-2015)

	(1)	(2)	(3)	(4)
ln local revenue per capita (t-1)	0.007	-	-	0.002
	(0.006)	-	-	(0.007)
ln local expenditure per capita (t-1)	-	-0.011	-	-0.013
	-	(0.017)	-	(0.017)
local share revenue (t-1)	-	-	0.090	0.082
	-	-	(0.067)	(0.075)
Wind speed (km/hr)	0.012 ***	0.012 ***	0.012 ***	0.012 ***
	(0.001)	(0.001)	(0.001)	(0.001)
ln population	0.016	0.002	0.010	-0.002
	(0.021)	(0.028)	(0.022)	(0.029)
Y_2008	-0.058 ***	-0.057 ***	-0.058 ***	-0.057 ***
	(0.013)	(0.013)	(0.013)	(0.013)
Y_2009	0.052 ***	0.053 ***	0.053 ***	0.054 ***
	(0.014)	(0.014)	(0.014)	(0.014)
Y_2010	-0.048 ***	-0.046 ***	-0.047 ***	-0.046 ***
	(0.008)	(0.008)	(0.008)	(0.008)
Y_2011	0.004	0.007	0.005	0.007
	(0.011)	(0.011)	(0.011)	(0.011)
Y_2012	0.003	0.008	0.005	0.007
	(0.010)	(0.011)	(0.010)	(0.011)
Y_2013	0.007	0.012	0.008	0.010
	(0.013)	(0.013)	(0.013)	(0.013)
Y_2014	-0.064 ***	-0.059 ***	-0.062 ***	-0.060 ***
	(0.012)	(0.013)	(0.012)	(0.013)
Y_2015	-0.063 ***	-0.057 ***	-0.061 ***	-0.058 ***
	(0.010)	(0.011)	(0.010)	(0.011)
Observations	-	-	-	-
Log-Likelihood	-	-	-	-

Notes:

Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.13: Random Effects Model with year dummies: Annual deaths from tropical cyclones by municipality, Philippines (2007-2015)

	(1)	(2)	(3)	(4)	(5)
ln local revenue per capita (t-1)	-0.005 *	-	-	-0.011 ***	-0.008
	(0.003)	-	-	(0.003)	(0.004)
ln local expenditure per capita (t-1)	-	0.005	-	0.007	0.024 *
	-	(0.011)	-	(0.011)	(0.011)
local share revenue (t-1)	-	-	-0.010	0.065	0.067
	-	-	(0.033)	(0.045)	(0.045)
Wind speed (km/hr)	0.009 ***	0.009 ***	0.009 ***	0.009 ***	0.012 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
coastal	0.017 *	0.016 *	0.016 *	0.018 *	0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
ln population	0.058 ***	0.058 ***	0.056 ***	0.058 ***	0.060 ***
	(0.004)	(0.007)	(0.005)	(0.007)	(0.007)
Y_2008	-0.035 **	-0.034 **	-0.034 **	-0.036 **	-0.059 ***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)
Y_2009	0.063 ***	0.063 ***	0.063 ***	0.063 ***	0.050 ***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)
Y_2010	-0.037 ***	-0.038 ***	-0.037 ***	-0.037 ***	-0.050 ***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Y_2011	0.018	0.017	0.018	0.018	0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Y_2012	0.017	0.016	0.016	0.017	0.001
	(0.011)	(0.010)	(0.011)	(0.010)	(0.010)
Y_2013	0.038 **	0.037 **	0.038 **	0.037 **	0.004
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
Y_2014	-0.038 ***	-0.039 ***	-0.038 ***	-0.038 ***	-0.068 ***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
Y_2015	-0.045 ***	-0.047 ***	-0.046 ***	-0.045 ***	-0.066 ***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Observations	-	-	-	-	-
Log-Likelihood	-	-	-	-	-

Notes:
Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.14: Pooled Model with year dummies: Annual deaths from tropical cyclones by municipality, Philippines (2007-2015)

	(1)	(2)	(3)	(4)	(5)
ln local revenue per capita (t-1)	-0.005 *	-	-	-0.010 **	-0.008
	(0.003)	-	-	(0.003)	(0.004)
ln local expenditure per capita (t-1)	-	0.005	-	0.008	0.024 *
	-	(0.011)	-	(0.011)	(0.011)
local share revenue (t-1)	-	-	-0.009	0.063	0.067
	-	-	(0.034)	(0.046)	(0.045)
Wind speed (km/hr)	0.009 ***	0.009 ***	0.009 ***	0.009 ***	0.012 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
coastal	0.016 *	0.016 *	0.015 *	0.018 *	0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
ln population	0.057 ***	0.058 ***	0.056 ***	0.058 ***	0.060 ***
	(0.004)	(0.007)	(0.005)	(0.007)	(0.007)
Y_2008	-0.033 **	-0.032 **	-0.032 **	-0.033 **	-0.059 ***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)
Y_2009	0.064 ***	0.064 ***	0.064 ***	0.064 ***	0.050 ***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)
Y_2010	-0.036 ***	-0.037 ***	-0.036 ***	-0.036 ***	-0.050 ***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Y_2011	0.019 *	0.019	0.019	0.019	0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Y_2012	0.018	0.017	0.018	0.018	0.001
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
Y_2013	0.041 **	0.040 **	0.041 **	0.040 **	0.004
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
Y_2014	-0.035 ***	-0.036 ***	-0.036 ***	-0.036 ***	-0.068 ***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
Y_2015	-0.043 ***	-0.045 ***	-0.044 ***	-0.043 ***	-0.066 ***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Observations	-	-	-	-	-
Log-Likelihood	-	-	-	-	-

Notes:
Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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