Socioeconomic Determinants of Tropical Cyclone Mortality

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February 27, 2019

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Abstract

This paper analyzes the impacts of socioeconomic conditions on tropical cyclone mortality rates. Death tolls from these powerful storms can number in the thousands when human systems are overwhelmed. Yet most tropical cyclones do not result in death or disaster. What accounts for this extreme variation in impacts? And how can we prevent future mortality? In this paper I investigate the importance of governance, income and other development factors for cyclone mortality. Because tropical cyclone fatalities result from the localized interaction of the natural hazard and the human system, I construct a dataset that spatially interacts meteorological and socioeconomic data. This allows me to control for physical exposure at a high resolution and better isolate the relationships of interest. I find that national government effectiveness is associated with lower mortality from tropical cyclone events. I also find evidence that mortality is higher when storm exposure is concentrated over a subset of the population that is already less well off. These estimates are large, statistically significant and robust to alternative specifications.

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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) (Knapp et al. 2010; Guha-Sapir 2018).

What accounts for the extreme variation in the impacts of tropical cyclones? And how can we prevent mortality from future storms? In this paper 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.

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, Dao, and Herold 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, Dao, and Herold 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, Dao, and Herold 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.

1.1.1 Vulnerability theory

This paper 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 (Adger 2006; 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; Adger 2006). 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.

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, Chiabai, and Muehlenbachs 2006; Brooks, Adger, and Kelly 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, Chiabai, and Muehlenbachs (2006) and Brooks, Adger, and Kelly (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 paper 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, Dao, and Herold (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 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.

2.1 Mortality data and unit of analysis

This paper 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

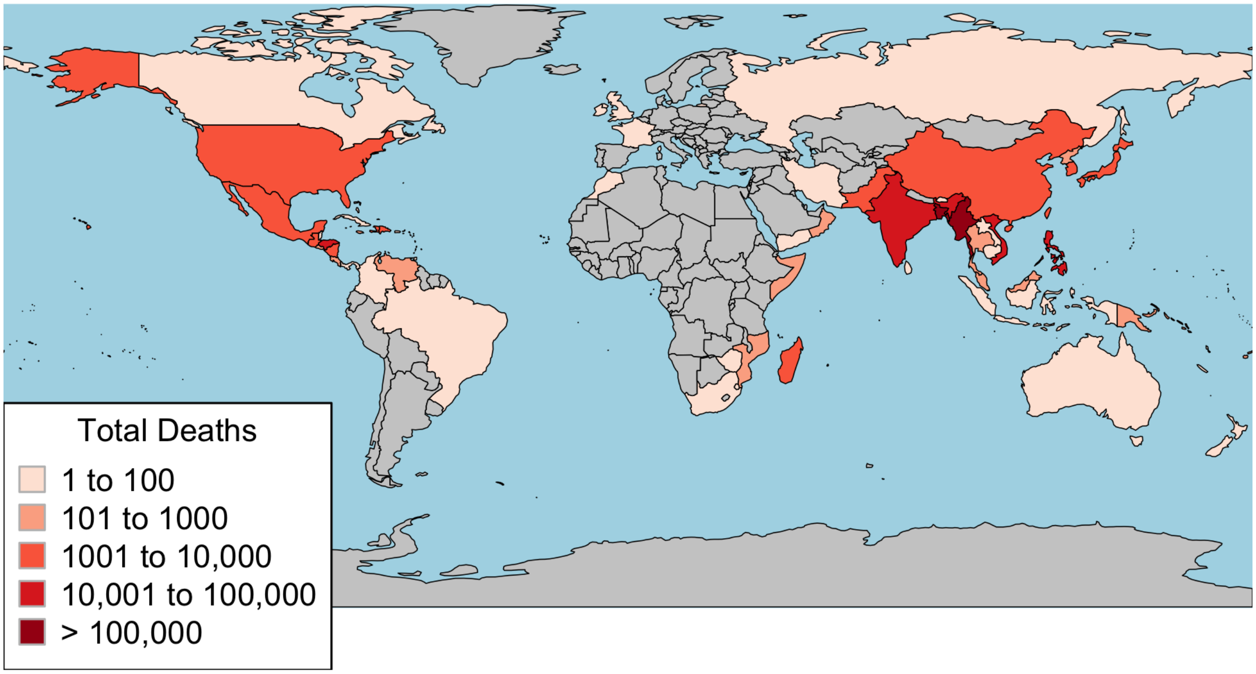

Figure 1: Cumulative deaths from tropical cyclone disasters, 1979 to 2016. Based on data from the EM-DAT (Guha-Sapir 2018).

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 1 maps total deaths by country over the 1979 to 2016 study period using data from the EM-DAT.

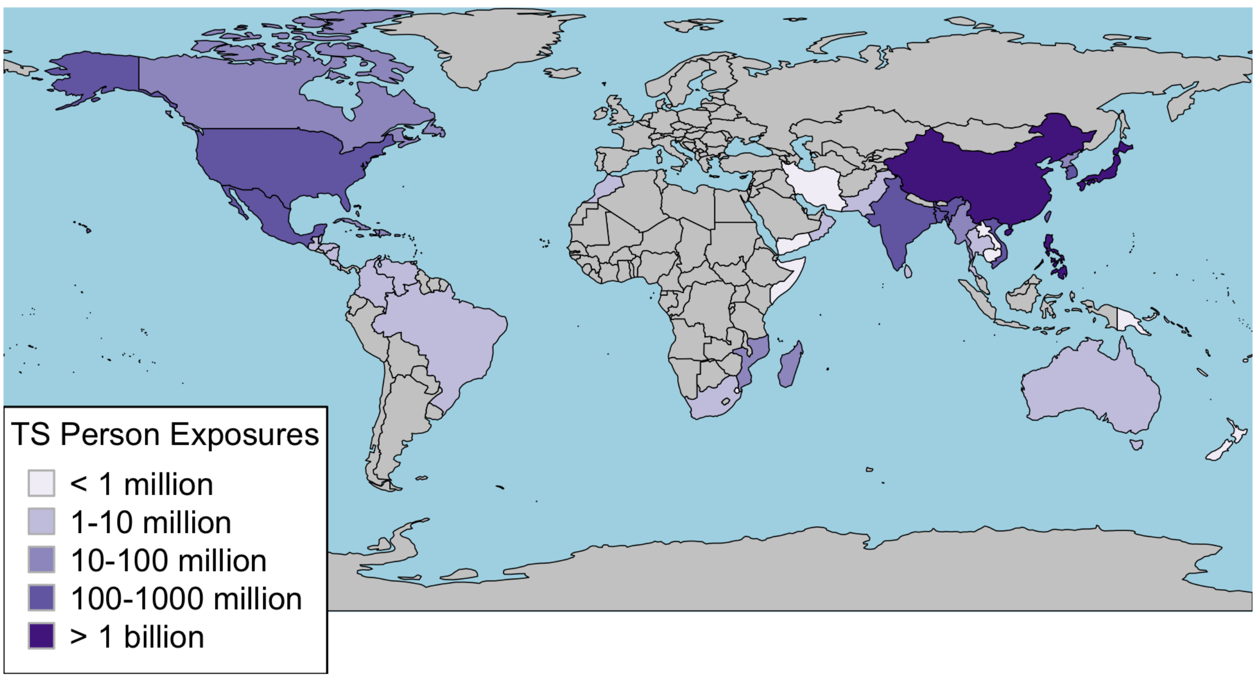

Figure 2: Cumulative population exposure to tropical storms and cyclones (sustained winds > 63 km/hr) from 1979 to 2016. See Section 2.2 and Table 2.1 for a description of the population exposure variables. Based on data from CIESEN (2017a), CIESEN (2017b), and Knapp et al. (2010).

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) geo-referenced 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 manually 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, Darling, and Rahn (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 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, 2017b).

Rainfall exposure is based on the CPC Global Unified Gauge-Based Analysis of Daily Precipitation dataset, available at a 0.5 degree resolution from 1979 to present (NOAA 2018).

[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.

[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.

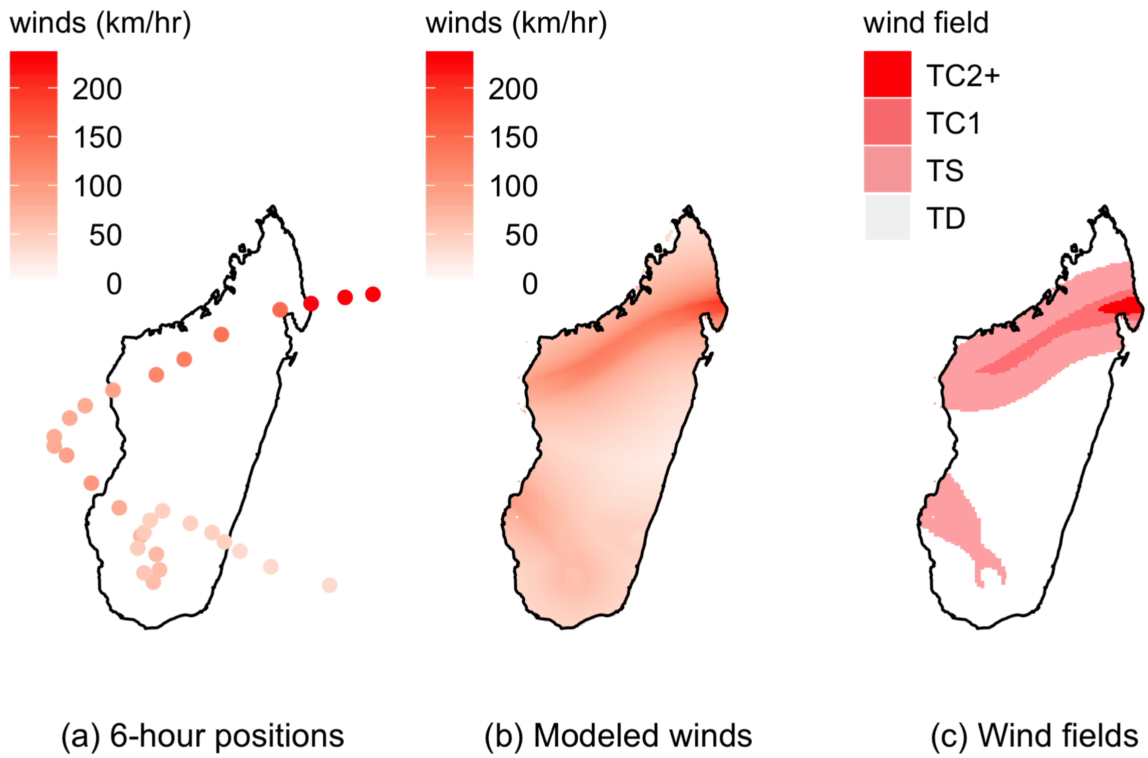

Figure 3: Modeling tropical cyclone wind fields for Cyclone Gafilo (2004) in Madagascar. I begin with (a) the 6-hourly wind speeds from the International Best Track Archive for Climate Stewardship (IBTrACS) (Knapp et al. 2010). Using a parametric wind speed model (Anderson et al. 2017; Willoughby, Darling, and Rahn 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.

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.

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

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).

2.3 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

> perceptions 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, 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 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.

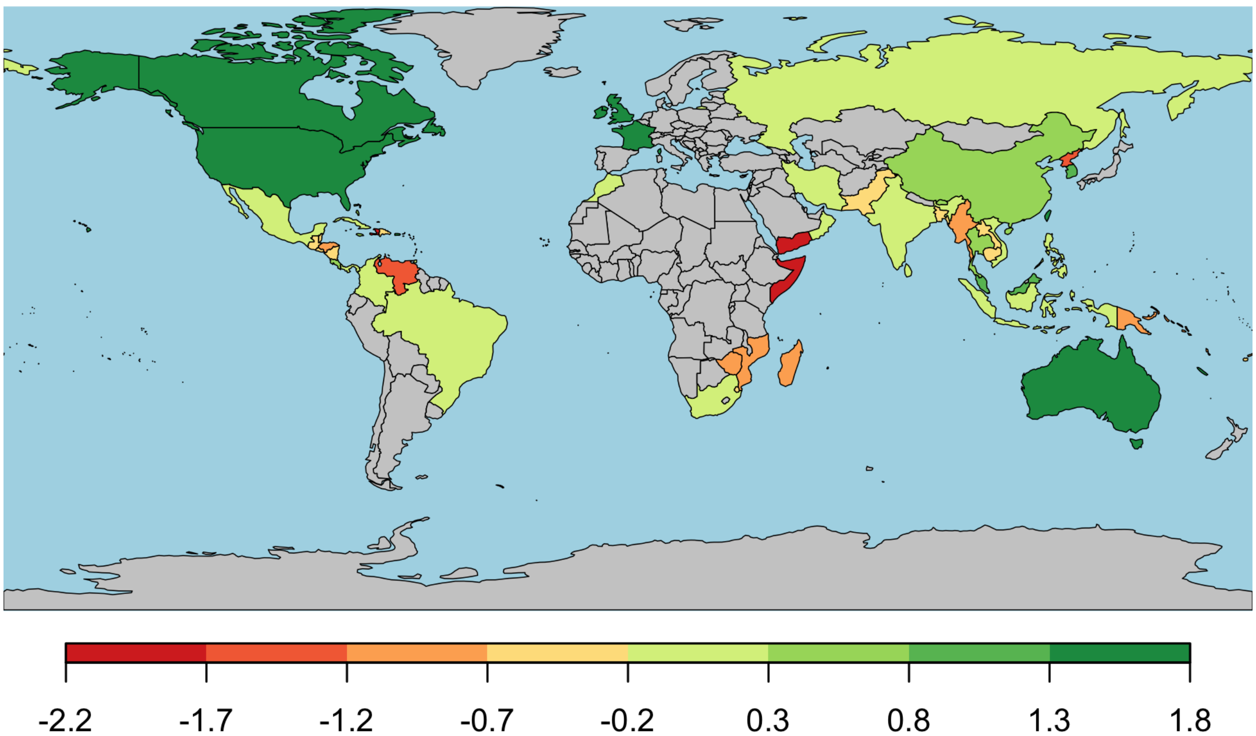

Figure 4: National government effectiveness scores (2016) for tropical cyclone affected countries. Countries mapped experienced tropical cyclone mortality between 1979 and 2016. Countries are shaded in grey if 2016 WGI are not available or the country has not experienced cyclone deaths during this period. Higher scores indicate more effective governance. Data from the World Governance Indicators (WGI) (Kaufmann 2010).

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

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, Wimmer, and Min 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 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, 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).

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 1-3, following Greene (2012, 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. I therefore estimate robust standard errors for all negative binomial regressions presented in this analysis. The NB2 model is

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

where

$$\lambda_i = \exp(\mathbf{x}_i'\boldsymbol{\beta}), \tag{2}$$

and

$$r_i = \lambda_i/(\theta + \lambda_i). \tag{3}$$

The characteristics of each country-storm-event i, represented by the vector $\mathbf{x}_i$, include socioeconomic 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, 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.

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 4.1 and the 1979-2016 subnational analysis in Table 4.3. 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.

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 4.1, 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 4.1, 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 4.1, 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 4.1, columns (2, 5 and 6)). The effects of infant mortality and education also lose statistical significance in the joint model (Table 4.1, column (6)). In contrast, the government effectiveness coefficient remains large and statistically significant (Table 4.1, column (6)).

Table 4.1: 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 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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 4.1, 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 4.1, columns (1)). Adding GDP per capita to the model, this falls to a 50% decrease in mortality per standard deviation of government effectiveness (Table 4.1, 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 4.1, column (6)).

The problem of multicollinearity between development factors has posed long-standing 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)).

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 4.1. 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.

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, Chiabai, and Muehlenbachs (2006); Brooks, Adger, and Kelly (2005); Hsiang and Narita (2012); Kahn (2005) and 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 underreport 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 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

Table 4.2: 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

effectiveness and real GDP per capita as well as controls for population exposure.

The results, presented in Table 4.2, 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.

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 4.3.

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 mortality ($p < 0.05$) (see Table 4.3, 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 4.3, 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 4.3. 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.

[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.

Table 4.3: 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 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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 4.3 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.

5 Conclusion

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 (Peduzzi et al. 2012; Mendelsohn et al. 2012; Walsh et al. 2016).

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, Adger, and Kelly 2005; Denton et al. 2014; Stern and Wilbanks 2009).

The results presented in this paper 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 scenarious. 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.

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A Supplemental Tables

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 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.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	Winds 63-119 km/hr	Winds > 119 km/hr
	(1)	(2)	(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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.