Socioeconomic Determinants of Tropical Cyclone Mortality

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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 1978 and 2016, tropical cyclone disasters have killed over 771,000 people across 97 countries (Guha-Sapir 2018). 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 damages from the storm were estimated at $4 billion. 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. Of the 103 tropical cyclones recorded in 2008, twenty-nine resulted in disaster and loss of life (Guha-Sapir 2018; Knapp et al. 2010).

Two questions naturally arise. What accounts for the extreme variation in the impacts of tropical cyclones? And how can we prevent mortality from future storms? From a public policy perspective, we are particularly interested in risk factors that can be targeted by social and economic policy. Do gains in economic growth, institutional capacity and human capital reduce tropical cyclone mortality risk? And at what scale do these mechanisms operate?

To investigate these questions, I construct a novel dataset of over one thousand tropical cyclone disasters in 59 countries from 1978 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 corrects for potential biases in model estimates. This improves our ability to identify statistically significant 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 government effectiveness and other national development factors on cyclone fatalities from 1996 to 2016. Next, I test whether subnational conditions amongst the population exposed to hazardous winds from the storm help to explain variation in event mortality counts within countries during the 1978 to 2016 period. I present several results that are new to the literature.

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 econometric specifications. An increase of one standard deviation in government effectiveness is associated with more than a 50% decrease in event mortality. 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 link 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 one-third or more in event mortality. This basic result is robust to alternative definitions of exposure and econometric 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, this tells us that national estimates of vulnerability may mask important subnational heterogeneities.

1.1 Related literature

This paper is motivated by a theoretical literature and case study evidence that suggest an important but complex relationship between development and vulnerability to natural hazards (e.g., Adger 2003; Blaikie et al. 2004; Denton et al. 2014). The decision to construct subnational socioeconomic variables is based on work about the spatial nature of risk and development (Blaikie et al. 2004) and emphasis on the multiple scales of vulnerability and resilience in the theoretical literature (e.g., Turner et al. 2003; Cutter et al. 2008). The hypotheses tested in this paper draw on work such as Adger (2003) and Eakin and Lemos (2006), which highlight the direct and indirect mechanisms by which national governments may influence levels of adaptation to hazard.

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). Because these previous studies do not include multiple development factors in a single model, they cannot speak – for example – to the importance of governance independent of income, or vice versa. Given the strong correlation between GDP per capita and other development factors (i.e., governance, health and education), it is therefore unclear whether income or some other aspect of development drives this relationship.

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 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 suffer from potential biases.

In contrast, in this analysis I control for storm exposure when estimating relationships between socioeconomic factors and mortality. Tropical cyclones are highly varied in their intensity and exposure patterns. Failing to control for this variation may be particularly problematic if socioeconomic variables are correlated with tropical cyclone exposure. For example, if tropical cyclones have lasting negative impacts on economic growth (Hsiang and Jina 2014), over time income might become negatively correlated with tropical cyclone exposure and result in an overestimate of the income-mortality relationship.

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 a more recent parametric wind speed model and adding rainfall.

The key contribution of this paper is to estimate a multivariate model of cyclone mortality, including national and regional (wind-field level) socioeconomic variables. Both Hsiang and Narita (2012) and Peduzzi et al. (2012) observe a correlation between 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.

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. And when intense storms do strike land, minor differences in storm trajectory can have large implications for the number of people exposed to hazardous conditions. Further, we are interested not only in the number of people exposed at different intensities, but also the local socioeconomic conditions of the affected population.

We therefore require 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 1978-2016. For additional details and replication please see the forthcoming 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 International Disaster Database, the source of our cyclone mortality data (Guha-Sapir 2018).

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 is obtained from the Best Track Archive for Climate Stewardship (IBTrACS) Project, and includes 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 consists 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).[1] I then rasterize the grid winds (at a 2.5 arc-minute resolution) and map the spatial extent of the tropical storm (63-118

[1]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.

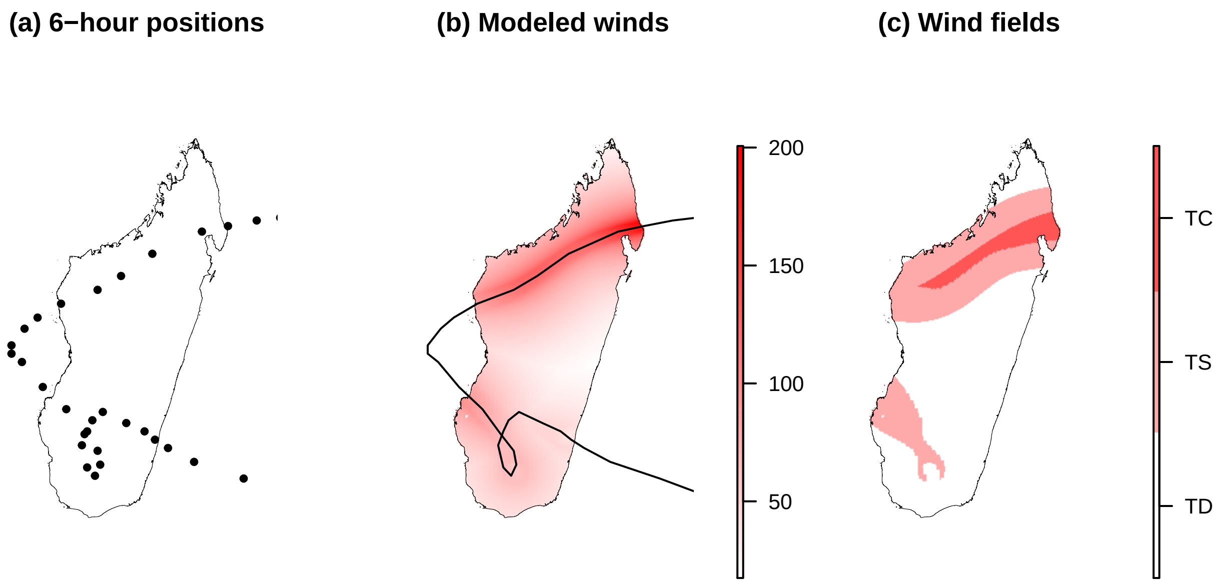

Figure 1: Modeling tropical cyclone wind fields for Cyclone Gafilo (2004) in Madagascar. I begin with (a) the 6 hourly IBTrACS geo-referenced wind speeds, then (b) model the maximum sustained wind speed over land at a 2.5 arc-minute (5km) resolution using stormwindmodel based on Willoughby et al. (2006), and finally (c) define the spatial extent of the TS (Tropical Storm: 63-118 km/hr) and TC (Tropical Cyclone: $>$ 118 km/hr) wind fields.

km/hr) and tropical cyclone ($>$ 119 km/hr) force wind fields over land by country. Figure 1 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). While rainfall data is already available in spatial form, it is not linked to specific storm events. For each country-storm event, I therefore take the maximum total rainfall experienced by any grid cell in the country, during the storm, and within a 500km buffer of the storm track.

In Table 1 I describe the four types of physical control variables constructed to measure hazard intensity and exposure in this analysis, as well as the sources they are drawn from.

Table 1: Summary of hazard intensity and exposure variables

Variable	Description	Data.sources
Population exposed (millions)	The size of the population (in millions) exposed to winds above a certain threshold (within the country). Population exposed is constructed for the tropical storm threshold ($>$ 63 km/hr) and the tropical cyclone threshold ($>$ 119 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).
Average intensity of exposure (km/hr)	The population-weighted average intensity (km/hr) of exposure within a given wind field. First, the wind field of interest is defined (i.e. tropical cyclone force winds of $>$ 119 km/hr). Then the average intensity is computed by multiplying the sustained wind speed and population for each 2.5 arc-minute grid cell, summing the products, and dividing by the total wind field population.	ibid.
Maximum wind speed exposure (km/hr)	The maximum wind speed (km/hr) in a populated 2.5 arc-minute grid-cell (within the country).	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 is measured using the World Governance Indicators dataset, a set of subjective and normalized measures of governance available starting in 1996 (Kaufmann 2010). Each year has approximately zero mean, unit standard deviation, and a range of roughly -2.5 to 2.5 for the global dataset (Kaufmann 2010). National data on income, health and education is taken from the World Development Indicators (see Table 2).[2]

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, Wimmer, and Min 2010; Vogt et al. 2015; Wucherpfennig et al. 2011).

In Table 2 I describe the key socioeconomic variables and the sources they are drawn from.

[2] I use GDP per capita and Infant Mortality Rate variables from the previous year, as large disasters may impact these variables in the storm year.

Table 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

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) (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. 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 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 squared (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 $\text{E}[\ln y \mid \mathbf{x}] = \mathbf{x}_i'\boldsymbol{\beta}$ does not imply $\text{E}[y \mid \mathbf{x}] = \exp(\mathbf{x}_i'\boldsymbol{\beta})$ (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, our 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. These results suggest that single-variable models in previous studies may overstate the importance of national income for storm deaths. 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 results of the negative binomial models in this paper are presented as Incident Rate Rations (IRRs), obtained by exponentiating the estimated coefficients. Thus, 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

In Table 3 I present summary results of the 1996-2016 national cyclone mortality analysis. I find 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 3, column (2)). An increase in government effectiveness of one standard deviation is associated with a 56% decrease in disaster mortality (Table 3, column (2)). Estimates of the governance coefficient from comparable OLS models are large and highly statistically significant in Table 3, columns (4) and (6).

Table 3 also illustrates the importance of controlling for physical exposure. I exclude the physical exposure controls in columns (1), (3) and (5) of Table 3 (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 3, column (1)) is $1.38e - 40$ times as likely as the model with the physical controls (Table 3, column (2)).

Due to correlation amongst socioeconomic variables in the dataset, the combination of socioeconomic variables does impact the magnitude of the governance coefficient. For example, including GDP per capita (versus only governance) attenuates the magnitude of the governance estimate from a 73% to a 56% decrease in mortality per standard deviation in government effectiveness (see Table 4, columns (1) and (5)). However, in Table 4 I present several negative binomial specifications that illustrate the robustness of the governance result. Government effectiveness remains a large and highly statistically significant predictor with the inclusion of health and education variables to the model (see Table 4, columns (1, 5-7)).

Previously published single-variable models of cross-country variation in tropical cyclone mortality have found GDP per capita to be negatively correlated with cyclone mortality. I recreate this finding in Table 4, 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 an 80% decrease in deaths (Table 4, column (2)). With the addition of government effectiveness to the model, this falls to 49% (Table 4, column (5)). If we add infant mortality and education, the estimated coefficient is no longer statistically significant (Table 4, column (7)). Thus, while GDP per capita may indeed be an effective predictor of a country's vulnerability to tropical cyclone mortality, it is unclear what if any causal role is played by income itself. This is also true of infant mortality and education. Including only one socioeconomic variable at a time, each of the four national development indicators tested (government effectiveness, GDP per capita, infant mortality and education) in Table 4, columns (1–4) is a highly statistically significant ($p < 0.001$) predictor of tropical cyclone event mortality when controlling for exposure. Only the government effectiveness coefficient remains large and statistically significant when all four are included in a single model (Table 4, column (7)).

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. 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 3: 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	0.597	0.356 ***	-0.436 **	-0.535 ***	-0.526 **	-0.727 ***
	(0.177)	(0.091)	(0.145)	(0.139)	(0.178)	(0.176)
Ln real GDP per capita (t-1)	0.392 *	0.558 *	-0.221	-0.279 *	-0.225	-0.238
	(0.145)	(0.134)	(0.123)	(0.119)	(0.142)	(0.138)
Pop. (millions) exposed to winds 63-118 km/hr	-	1.008	-	0.009 *	-	0.007
	-	(0.007)	-	(0.004)	-	(0.004)
Pop. (millions) exposed to winds > 119 km/hr	-	1.321 ***	-	0.108 ***	-	0.112 ***
	-	(0.100)	-	(0.029)	-	(0.029)
Average wind speed exposure (63-119 km/hr)	-	0.999	-	0.004 *	-	0.004
	-	(0.004)	-	(0.002)	-	(0.002)
Average wind speed exposure (> 119 km/hr)	-	1.004 *	-	0.002 *	-	0.001
	-	(0.002)	-	(0.001)	-	(0.001)
Maximum rainfall exposure (mm)	-	1.004 ***	-	0.002 ***	-	0.002 ***
	-	(0.001)	-	(0.000)	-	(0.000)
Time (years)	0.952	0.961	-0.040 ***	-0.038 ***	-0.026 *	-0.026 *
	(0.034)	(0.020)	(0.010)	(0.010)	(0.012)	(0.011)
Geography	regions	regions	regions	regions	regions	regions
Observations	795	795	795	795	614	614

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, 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 4: National Determinants of Mortality from TC Events (1996-2016): Additional Negative Binomial Regression Models

	IRR (1)	IRR (2)	IRR (3)	IRR (4)	IRR (5)	IRR (6)	IRR (7)
Government Effectiveness	0.190 ***	-	-	-	0.356 ***	0.320 ***	0.206 ***
	(0.028)	-	-	-	(0.091)	(0.049)	(0.066)
Ln real GDP per capita (t-1)	-	0.279 ***	-	-	0.558 *	-	1.259
	-	(0.038)	-	-	(0.134)	-	(0.380)
National infant mortality rate (t-1)	-	-	1.088 ***	-	-	1.034 ***	1.009
	-	-	(0.006)	-	-	(0.007)	(0.019)
Primary school enrollment (% net)	-	-	-	0.907 ***	-	-	1.012
	-	-	-	(0.012)	-	-	(0.025)
Pop. (millions) exposed to winds 63-118 km/hr	1.007	1.004	0.994	0.989	1.008	1.004	1.012
	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)
Pop. (millions) exposed to winds > 119 km/hr	1.339 ***	1.313 ***	1.327 ***	1.563 ***	1.321 ***	1.330 ***	1.518 ***
	(0.103)	(0.101)	(0.098)	(0.111)	(0.100)	(0.101)	(0.104)
Average wind speed exposure (63-119 km/hr)	0.999	0.998	1.003	0.994	0.999	1.001	0.999
	(0.004)	(0.004)	(0.004)	(0.007)	(0.004)	(0.004)	(0.004)
Average wind speed exposure (> 119 km/hr)	1.004	1.004 *	1.003	1.003	1.004 *	1.003	1.004 *
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Maximum rainfall exposure (mm)	1.004 ***	1.003 ***	1.004 ***	1.003 ***	1.004 ***	1.004 ***	1.003 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time (years)	0.946 *	0.971	0.966	1.015	0.961	0.957	0.987
	(0.023)	(0.017)	(0.026)	(0.020)	(0.020)	(0.025)	(0.020)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	827	795	806	471	795	806	453

Notes: Negative binomial results are presented as Incident Rate Rations (IRRs), obtained by exponentiating the estimated coefficients. Thus, 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.1.1 Robustness checks

The main results of this analysis are robust to various permutations of the model and the dataset. In the Appendix Tables 8 and 10 I present OLS estimates comparable to the negative binomial results in Table 4. Government effectiveness has a large and highly statistically significant association with lower mortality in all OLS specifications tested in Appendix Tables 8 and 10.

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 is consistently negative (IRR < 1). However, statistical significance varies depending on the combination of socioeconomic variables included in the model (see Appendix Tables 7, 9 and 11). Interestingly, when we include country controls in Appendix Table 7, column (7), the negative binomial estimate of GDP per capita is very large and regains its statistical significance in the multivariate negative binomial model. In the comparable OLS models the GDP estimates are not statistically significant (see column (7) of Appendix Tables 9 and 11). A within-country trend in GDP per capita also appears to be predictive of cyclone mortality in the 1978-2016 analysis, 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., this paper; 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. For example, it may be that countries with less government capacity and less resources are more likely to underreport deaths. While EM-DAT's triangulation between government, United Nations (UN) and other non-governmental sources works to minimize this, it could potentially result in an attenuation bias that we cannot easily test or correct for.

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, which would once again introduce the potential

Table 5: Inclusion of exposures (> 63 km/hr sustained winds over inhabited land) in the EM-DAT from a logistic regression model

	(1)
Government Effectiveness	-0.537 **
	(0.177)
Ln real GDP per capita (t-1)	-0.328 *
	(0.149)
Time (years)	0.033 **
	(0.013)
Population exposed to winds > 63 km/hr	0.000 ***
	(0.000)
Average wind speed exposure (> 63 km/hr)	0.024 ***
	(0.003)
Maximum rainfall exposure (mm)	0.005 ***
	(0.001)
Observations	1155

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

for attenuation bias in our estimates. On the other hand, we might also be concerned about under-reporting by less-developed countries as a result of lower reporting 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 the size of the intensity and population exposed.

The results, presented in Table 5, indicate that tropical cyclone exposures that occur in wealthier countries with more effective governments are less likely to be included in the EM-DAT. This result is consistent with the hypothesis that more developed countries have a higher capacity to avert disaster when exposed to hazard. Further, the omission of zero-death exposure events that correlate with better governance and higher incomes may introduce an attenuation bias into our estimates of the effects of governance and other socioeconomic variables on mortality. This would suggest that our already quite large estimates of the impact of governance, as well as GDP per capita, in the above models may be lower bounds (Tables 3 and 4).

4.2 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 (1978 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 6.

I find that death tolls are higher when infant mortality rates are elevated within the cyclone wind field. As described in Table 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 rated as a tropical storm or higher.[3] For this group of events I find that an increase of one standard deviation in the local IM ratio is associated with a 38% increase in event mortality ($p < 0.05$) (see Table 6, 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 a 66% increase in mortality (see Table 6, 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 6. This merits further study, especially as Kahn (2005) found ethnic fractionalization to be correlated with lower 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 provides support for theory and case study evidence that emphasize the multi-scalar nature of vulnerability and resilience. Whether this indicates the importance of infant mortality itself or some other correlate is not clear. Elevated infant mortality may be symptomatic of poverty, weak institutions, a lack of transportation infrastructure, powerlessness or exclusion. In other words, we can paint a multitude of reasonable mechanisms consistent with this finding.

[3] 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.

4.2.1 Robustness checks

I include estimation of comparable OLS models in the Appendix Tables 12 and 13. For events rated as a tropical storm or higher, the IM ratio coefficients in column (1) of Tables 12 and 13 are consistently positive but not statistically significant ($p > 0.05$). The IM ratio for the more intense, cyclone-force wind fields remains statistically significant ($p < 0.05$) in all OLS models (see column (3) in Tables 12 and 13).[4]

[4]One potential concern is that infant mortality might be elevated in certain parts of the country because of impacts from previous tropical cyclones. While I cannot rule out endogeneity bias, I find that exposure is actually (on average) negatively correlated with the IM ratio variables.

Table 6: Subnational Determinants of Mortality from TC Events (1978-2016): 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)	2.751 *	3.053 *	-
	(1.146)	(1.569)	-
Excluded ethnic group in (wind field > 63 km/hr)	0.673	0.682	-
	(0.376)	(0.571)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	3.970 ***
	-	-	(1.614)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	1.643
	-	-	(0.835)
National infant mortality rate (t-1)	1.011	1.001	1.029 *
	(0.009)	(0.013)	(0.012)
Ln real GDP per capita (t-1)	0.287 ***	0.271 ***	0.297 ***
	(0.063)	(0.082)	(0.097)
Pop. (millions) exposed to winds 63-118 km/hr	1.013 *	1.006	1.030 **
	(0.006)	(0.008)	(0.010)
Pop. (millions) exposed to winds > 119 km/hr	1.553 ***	-	1.554 ***
	(0.096)	-	(0.103)
Average wind speed exposure (63-119 km/hr)	1.008	1.003	1.020
	(0.015)	(0.021)	(0.016)
Average wind speed exposure (> 119 km/hr)	1.000	-	1.000
	(0.002)	-	(0.012)
Geography	countries	countries	countries
Observations	624	374	242

Notes: Negative binomial results are presented as Incident Rate Rations (IRRs), obtained by exponentiating the estimated coefficients. Thus, 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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 development 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. It also suggests several natural extensions to this work with useful policy implications. For example, how do the determinants of national mortality differ from economic risk factors? Do the distribution of impacts within countries follow socio-economic patterns? And what are the distributional effects of these storms? The basic approach presented here can be adapted to the study of additional hazards, scales and outcomes.

6 Appendix: Robustness of National Determinants of Cyclone Mortality (1996-2016)

Table 7: 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)	IRR (7)
Government Effectiveness	0.397 *	-	-	-	0.676	0.302 **	0.352
	(0.160)	-	-	-	(0.295)	(0.126)	(0.218)
Ln real GDP per capita (t-1)	-	0.160 ***	-	-	0.179 **	-	0.036 ***
	-	(0.085)	-	-	(0.101)	-	(0.036)
National infant mortality rate (t-1)	-	-	1.013	-	-	1.029 *	0.983
	-	-	(0.012)	-	-	(0.012)	(0.031)
Primary school enrollment (% net)	-	-	-	1.024	-	-	1.015
	-	-	-	(0.027)	-	-	(0.038)
Pop. (millions) exposed to winds 63-118 km/hr	1.004	1.001	1.003	1.010	1.001	1.002	1.009
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
Pop. (millions) exposed to winds > 119 km/hr	1.296 ***	1.305 ***	1.329 ***	1.470 ***	1.301 ***	1.322 ***	1.521 ***
	(0.089)	(0.089)	(0.087)	(0.091)	(0.089)	(0.087)	(0.099)
Average wind speed exposure (63-119 km/hr)	1.007 *	1.007 *	1.008 *	1.008 **	1.007 *	1.008 *	1.008 **
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Average wind speed exposure (> 119 km/hr)	1.003	1.003	1.003	1.003	1.003 *	1.003	1.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Maximum rainfall exposure (mm)	1.002 ***	1.003 ***	1.002 ***	1.002 ***	1.003 ***	1.003 ***	1.003 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time (years)	0.952 **	1.005	0.955 *	0.975	1.006	0.979	1.042
	(0.016)	(0.020)	(0.019)	(0.019)	(0.020)	(0.019)	(0.029)
Geography	country	country	country	country	country	country	country
Observations	827	795	806	471	795	806	453

Notes: Negative binomial results are presented as Incident Rate Rations (IRRs), obtained by exponentiating the estimated coefficients. Thus, 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 8: Robustness: National Determinants of Mortality from TC Events (1996-2016), OLS Regressions of log (deaths + 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government Effectiveness	-0.786 ***	-	-	-	-0.535 ***	-0.588 ***	-0.641 ***
	(0.062)	-	-	-	(0.139)	(0.086)	(0.152)
Ln real GDP per capita (t-1)	-	-0.679 ***	-	-	-0.279 *	-	-0.153
	-	(0.056)	-	-	(0.119)	-	(0.164)
National infant mortality rate (t-1)	-	-	0.035 ***	-	-	0.015 **	-0.004
	-	-	(0.004)	-	-	(0.005)	(0.009)
Primary school enrollment (% net)	-	-	-	-0.055 ***	-	-	-0.005
	-	-	-	(0.010)	-	-	(0.014)
Pop. (millions) exposed to winds 63-118 km/hr	0.009 *	0.009 *	0.006	-0.000	0.009 *	0.008 *	0.007
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Pop. (millions) exposed to winds > 119 km/hr	0.109 ***	0.112 ***	0.119 ***	0.130 **	0.108 ***	0.115 ***	0.125 ***
	(0.029)	(0.030)	(0.032)	(0.040)	(0.029)	(0.030)	(0.037)
Average wind speed exposure (63-119 km/hr)	0.003 *	0.004 *	0.003	0.002	0.004 *	0.004 *	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Average wind speed exposure (> 119 km/hr)	0.002 *	0.002 *	0.001	0.002	0.002 *	0.002 *	0.002 *
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Maximum rainfall exposure (mm)	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	-0.045 ***	-0.030 **	-0.024 *	-0.019	-0.038 ***	-0.036 ***	-0.027 *
	(0.009)	(0.010)	(0.010)	(0.012)	(0.010)	(0.010)	(0.012)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	827	795	806	471	795	806	453

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

Table 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)	(7)
Government Effectiveness	-0.773 **	-	-	-	-0.479	-0.874 **	-0.656
	(0.277)	-	-	-	(0.286)	(0.297)	(0.394)
Ln real GDP per capita (t-1)	-	-1.298 ***	-	-	-1.141 **	-	-1.634
	-	(0.339)	-	-	(0.345)	-	(0.842)
National infant mortality rate (t-1)	-	-	0.000	-	-	0.008	-0.036
	-	-	(0.010)	-	-	(0.010)	(0.022)
Primary school enrollment (% net)	-	-	-	-0.005	-	-	-0.022
	-	-	-	(0.021)	-	-	(0.027)
Pop. (millions) exposed to winds 63-118 km/hr	0.015 ***	0.015 ***	0.015 ***	0.015 **	0.015 ***	0.015 ***	0.015 **
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Pop. (millions) exposed to winds > 119 km/hr	0.112 ***	0.110 ***	0.117 ***	0.138 ***	0.109 ***	0.117 ***	0.128 **
	(0.029)	(0.030)	(0.030)	(0.041)	(0.029)	(0.030)	(0.040)
Average wind speed exposure (63-119 km/hr)	0.004 *	0.004 *	0.004 *	0.005 *	0.004 *	0.004 *	0.005 *
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Average wind speed exposure (> 119 km/hr)	0.002	0.002 *	0.002 *	0.002 *	0.002 *	0.002 *	0.003 *
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Maximum rainfall exposure (mm)	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	-0.049 ***	-0.015	-0.056 ***	-0.035 **	-0.016	-0.041 **	-0.014
	(0.010)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.018)
Geography	countries	countries	countries	countries	countries	countries	countries
Observations	827	795	806	471	795	806	453

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

Table 10: Robustness: National Determinants of Mortality from TC Events (1996-2016), OLS Regressions of ln (deaths)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government Effectiveness	-0.953 ***	-	-	-	-0.727 ***	-0.815 ***	-0.818 ***
	(0.079)	-	-	-	(0.176)	(0.104)	(0.208)
Ln real GDP per capita (t-1)	-	-0.739 ***	-	-	-0.238	-	-0.228
	-	(0.065)	-	-	(0.138)	-	(0.194)
National infant mortality rate (t-1)	-	-	0.034 ***	-	-	0.008	-0.007
	-	-	(0.005)	-	-	(0.005)	(0.010)
Primary school enrollment (% net)	-	-	-	-0.040 **	-	-	0.018
	-	-	-	(0.012)	-	-	(0.017)
Pop. (millions) exposed to winds 63-118 km/hr	0.007	0.006	0.001	-0.006	0.007	0.006	0.005
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Pop. (millions) exposed to winds > 119 km/hr	0.107 ***	0.118 ***	0.123 ***	0.138 ***	0.112 ***	0.116 ***	0.133 ***
	(0.029)	(0.030)	(0.031)	(0.039)	(0.029)	(0.030)	(0.038)
Average wind speed exposure (63-119 km/hr)	0.003	0.004	0.003	0.003	0.004	0.003	0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Average wind speed exposure (> 119 km/hr)	0.001	0.001	0.001	0.002	0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Maximum rainfall exposure (mm)	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	-0.029 **	-0.017	-0.011	-0.012	-0.026 *	-0.025 *	-0.022
	(0.011)	(0.011)	(0.011)	(0.014)	(0.011)	(0.012)	(0.014)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	635	614	617	362	614	617	351

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

Table 11: Robustness: National Determinants of Mortality from TC Events (1996-2016), OLS Regressions of ln (deaths) with Country Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government Effectiveness	-0.809 *	-	-	-	-0.634	-0.868 *	-0.897
	(0.337)	-	-	-	(0.352)	(0.376)	(0.553)
Ln real GDP per capita (t-1)	-	-0.921 *	-	-	-0.734	-	-1.861 *
	-	(0.382)	-	-	(0.390)	-	(0.933)
National infant mortality rate (t-1)	-	-	-0.010	-	-	-0.002	-0.018
	-	-	(0.010)	-	-	(0.012)	(0.025)
Primary school enrollment (% net)	-	-	-	0.038	-	-	0.032
	-	-	-	(0.022)	-	-	(0.031)
Pop. (millions) exposed to winds 63-118 km/hr	0.010 *	0.009 *	0.010 *	0.010	0.009 *	0.009 *	0.010
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)
Pop. (millions) exposed to winds > 119 km/hr	0.111 ***	0.114 ***	0.118 ***	0.143 ***	0.113 ***	0.118 ***	0.138 ***
	(0.029)	(0.030)	(0.031)	(0.041)	(0.029)	(0.030)	(0.041)
Average wind speed exposure (63-119 km/hr)	0.006 **	0.006 **	0.005 *	0.006 *	0.006 **	0.006 **	0.007 **
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Average wind speed exposure (> 119 km/hr)	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Maximum rainfall exposure (mm)	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	-0.033 **	-0.012	-0.049 ***	-0.035 *	-0.011	-0.034 *	0.003
	(0.011)	(0.016)	(0.014)	(0.015)	(0.016)	(0.017)	(0.024)
Geography	countries	countries	countries	countries	countries	countries	countries
Observations	635	614	617	362	614	617	351

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

7 Appendix: Robustness of Subnational Determinants of Cyclone Mortality (1978-2016)

Table 12: Robustness: Subnational Determinants of Mortality from TC Events (1978-2016), 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)	0.552	0.390	-
	(0.350)	(0.442)	-
Excluded ethnic group in (wind field > 63 km/hr)	-0.274	0.029	-
	(0.292)	(0.403)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.269 *
	-	-	(0.497)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	-0.243
	-	-	(0.438)
National infant mortality rate (t-1)	0.012	0.017	0.003
	(0.008)	(0.010)	(0.012)
Ln real GDP per capita (t-1)	-1.149 ***	-1.273 ***	-1.135 ***
	(0.221)	(0.301)	(0.326)
Pop. (millions) exposed to winds 63-118 km/hr	0.030 ***	0.028 ***	0.035 ***
	(0.006)	(0.008)	(0.009)
Pop. (millions) exposed to winds > 119 km/hr	0.171 ***	-	0.160 **
	(0.051)	-	(0.054)
Average wind speed exposure (63-119 km/hr)	0.007	0.007	0.017
	(0.009)	(0.013)	(0.015)
Average wind speed exposure (> 119 km/hr)	0.003 **	-	0.014
	(0.001)	-	(0.009)
Geography	countries	countries	countries
Observations	624	374	242

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 13: Robustness: Subnational Determinants of Mortality from TC Events (1978-2016), 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)	0.295	0.119	-
	(0.345)	(0.417)	-
Excluded ethnic group in (wind field > 63 km/hr)	-0.073	0.113	-
	(0.323)	(0.448)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.229 *
	-	-	(0.518)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	0.070
	-	-	(0.468)
National infant mortality rate (t-1)	0.010	0.002	0.017
	(0.008)	(0.010)	(0.012)
Ln real GDP per capita (t-1)	-0.783 ***	-0.732 **	-0.935 **
	(0.203)	(0.274)	(0.298)
Pop. (millions) exposed to winds 63-118 km/hr	0.025 ***	0.021 **	0.035 ***
	(0.006)	(0.008)	(0.009)
Pop. (millions) exposed to winds > 119 km/hr	0.178 ***	-	0.156 **
	(0.050)	-	(0.050)
Average wind speed exposure (63-119 km/hr)	-0.001	-0.009	0.023
	(0.010)	(0.013)	(0.017)
Average wind speed exposure (> 119 km/hr)	0.003	-	0.010
	(0.001)	-	(0.010)
Geography	countries	countries	countries
Observations	554	325	221

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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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