Government effectiveness and institutions as determinants of tropical cyclone mortality*

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Abstract

Strong institutions as well as economic development are generally understood to play critical roles in protecting societies from the adverse impacts of natural hazards, such as tropical cyclones. The independent effect of institutions on reducing these risks, however, has not been confirmed empirically in previous global studies. As a storm's path and intensity influence the severity of the damages and may be spatially correlated with human vulnerabilities, failing to accurately capture the physical exposure in an econometric analysis may result in imprecise and possibly biased estimates of the influence of the independent variables. Here, we develop a novel approach to control for physical exposure by spatially interacting meteorological and socioeconomic data for over one-thousand tropical cyclone disasters from 1979 to 2016. We find new evidence that higher levels of national government effectiveness are associated with lower tropical cyclone mortality, even when controlling for other socioeconomic conditions such as GDP per capita. Within countries, deaths are higher when strong winds are concentrated over areas of the country with weaker or less inclusive institutions. These results suggest that policies and programs to enhance institutional capacity and governance can support risk reduction from extreme weather events.

Keywords: tropical cyclones, disasters, institutions, vulnerability

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1 Introduction

Between 1979 and 2016 over 418,000 people across 85 countries lost their lives in tropical cyclone disasters. Out of over 4,000 tropical storms and cyclones recorded during this period, about 20% triggered humanitarian disasters and less than 5% resulted in more than 100 deaths (Guha-Sapir, 2018; Knapp et al., 2010). As recently as 2008 a single storm, the Cyclone Nargis, killed over 138,000 people in Myanmar. Nargis was a powerful Category 3 or 4 storm at landfall, but storms of similar intensity struck several other countries that year with far fewer fatalities (Guha-Sapir, 2018; Knapp et al., 2010). Understanding what drives this extreme variation in impacts may provide guidance on how we can prevent mortality from future storms, and may be of increasing importance as countries grapple with complex vulnerabilities to extreme weather events under climate change (IPCC, 2014). This paper investigates how levels of institutional, economic, and human development (collectively referred to as 'development') affect levels of tropical cyclone mortality. We focus in particular on the role of institutional quality in reducing tropical cyclone deaths, going beyond previous efforts in two important ways. First, we establish an empirical association between national government effectiveness and tropical cyclone deaths that cannot be explained away by income, health or education. Second, we present the first global analysis showing that the quality and inclusiveness of subnational institutions in the exposure zone are also associated with reduced mortality.

Natural hazards, including tropical cyclones, result in humanitarian disaster only when vulnerable human systems are exposed to hazardous conditions. This can be represented as follows (e.g. Alexander, 1991; Blaikie et al., 2004; United Nations International Stratety for Disaster Reduction, 2015):

$$risk = f(hazard, exposure, vulnerability); \tag{1}$$

where the $risk$, in this case the probability of mortality from tropical cyclones, is a function of the $hazard$ (the frequency and intensity of storms), $exposure$ (the assets or population in the hazard zone), and the $vulnerability$ (susceptibility to harm) of the exposed population. Empirical efforts to relate vulnerability and risk will therefore be confounded by hazard and exposure if these variables are not also accounted for.

Studies of vulnerability that include multiple classes of hazard are unable to control for intensity and exposure, as comparison across event types (i.e. earthquakes, storms, floods and heat waves) is not straightforward. As a result, estimates of socioeconomic risk factors for vulnerability will be imprecise. Indeed, previous large-N empirical efforts have been unable to provide statistical evidence of the relative importance of different socioeconomic risk factors for natural disaster mortality (Alberini et al., 2006; Brooks et al., 2005). Democracy and other institutional variables are found to be correlated with natural disaster deaths, but these effects are not precisely estimated when considered in combination with other possible explanatory variables such as GDP per capita (Brooks et al., 2005; Kahn, 2005). Furthermore, if hazard is correlated with socioeconomic conditions, the failure to control for characteristics of hazard exposure can result in biased estimates. For example, in Figure 1 we illustrate how from 1996 to 2016 countries with more effective governments had lower mortality from tropical cyclones even though their population exposure was slightly higher. Correlation between tropical cyclone exposure and socioeconomic variables could be incidental, or arise from the impacts of storms on socioeconomic development in areas of repeated exposure (e.g. Anttila-Hughes and Hsiang, 2013; Hsiang and Jina, 2014).

Studies restricted to a particular class of hazard are better able to account for variations in intensity and exposure. Recent studies of tropical cyclone risk (Peduzzi et al., 2005) and adaptation (Hsiang and Narita, 2012) that include physical hazard observe that storms of similar intensity tend to have higher numbers of deaths when they strike countries with lower GDP per capita. The identification of GDP per capita as a proxy for tropical cyclone vulnerability is useful for identifying at-risk countries and developing indices of vulnerability, but provides limited insight for guiding risk reduction activities. Average income is highly correlated with other development factors, such as governance, health and education. Because existing tropical cyclone studies do not include multiple development factors in a single model, it is unclear whether income or other facets of development drive the observed relationship (Camargo and Hsiang, 2015; Hsiang and Narita, 2012; Peduzzi et al., 2012). The association between higher levels of GDP per capita and lower disaster deaths may be explained in several ways. Countries with higher average incomes may be more likely to invest directly in assets and activities that reduce risk, collectively or individually. The effect of income may also be a proxy for other correlated aspects of development that have also been theorized to reduce disaster deaths, such as higher levels of social capital, human capital, and better quality institutions (Adger et al., 2003; Blaikie et al., 2004; Pachauri and Mayer, 2015). Additionally, the effects of development on risk are not unambiguously positive; growth-targeting policies and activities may inadvertently exacerbate or create new vulnerabilities (Adger et al., 2003; Blaikie et al., 2004; Denton et al., 2014). For example, the unregulated growth of coastal economies is frequently accompanied by the destruction of natural storm buffers such as coastal wetlands (Blaikie et al., 2004).

The quality and inclusiveness of institutions may be a particularly important factor for adaptation and risk reduction (Aldrich, 2012; Blaikie et al., 2004; Ensor et al., 2015; Fankhauser and Burton, 2011; Pachauri and Mayer, 2015). 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). The overall effectiveness of national

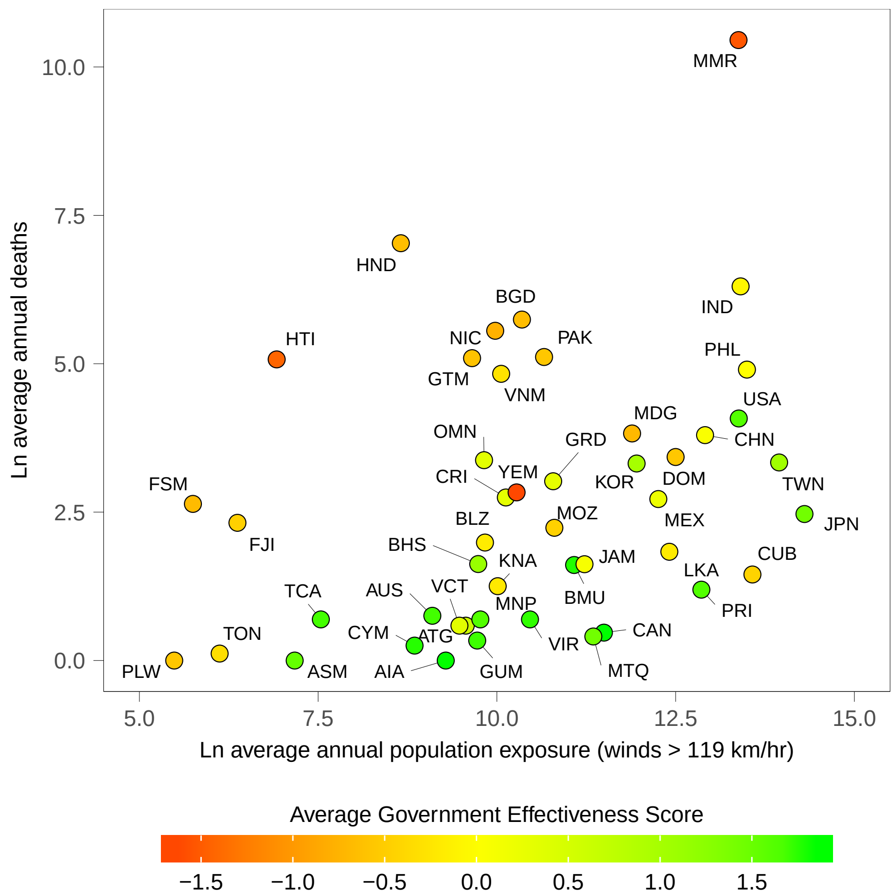

Figure 1: Governance, mortality and exposure for tropical-cyclone affected countries, 1996-2016. Average national government effectiveness scores from 1996 to 2016 are taken from the World Governance Indicators; higher scores indicate more effective governance (Kaufmann et al., 2010). Average annual tropical cyclone disaster deaths from 1996-2016 are based on data from the EM-DAT (Guha-Sapir, 2018). Average annual population exposure to tropical cyclone strength winds (exceeding 119 km/hr) is modeled by country from 1996-2016 (author calculations based on data and models by (Anderson et al., 2017; Knapp et al., 2010; Willoughby et al., 2006)). Exposure from tropical cyclones occurring in the Indian Ocean Basin may be underestimated due to missing storm tracks in the underlying data. This region is therefore excluded from the main empirical analysis (see SI for details).

governments, including their ability to conceive and implement responsive public policies and services, is therefore critical to the implementation of many disaster risk reduction activities. Even economically underdeveloped countries with high functioning states and civil societies have repeatedly demonstrated their capacity for adaptation to hazards (Adger, 2003). In contrast, governance failures have been implicated in some of the deadliest tropical cyclone 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 138,000 people in Myanmar (Guha-Sapir, 2018; Howe and Bang, 2017). Governance is also an important complement to financial resources for disaster risk reduction. For example, the state is an important intermediary in receiving and disbursing disaster aid and other multilateral finance transfers, such as those negotiated through the United Nations Framework Convention on Climate Change (Eakin and Lemos, 2006). Further, the effectiveness of national and international policies and programs will often depend upon implementation by local institutions.

Exposure to tropical cyclones is highly heterogeneous across but also within countries, with affected areas concentrated in coastal regions between 10 and 30 (-/+) degrees latitude (see Figure 2). Existing global studies of disaster mortality from tropical cyclones and other climate hazards are restricted to the country level (Alberini et al., 2006; Brooks et al., 2005; Hsiang and Narita, 2012; Kahn, 2005; Peduzzi et al., 2012), and therefore do not consider how institutions, socioeconomic conditions, and settlement patterns may differ from national averages in storm-affected regions. As a result, our understanding of the scale at which mechanisms operate to produce tropical cyclone vulnerability is limited. For example, to the extent that income is protective against tropical cyclone mortality, is this because national governments have more resources or because individuals are, on average, wealthier in the impact zone?

In this analysis, we address the limitations of previous efforts by testing for the importance of multiple risk factors at both the national and subnational level, using models that explicitly account for hazard exposure. We construct a new 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, we use spatial methods to match meteorological and socioeconomic data for each storm. Time-variant gridded population estimates and socioeconomic data 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 (CIESEN, 2005, 2017b; Anderson et al., 2017; Walsh et al., 2016; Knapp et al., 2010; NOAA, 2018). 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. Doing so improves our ability to identify relationships between socioeconomic factors and mortality. Second, we are able to study the importance of both national risk factors and local conditions in the exposure zone. Finally, because we construct hazard and exposure measures for all recorded tropical cyclones, we can examine the characteristics of storms that were not associated with a recorded disaster. This is a useful check on potential selection and measurement error issues in this literature, and provides additional insight into conditions under which tropical cyclone disaster may be avoided.

2 Results

The effects of institutions, income, and human development on tropical cyclone mortality are estimated via two sets of multivariate negative binomial regression models. The first set of models tests the importance of different national development characteristics on cyclone deaths. In addition to confirming the correlation between several facets of development and disaster deaths in the existing literature (Alberini et al., 2006; Brooks et al., 2005; Hsiang and Narita, 2012; Kahn, 2005; Peduzzi et al., 2012), our country-level models establish new evidence of a robust association between national government effectiveness and mortality from tropical cyclones. Government effectiveness is represented in our models using annual country-level scores, published by the World Governance Indicators and designed to capture the overall quality and independence of public policy and service delivery (Kaufmann et al., 2010). The second set of models investigates the importance of subnational development patterns for tropical cyclone risk. Socioeconomic conditions in the path of the storm are found to have a large effect on expected mortality. Importantly, we control for hazard exposure in all specifications presented (see SI Table 1 for a description of hazard exposure variables).

2.1 National government effectiveness and socioeconomic conditions

Government effectiveness, real GDP per capita, infant mortality rates and primary school enrollment are each good predictors of cyclone mortality in a country-level model that controls for hazard exposure. Including only one socioeconomic variable at a time, each of these four development indicators is a highly statistically significant predictor of tropical cyclone deaths (Table 5 (1-4)). This is consistent with existing evidence that GDP per capita is a useful proxy for tropical cyclone vulnerability (Hsiang and Narita, 2012; Peduzzi et al., 2012); an increase of one log-unit of GDP per capita is predictive of a 72% decrease in deaths in a model with no other socioeconomic variables. However, because governance, income, health and education are highly correlated, the independent effects of these variables

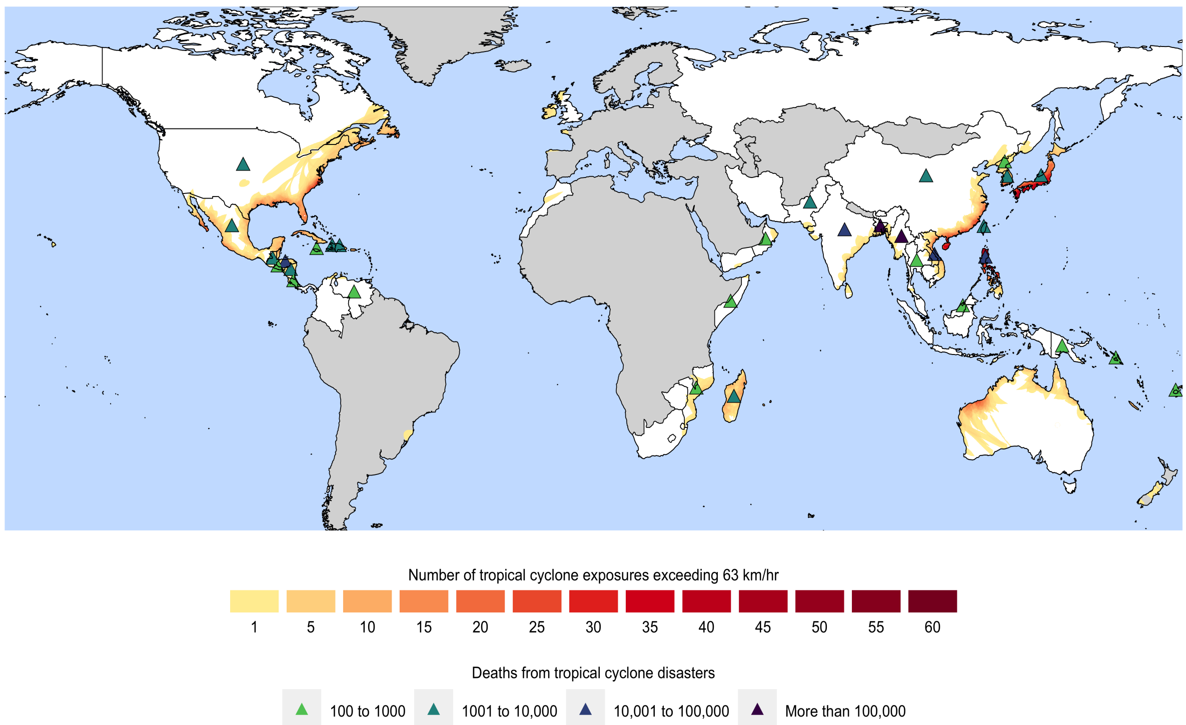

Figure 2: National tropical cyclone disaster deaths and subnational wind exposure (1979-2016). Total mortality is indicated by the shaded triangles for all countries with at least 100 total deaths from 1979-2016 (Guha-Sapir, 2018). Areas shaded in gray indicate countries that have not experienced tropical cyclone deaths during this period. The frequency of exposure to winds exceeding 63 km/hr are mapped at a 2.5 min (approximately 5 km) resolution (author calculations based on data and models by (Anderson et al., 2017; Knapp et al., 2010; Willoughby et al., 2006)). Exposure from tropical cyclones occurring in the Indian Ocean Basin may be underestimated due to missing storm tracks in the underlying data. This region is therefore excluded from the main empirical analysis (see SI for details).

cannot be identified by models with only a single socioeconomic variable.

To disaggregate the relationship, we test multiple aspects of national development in combination. This yields evidence of a large and statistically significant association between national government effectiveness and lower cyclone mortality. In a model with no other socioeconomic variables, a one standard deviation increase in government effectiveness is associated with a 67% decrease in deaths (Table 5 (1)). As illustrated in Figure 3, when we add GDP per capita and infant mortality to the model government effectiveness remains practically and statistically significant, accounting for a 43% decrease in mortality per standard deviation (Table 5 (6)). If we also include education this reduces the number of observations due to missing data, but once again the effect of governance remains large and statistically significant (Table 5 (7)).

In contrast, GDP per capita, health, and education are more sensitive to multivariate specifications. The decrease in mortality associated with a one standard deviation increase in log-unit GDP per capita falls from 72% to 52% when we add government effectiveness to the income-only model, remaining statistically significant (Table 5 (5)). However, GDP per capita loses statistical significance with the addition of infant mortality and education to the model (Table 5 (6-7)). The effects of infant mortality and education also lose statistical significance in the joint model. Our main results of the country-level analysis are robust to a range of permutations of the model and the dataset, including OLS estimation, as described in SI Section B.

2.1.1 Disasters versus hazard exposures

The source of the mortality data for this analysis is the Emergency Events Database (EM-DAT), a global database of disasters based on data from governments, UN-agencies and other non-governmental organizations. This raises two key concerns when these data are utilized to validate theories of vulnerability to natural hazards. First, when disaster is averted, perhaps due to the actions of effective and well-endowed institutions, hazard events are not represented in the EM-DAT. Second, the reliance on self-reported data creates the possibility of measurement error: for example under-reporting of deaths in countries with lower institutional capacity or corruption. This has implications beyond this analysis, as the EM-DAT database is the primary source of mortality data used in global studies of the risks posed by tropical cyclones and other natural hazards (e.g. Alberini et al., 2006; Brooks et al., 2005; Hsiang and Narita, 2012; Kahn, 2005; Peduzzi et al., 2012). The potential biases introduced by studying disasters versus hazards has been acknowledged by previous studies (e.g. Peduzzi et al., 2012), but has not previously been assessed empirically.

In order to compare tropical cyclones that do and do not result in disasters recorded by the EM-DAT, we construct a dataset that includes all country-storm exposures from

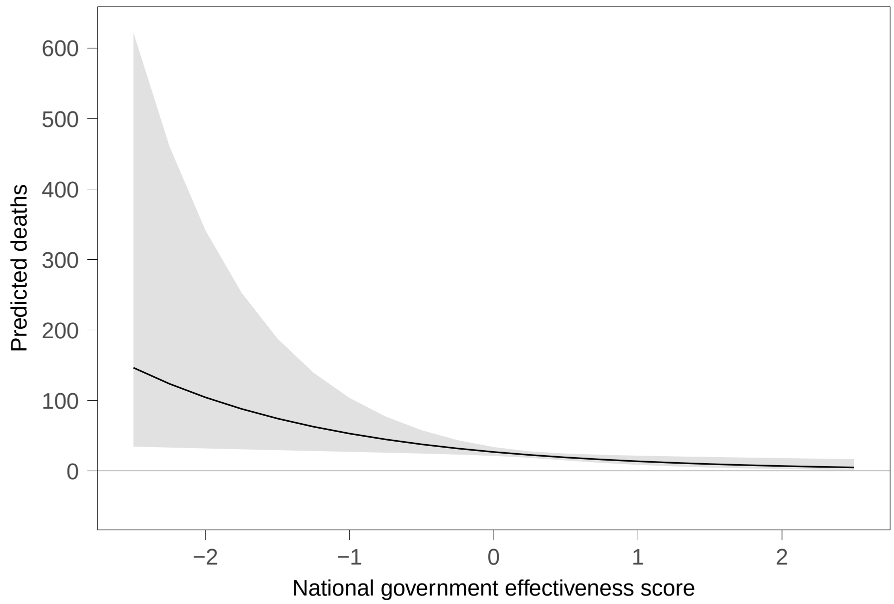

Figure 3: Predicted effects of national government effectiveness score on deaths, based on model (6) in Table 5. The shaded area represents the 95% confidence interval. Variables not shown, including real GDP per capita and infant mortality, are held at mean values for prediction.

1996 to 2016 based on the IBTrACS dataset. We can then estimate a logistical regression model of the probability that an instance of tropical cyclone exposure is included in the EM-DAT, given a vector of regressors that includes government effectiveness and real GDP per capita as well as controls for population exposure. Our results indicate that tropical cyclone exposures that occur in wealthier countries with more effective governments are less likely to be included in the EM-DAT (see Table 9). While we cannot completely disentangle the selection effects, this result indicates that selection bias does not account for the direction of the governance-mortality estimates in our main results and lends further support to our hypothesis that more developed countries have a higher capacity to avert disaster when exposed to hazard. We provide a detailed description of the EM-DAT dataset and further analysis of the robustness of these results to selection bias and measurements error in SI Section A.

2.2 Institutions and socioeconomic conditions in the cyclone wind-field

We also investigate whether storms have higher death tolls when exposure occurs in a part of a country with relatively weaker or less inclusive institutions. We select infant mortality rates (IMR) and settlements of politically excluded ethnic groups as proxies for the quality

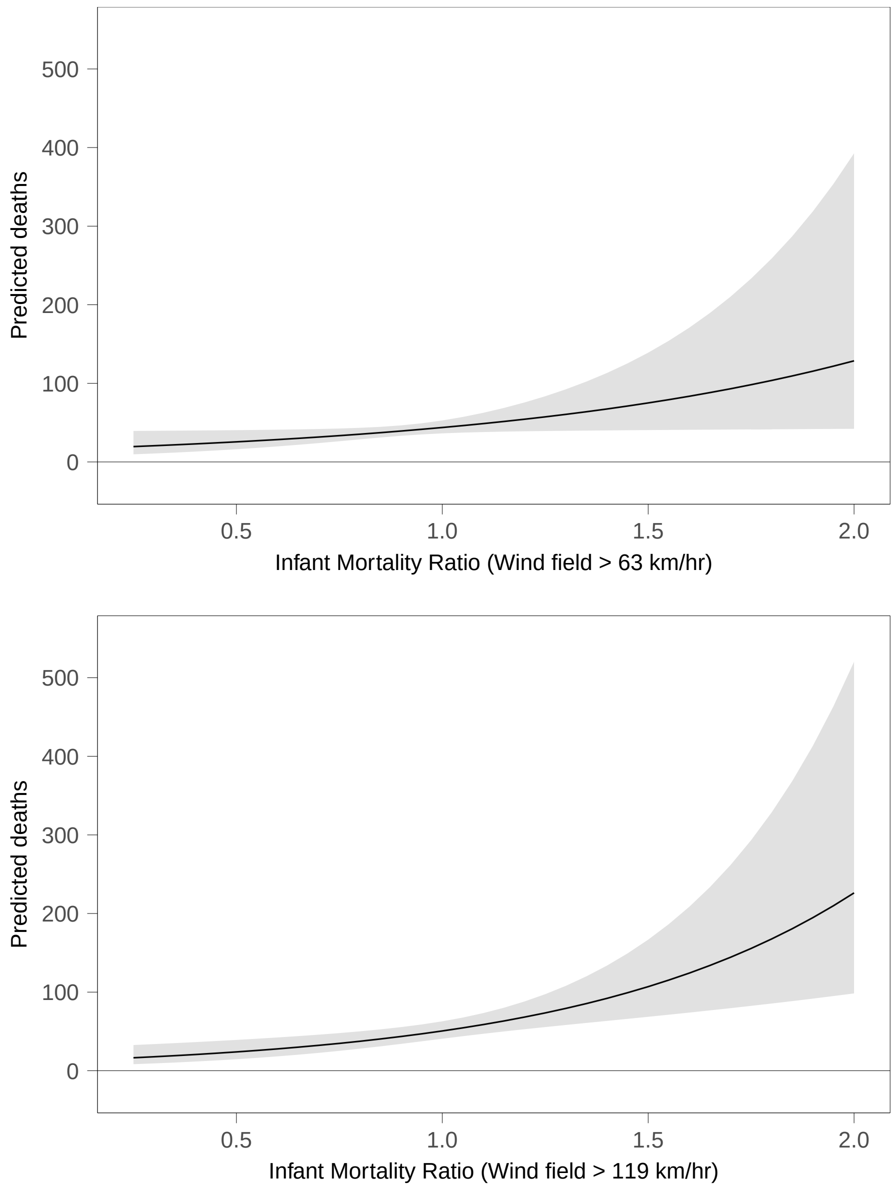

Figure 4: Predicted effects of the wind-field infant mortality ratio (IM ratio) on deaths. The IM ratio is the ratio of the infant mortality rate in the storm wind field compared to the national average. The top panel represents the predicted effect of the IM ratio in the tropical storm exposure zone ($>$ 63 km/hr). The bottom panel represents the expected effects of the IM ratio in the more intense tropical cyclone exposure zone ($>$ 119 km/hr). Predictions are based on models (1) and (3) of Table 12, respectively. The shaded areas represent the 95% confidence intervals.

and inclusiveness of institutions at the wind-field level. We exploit the spatial variability in where storms occur over nearly four decades (1979 to 2016) to capture whether the population in the wind-field is relatively better or worse off than the national average by these metrics. This allows us to compare outcomes across events that occurred in the same country but under different local institutional and socioeconomic conditions. (See Materials & Methods and SI Section A for details of how the wind field variables in this section are constructed.)

We test whether elevated infant mortality rates amongst the population living in the storm's wind-field are associated with an increase in mortality from tropical cyclones. Using a model that controls for national socioeconomic conditions as well as hazard exposure, we find that death tolls are higher when infant mortality rates are elevated within the cyclone wind field (IM ratio > 1). The predicted effects of the wind-field infant mortality ratio (IM ratio) on deaths are illustrated in Figure 4. An increase of one standard deviation in the IM ratio for the population in the tropical storm-strength wind field (sustained winds $>$ 63 km/hr) is associated with a 41% increase in event mortality (Table 12 (1)). At higher wind speeds the magnitude and statistical significance of the effect increases; a one standard deviation increase in the IM ratio for the tropical cyclone-strength wind field ($>$ 119 km/hr) is associated with an 80% increase in mortality (Table 12 (3)). The results for the more intense tropical cyclone wind fields are robust to various permutations of the model and the dataset, while the result for the tropical storm-strength wind field are more sensitive (SI Section B). We tested and did not find statistically significant evidence that the settlement of politically excluded ethnic groups in the wind field is associated with higher tropical cyclone mortality (see SI Section B for results and discussion).

We acknowledge that the statistical relationship between elevated infant mortality rates and disaster deaths may be interpreted in several ways. However, the importance of within-country variation in infant mortality rates demonstrates that disaster deaths are not only a function of the national context and hazard exposure. Mortality also depends upon local vulnerabilities, such as weak institutional capacity in the affected areas. Local conditions may be particularly important in areas that are exposed to sustained wind speeds in excess of 119 km/hr, the "very dangerous" threshold for tropical cyclone winds (NOAA, 2020).

3 Discussion

Our analysis generates novel empirical support for the role of governments and institutions in reducing tropical cyclone risk. First, we show that national government effectiveness is associated with lower mortality from tropical cyclones, independent of GDP per capita, health, and education. We then demonstrate the importance of within-country heterogeneities in vulnerability through the first global analysis of subnational institutional quality and tropical cyclone risk. Specifically, we find that death tolls are higher when infant mortality rates, a proxy for the quality and inclusiveness of local institutions, are elevated compared to the national average within the cyclone wind field. These results contribute to general theories of how effective and inclusive institutions can potentially moderate vulnerability and foster resilience to a range of shocks and stressors.

Our findings are salient to current questions about the role of institutions and economic development in risk reduction policies; questions made more urgent under climate change. The intensity and rainfall of the strongest tropical cyclones are expected to increase with warming seas (Christensen et al., 2013; IPCC, 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). Many tropical cyclone affected countries will also face increased risk from other climate change impacts, including extreme weather events such as droughts, floods and heat waves (IPCC, 2014). These challenges escalate as countries continue to struggle to eradicate poverty, hunger, disease, illiteracy, environmental degradation, and discrimination against women (IPCC, 2014; UN, 2015). Our analysis suggests that effective, multi-level institutions play an important role in the success of tropical cyclone risk reduction strategies; this is important in part because enhancing institutions may also benefit efforts to address these coinciding challenges.

We acknowledge several limitations of this work. First, we rely on data that includes only direct, short-term deaths and therefore our analysis does not capture how institutions and socioeconomic conditions may mediate longer-term mortality (Anttila-Hughes and Hsiang, 2013; Kishore et al., 2018). Second, our data and research design are not suitable for demonstrating causality. The challenges of overcoming multicollinearity in the analysis of observational data, and in particular disentangling the complex processes that underlie the correlation between income and institutions, are well-documented (e.g. Acemoglu et al., 2008; Boix, 2011; La Porta et al., 1999; Putnam, 1994). Our results do, however, go beyond previous efforts by demonstrating that there is an association between national government effectiveness and tropical cyclone mortality that cannot be explained by income, health or education. Finally, focusing on a single class of hazard limits our ability to generalize beyond tropical cyclones. Fortunately, our approach can be adapted to the study of additional hazards, scales and outcomes to gain further insight into the intersections of development and disaster risk.

4 Materials and Methods

Humanitarian disasters occur when a population is exposed to hazard and is unable to adapt or cope. Understanding mortality from tropical cyclones therefore requires information about the spatial intersection of physical hazards and socioeconomic systems at a high resolution. Here, we describe the methods and data sources used to build our event-based dataset of tropical cyclone disasters that extends from 1979 to 2016. This is followed by a description of the econometric methods that underlie our results.

Tropical cyclone exposure occurs when people or other assets are present in the hazard area. Our approach therefore recognizes the importance of accurately accounting for the number of people exposed to hazardous conditions, the intensity of exposure, and the local socioeconomic conditions of the affected population. 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 the severity of the shock. 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. Thus, we develop a method to match storms tracks to disaster data, parametrically model the spatial extent of storm exposure, and then determine the size and socioeconomic conditions of the exposed population for each event. The underlying data and methods developed to build the final dataset are described in further detail in SI Section A.

4.1 Dataset

The principal outcome variable for this analysis is the number of deaths by country-storm disaster event. While we draw on subnational data specific to the area of the country impacted by the storm, for each event these data are aggregated to the country-storm disaster unit of analysis. Our criteria for disaster (detailed in SI Section A) follows the EM-DAT, the source of the disaster mortality data for this analysis (Guha-Sapir, 2018). As illustrated in Figure 2, analysis of the EM-DAT data in concert with modeled storm winds demonstrates that tropical cyclone mortality risk is highly heterogeneous both across and within countries.

4.1.1 Measures of hazard intensity and exposure

Data on storms and disasters do not share a common identifier system. The EM-DAT disaster mortality data and storm tracks were therefore matched using a spatial algorithm that, for each disaster, looks for the closest storm in space and time. Tropical cyclone data were obtained from the Best Track Archive for Climate Stewardship (IBTrACS) Project (Knapp et al., 2010). Automated matches between the EM-DAT and IBTrACS were 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 published by governments and meteorological agencies were consulted.

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, track data is interpolated and winds are modeled using a parametric tropical cyclone model (Willoughby et al., 2006). This is implemented using a globally adapted version of *stormwindmodel* in R (see SI for details) (Anderson et al., 2017). The modeled winds are then rasterized at a 2.5 arc-minute resolution, and the spatial extent of the wind fields over land is mapped for each country-storm event. This is performed for multiple wind thresholds. Figure 5 illustrates the steps of this process for a single country-storm 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. Time-variant, subnational population estimates from the Center for International Earth Science Information Network's (CIESEN) Global Population Count Grid Time Series Estimates and Gridded Population of the World (Version 4.10) are interacted with the modeled wind fields to estimate the size of the populations exposed to winds of different intensities (CIESEN, 2017a,b). 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). Rainfall is represented by the maximum total rainfall over the duration of the storm for any grid cell in the country and within a 500km buffer of the storm track.

This analysis is limited to the satellite-era (1979+) of wind and rainfall data. Indian Ocean tropical cyclones are excluded from the statistical analyses, as the best track data in IBTrACS are incomplete for this region over the study period (RMC, 2018). Outlier events with more than 5,000 deaths are also excluded. See the SI for additional documentation and sensitivity analysis; the main findings presented in this paper are robust to these decisions.

4.1.2 Socioeconomic variables

Country-level socioeconomic variables are matched to tropical cyclone events based on year and country. Government effectiveness scores from the World Governance Indicators (WGI) measure the quality of public policies and service delivery by formal institutions (Kaufmann et al., 2010). These scores are a subjective and normalized measure of governance at the

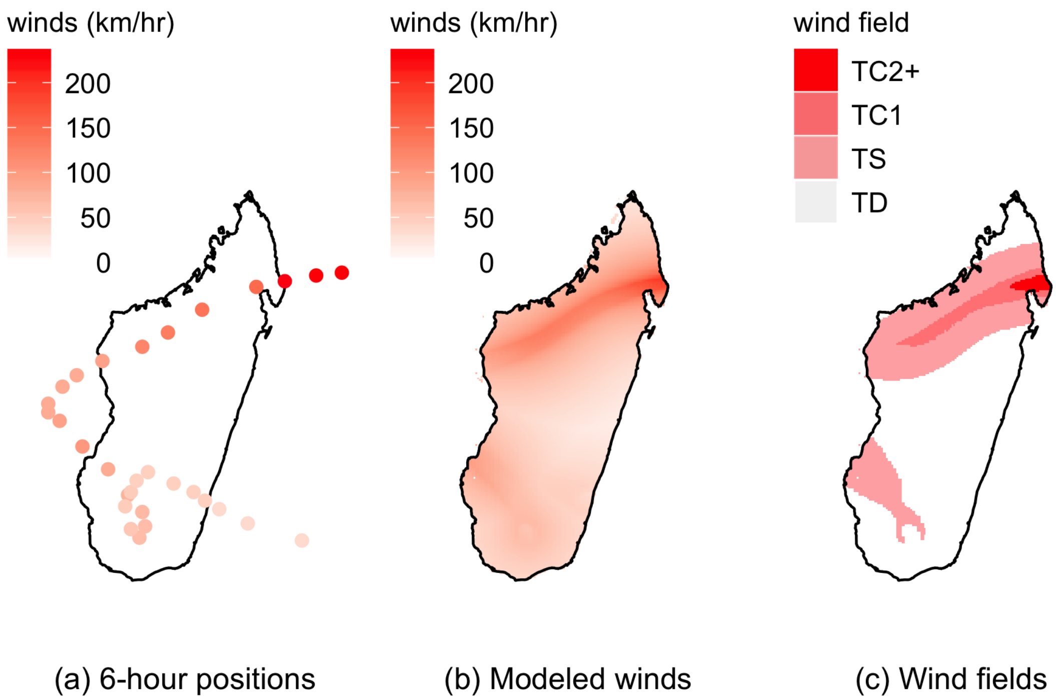

Figure 5: Modeling tropical cyclone wind fields for Cyclone Gafilo (2004) in Madagascar. I begin with (a) the 6-hourly wind speeds and locations (Knapp et al., 2010). Using a parametric wind speed model (Willoughby et al., 2006) implemented in the software R (Anderson et al., 2017), I then estimate (b) 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.

country level, available starting in 1996. National development data on income, health and education are taken from the World Development Indicators (WDI) (WDI, 2018) and other sources (Feenstra et al., 2015; Hong Kong Observatory, 2017; MOHW, 2017). GDP per capita and infant mortality rates are lagged by one year.

Within countries, local institutional quality and inclusion are proxied using subnational infant mortality rates and spatial data on the political exclusion of ethnic groups. For each storm, these variables are constructed for the tropical storm (> 63 km/hr) and tropical cyclone (> 119 km/hr) wind fields. The infant mortality ratio (IM ratio) is the ratio of the infant mortality rate (IMR) in the storm wind field to the national IMR, based on data from the Poverty Mapping Project's Global Subnational Infant Mortality Rates for the year 2000 (CIESEN, 2005). Country dummies are included in all subnational analysis, as the resolution of the subnational infant mortality data varies by country. Given that subnational IMR estimates are time-invariant, one concern is that infant mortality might be elevated in certain parts of the country due to the direct or indirect impacts of tropical cyclones. Robustness checks that recreate the main results excluding 1999-2000 and also for only post-2001 are therefore presented in SI Tables 13 & 14.

The population-weighted percentage of the wind field that is settled by an excluded ethnic group is also constructed. This is based on data from the Ethnic Power Relations (EPR) Dataset Family (Cederman et al., 2010; Vogt et al., 2015; Wucherpfennig et al., 2011). The 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.

4.2 Methods

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 deaths are non-negative integer values. The simpler Poisson model is not used because the data violate the equidispersion principle $E[y_i \mid \mathbf{x}_i] = Var[y_i \mid \mathbf{x}_i]$. The negative binomial regression model allows us to relax this assumption such that the variance depends on the mean and a dispersion parameter $\alpha = 1/\theta$. We use the Negbin 2 (NB2) form of the negative binomial regression model represented in equations 2-4, following Greene (Greene, 2012, p. 808). The NB2 model has several useful properties compared to other negative binomial models, including that it is robust to distributional misspecification (Cameron and Trivedi, 2013). However, model standard errors may be inconsistent in cases of distributional misspecification (Hilbe, 2014). We therefore estimate robust standard errors for all negative binomial regressions presented in this analysis. One alternative would be to cluster standard errors by year and country; we compute these for comparison and find that they are very similar to the White standard errors. Comparable ordinary least squares (OLS) regression estimates are also presented and discussed in SI Section B. The NB2 model is

$$\text{Prob}(Y = y_i \mid \mathbf{x}_i) = \frac{\Gamma(\theta + y_i)}{\Gamma(y_i + 1)\Gamma(\theta)} r_i^{y_i} (1 - r_i)^{\theta}, \tag{2}$$

where

$$\lambda_i = \exp(\mathbf{x}_i' \boldsymbol{\beta}), \tag{3}$$

and

$$r_i = \lambda_i / (\theta + \lambda_i). \tag{4}$$

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: $\boldsymbol{\beta}, \theta$.

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A Dataset

A.1 Dependent variable: tropical cyclone mortality

The tropical cyclone mortality data used in this analysis was obtained from the Emergency Events Database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the School of Public Health of the Université Catholique de Louvain in Brussels, Belgium (Guha-Sapir, 2018). The EM-DAT is a database of country-level information about disaster events, including deaths. Disaster events included in the EM-DAT must meet at least one of the following criteria: (1) 10 or more people were killed; (2) 100 or more people were affected; (3) a state of emergency was declared; or (4) a call for international assistance was issued. Our analysis follows this criteria for disasters, and is further limited to events of the subtype 'tropical cyclone' in the EM-DAT database.

According to data from the EM-DAT, tropical cyclones precipitated over 423,000 deaths from 1979 to 2016. Fatal tropical cyclone disasters occurred in 85 countries, but 95% of those deaths are concentrated in just 10 countries (Guha-Sapir, 2018). In order from most to least tropical cyclone deaths these are: Bangladesh (161,616 deaths), Myanmar (138,709), the Philippines (33,865), India (19,973), Honduras (14,847), Vietnam (10,379), China (9,023), Haiti (4,252), Nicaragua (3,884) and the United States (2,775). Further, just two storms account for more than half of the total deaths: the 1991 Cyclone Gorky in Bangladesh (138,866 deaths) and the 2008 Cyclone Nargis in Myanmar (138,366). Figure 6 maps total deaths by country over the 1979 to 2016 study period. Large outliers are excluded from the main dataset, but our findings are robust to this decision (see replication files and SI Section B).

The EM-DAT defines deaths as the "[n]umber of people who lost their life because the event happened." The EM-DAT also includes data on the number of people affected and economic damages from storms. The focus of this analysis is on mortality, both because of its first-order importance and also because the definition of a death is more likely to be consistently applied across a range of contexts and reporting systems. However, this does not fully address concerns about measurement error. As discussed in the main text, much of the empirical literature on mortality from tropical cyclones and other hazards relies heavily on data from the EM-DAT (e.g. Alberini et al., 2006; Brooks et al., 2005; Hsiang and Narita, 2012; Kahn, 2005; Peduzzi et al., 2012). It is therefore important that we consider how the database is constructed and the nature of the underlying data, which are compiled from various government and non-governmental agencies. There may be sources of measurement error in the data that we are unable to test or correct for. For example, it may be that countries with less government capacity and fewer resources are more likely to under-report deaths, or that death counts from high-casualty events are more likely to suffer from measurement error. While the EM-DAT's triangulation between government, United Nations (UN) and other non-governmental sources works to minimize this, they do rely on data from national and regional reporting systems which may vary in design and implementation. Additionally, as discussed in the main text, the EM-DAT is a database of disasters and not instances of hazard or potential disaster. It therefore 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 governments and 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 missing observations from less-developed countries in the EM-DAT. While we cannot fully disentangle these possible selection effects, by constructing a dataset of all country-storm exposures from 1996 to 2016 we are able to test if the EM-DAT is more or less likely to include disasters corresponding to tropical cyclone exposure occurring in countries with better governments and higher incomes. This analysis is discussed in the main text and results are reported in Table 9. In sum, we find that tropical cyclone events are more likely to be included in the EM-DAT when less-developed countries are exposed.

A.2 Control variables: hazard intensity and exposure

Our approach to constructing the hazard intensity and exposure variables is described in the main text. This section will revisit this methodology in additional detail. Table 1 describes the physical control variables constructed to measure hazard intensity and exposure in the analysis, as well as the sources they are drawn from. Descriptive statistics can be found in Tables 3 & 10. The cumulative population exposure from 1979 to 2016 is mapped by country in Figure 7.

A.2.1 Matching storms and disasters

Data on storms and disasters do not share a common identifier system; it is not obvious what storm in the meteorological database triggered each tropical cyclone disaster in the EM-DAT. Event mortality data from the EM-DAT reports disaster impacts from tropical cyclones by country-level event. Tropical cyclone data consisting of maximum sustained wind speed (MSWS) geo-referenced at 6-hour intervals are obtained from the Best Track Archive for Climate Stewardship (IBTrACS) Project (Knapp et al., 2010). One approach that has been utilized in the literature to overcome the disconnect between physical and socioeconomic data sources is to generate a country-year panel that estimates total annual exposure and also sums impact data by country-year, creating a panel dataset (Hsiang and Narita, 2012). However, in order to exploit variation in storm-specific exposure patterns, an event-based dataset is needed. We therefore follow a method similar to Peduzzi and co-authors (Peduzzi et al., 2005, 2012) and match IBTrACS and EM-DAT event records. The EM-DAT disasters and IBTrACs storms were matched using a spatial algorithm that, for each disaster, looks for matches between storms and disasters in space and time. The automated match was then manually reviewed for accuracy.

The six basic steps to the matching process are outlined below:

1. For each EM-DAT record, an algorithm first identifies all 6-hour IBTrACS records that match the EM-DAT event dates (+/- 1 day).

2. The minimum distance is calculated between the country where the EM-DAT event occurred and the location of each of the date-matched 6-hour IBTrACS records.

3. The storm track with the 6-hour IBTrACS record that has the shortest distance to the country is designated the 'best match.' Alternative storm-track matches and their shortest 6-hour match-distance are also saved.

4. Ambiguous matches are flagged for attention during manual review (i.e. when the minimum distance for an alternative storm is within 200 miles of the 'best match' or when minimum distance for the 'best match' is more than 200 miles).

5. This is repeated for each EM-DAT tropical cyclone disaster record.

6. Automated matches are reviewed for accuracy using fields (as available) including storm names; impact location notes; storm reports from meteorological agencies; government and media reports; and other sources of information on exposure, impacts and damages. Further details are available upon request (excluding the raw EM-DAT data, which is proprietary).

A.2.2 Modeling tropical cyclone winds

Next we translate the 6-hour storm positions into modeled wind fields. Constructing spatial maps of the wind fields at different intensities allows us to then determine the size and socioeconomic characteristics of the population most impacted by a storm. Tropical cyclone maximum sustained wind speeds were modeled for all tropical cyclones in the Best Track Archive for Climate Stewardship (IBTrACS) Project from 1979-2016 (Knapp et al., 2010) at a 2.5 arc-minute resolution using a parametric wind speed model (Willoughby et al., 2006).

Modeled winds are based on storm track data obtained from the IBTrACS Project (Version: v03r10) downloaded from the website on October 8, 2017 (NOAA, 2017). The IBTrACS Project, developed by the National Oceanic and Atmospheric Administration (NOAA) National Climate Data Center (NCDC), compiles best track data from forecast centers around the world to create a global dataset of tropical cyclone locations and intensities. According to the United States National Hurricane Center, a Best Track is:

> A subjectively-smoothed representation of a tropical cyclone's location and intensity over its lifetime. The best track contains the cyclone's latitude, longitude, maximum sustained surface winds, and minimum sea-level pressure at 6-hourly intervals. Best track positions and intensities, which are based on a post-storm assessment of all available data, may differ from values contained in storm advisories. They also generally will not reflect the erratic motion implied by connecting individual center fix positions.
>
> — United States National Hurricane Center, 2016

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 limited to 1979+ and allows for a linear time trend. IBTrACS does not presently correct for differences in agency data collection and processing methods; instead, IBTrACS provides an average (and other summary statistics) of available estimates as well as a compilation of the original source data from each agency (Knapp et al., 2010). This analysis uses the provided average and includes regional (for the national analysis) or country (for the subnational analysis) geographic controls in our preferred specifications to control for differences in data collection and processing by regional organizations.

Indian Ocean tropical cyclones are excluded from this analysis, primarily because the storm track data in IBTrACS appears to be incomplete for this region. During the data cleaning and matching process and based on comparison with the Indian Meteorological Department's Cyclone eAtlas-IMD (RMC, 2018) it was evident that many storms in the EM-DAT were missing from the IBTrACS within the time frame of this analysis (particularly through the 1990s). Secondary concerns include the prevalence of outlier events (i.e. Cyclone Nargis) and first-order importance of storm surge, which is not modeled in this analysis, for Indian Ocean tropical cyclones. Storm surge, particularly in the uniquely positioned Irrawaddy and Ganges-Brahmaputra-Meghna deltas, may not be well captured by modeled wind speeds for this region. However, the main results of the analysis are robust to the decision to exclude the Indian Ocean basin from this analysis (results not reported, see replication files).

Best Track data represent only the central track of a storm, geo-referenced at 6-hour intervals. A parametric wind speed model by Willoughby and co-authors (Willoughby et al., 2006) allows us to produce estimates of maximum sustained wind speed suitable for spatial matching with gridded population and socioeconomic data. Because a comprehensive global dataset including information storm radius and shape is not currently available, a key advantage of the Willoughby model for a global analysis covering the 1979-2016 time period is that it requires only central storm track data. However, this may limit its accuracy in modeling the size and shape of some storms, particularly those outside the Northwest Hemisphere and storms that undergo extratropical transition (Loridan et al., 2015). The Willoughby model has been implemented by Anderson and colleagues for the Northwest Hemisphere in an open source R software package *stormwindmodel* (Anderson et al., 2017). For the purposes of this analysis, the software was forked on GitHub and adapted for global use (available at https://github.com/liztennant/stormwindmodel). One limitation is that a small number of storms that cross between the Eastern and Western Hemispheres are not modeled.

For every storm between 1979 and 2016 in the IBTrACS data set, maximum sustained wind speeds were first modeled globally at a 0.5 degree resolution. Next, they were modeled at a 2.5 arc-minute resolution for all grid cells over land that exceeded 5 m/s (18 km/hr) in the initial courser run. From here we map the spatial extent of tropical storm (sustained winds greater than 18 m/s or 63 km/hr), tropical cyclone (sustained winds greater than 33 m/s or 119 km/hr), and intense tropical cyclone (sustained winds greater than 43 m/s or 154 km/hr) wind fields over land at the 2.5 arc-minute resolution.

A.2.3 Constructing hazard exposure variables

Once the wind hazard has been mapped, the wind fields are spatially matched with gridded, time-variant population data to construct estimates of population exposure to winds. Gridded population estimates are obtained from the Center for International Earth Science Information Network's (CIESIN) Global Population Count Grid Time Series Estimates (1970, 1980, 1990, 2000) and the Gridded Population of the World (Version 4.10) (2000, 2005, 2010, 2015, 2020) (CIESEN, 2017a,b). These 5- and 10-year estimates are interpolated for each 2.5 arc-minute grid cell using a natural spline to produce annual population estimates for each grid cell. For each storm in the dataset, we then sum the population for each grid cell that meets the wind threshold in the year that the storm occurred. This is done for the tropical storm ($>$ 18 m/s or 63 km/hr), tropical cyclone ($>$ 33 m/s or 119 km/hr), and intense tropical cyclone ($>$ 43 m/s or 153 km/hr) force wind fields.

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 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. Previous analyses of tropical cyclone exposure have typically not included rainfall (e.g. Hsiang and Narita, 2012; Peduzzi et al., 2012). However, the maximum rainfall variable is a relatively course indicator of hazard intensity and does not capture the size of the population exposed. More sophisticated estimates were beyond the scope of this analysis due to the low resolution of the available rainfall data, and because what constitutes potentially dangerous or damaging exposure from rainfall may be more heterogeneous than in the case of wind speed (i.e. dependent on local hydrology). That even a course rainfall intensity metric appears to have predictive power for mortality, independent of wind exposure, in many of the models estimated in this analysis suggests that it may be a worthwhile to explore better rainfall hazard and exposure metrics in future research efforts.

A.3 Independent variables: institutions, income, and human development

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

A.3.1 National government effectiveness, income, health and education

The WGI government effectiveness scores are a subjective and normalized measure of governance at the country level. They are designed to capture:

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

For each year, government effectiveness has approximately zero mean, unit standard deviation, and a range of roughly -2.5 to 2.5 for the global dataset (Kaufmann et al., 2010). The WGI are available biannually from 1996 to 2002 and then annually (Kaufmann et al., 2010). Storms in the 1996 to 2016 dataset are matched to the nearest annual governance score by storm date. Figure 8 maps WGI government effectiveness scores in 2016 for countries that experienced tropical cyclone deaths between 1979 and 2016.

Country-year panel data on income, health, and education (see Table 2) are matched to tropical cyclone events based on the country and year in which the storm occurred. Real

GDP per capita is obtained from the World Bank's World Development Indicators (WDI), supplemented by the Penn World Tables (World Bank, 2019; Feenstra et al., 2015). Infant mortality rates are also primarily taken from the WDI (World Bank, 2019). The WDI are supplemented by data from the Hong Kong Census and Statistics Department and the Taiwan Ministry of Health and Welfare (C&SD, 2016; MOHW, 2017). As illustrated in the descriptive statistics (see Table 3), countries affected by tropical cyclone disasters fall across the development spectrum, from Least Developed Countries to wealthy nations. The GDP per capita and infant mortality rate variables are lagged by one year to address possible endogeneity.

Tropical cyclones affect many small island territories with varying degrees of sovereignty. While physical variables (i.e. population exposure) are based on the geographic territory impacted, I designate the relevant 'national' government based on responsibility for disaster management in that territory. For example, there is evidence that the UK government and military played a major role in responding to disasters during the colonial period in Hong Kong, so for the purposes of this analysis Hong Kong is designated as part of the United Kingdom from 1979-1996. Following the handover to China in July of 1997, the territory is designated the Hong Kong Special Administrative Region (SAR) of China and treated as distinct from the People's Republic of China. This is because the SAR appears to play the primary role in tropical cyclone preparedness and response. For example, the Hong Kong Observatory is the responsible government department for "issuing warnings on weather-related hazards" (Hong Kong Observatory, 2017) and reports on tropical cyclone disaster events are issued by the the Hong Kong SAR government (for examples see ReliefWeb). If a territory is designated as distinct from a disaster governance perspective, but territory-level data is not available, events impacting that territory are considered missing observations and excluded from the analysis. Detailed notes on these decisions are available upon request.

A.3.2 Socioeconomic conditions in the impact zone

We construct two classes of wind-field level variables based on subnational data. For each storm, these variables are constructed for populations living within the tropical storm ($>$ 63 km/hr) and tropical cyclone ($>$ 119 km/hr) wind-fields. 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 average national IMR. This is based on data from the Global Subnational Infant Mortality Rates for the year 2000 from the Poverty Mapping Project (CIESEN, 2005). Because the resolution of the subnational infant mortality data is highly variable, I include country controls in all models containing the infant mortality ratio variables.

The second subnational variable is the population-weighted percentage of the wind field that is settled by an excluded ethnic group. This is based on data from the Ethnic Power

Relations (EPR) Dataset Family (Cederman et al., 2010; Vogt et al., 2015; Wucherpfennig et al., 2011). EPR provides annual data on politically relevant ethnic groups' access to state power, and classifies groups as excluded if they are powerless, discriminated or self-excluded according to the following definitions:

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

In Table 2 I describe the key socioeconomic variables and the sources they are drawn from. See Tables 3 & 10 for descriptive statistics.

B Results

The main results from the 1996-2016 national cyclone mortality analysis are presented in Table 5 and the 1979-2016 subnational analysis in Table 12. These are discussed in the main text; this section focuses primarily on robustness checks to the preferred specifications. Statistical tables supporting the main and supplementary texts are presented in SI Section C.

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

All negative binomial regression results in the main text and supplementary information are presented as Incident Rate Ratios (IRRs), obtained by exponentiating the estimated coefficients of the negative binomial regression models. Thus, the null hypothesis is $H_0 : IRR = 1$. If the regression coefficient is negative the $IRR < 1$ and if the regression 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.

B.1 National development and disaster mortality: robustness checks

The main results of the analysis of national socioeconomic determinants of tropical cyclone mortality are robust to various permutations of the model and the dataset. In Tables 7 and 8 I present OLS estimates comparable to the main negative binomial results in Table 5. As in the main results, government effectiveness has a large and statistically significant association with lower mortality in all OLS specifications tested in Tables 7 and 8. This also holds for various permutations of the dataset; for example, including outliers or events in the Indian Ocean basin (results not reported, see replication files).

However, these results are somewhat sensitive to the choice of geographic controls. Specifically, the government effectiveness result is not supported by a model that relies purely on within country variation. This is due to the relative stability of government effectiveness within most countries from 1996-2016; the span for which the World Governance Indicators are available. It is due to this insufficient variation in within country government effectiveness that we include regional but not country geographic controls in the preferred specifications (Table 5). Excluding these regional controls has a modest effect on the coefficients and standard errors, but the main results hold (see Table 6).

B.2 Institutions and socioeconomic conditions in the cyclone wind-field: ethnic marginalization

In order to test the hypothesis that ethnic marginalization in the wind field increases mortality, we evaluate the extent to which the storm wind field overlaps with the settlement of a politically excluded ethnic group. The direction of the coefficients for excluded settlements on cyclone mortality are consistent with our hypothesis in the preferred specifications (Table 12), but we do not detect a statistically significant relationship in any model tested (Tables 12 - 16). Previous work has in fact found some evidence that higher levels of ethnic fractionalization are correlated with lower disaster mortality at the country level (Kahn, 2005). Our results may be explained in several ways. These groups, although politically excluded, may 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 indigenous knowledge and institutions or strong social capital at the local level. Alternatively, it could simply be that our measure captures only the extent of settlements of excluded groups, not the density of settlement by excluded groups in these areas. Further, we have no data on whether mortality is higher or lower amongst members of an excluded group.

B.3 Institutions and socioeconomic conditions in the cyclone wind-field: robustness checks

The association between elevated infant mortality rates in the tropical cyclone-force wind field ($>$ 119 km/hr) and increased disaster mortality appears to be highly robust. However, when the wind field is defined at a lower intensity ($>$ 63 km/hr) estimates remain positive but lose statistical significance in some alternative specifications.

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. As the subnational IMR estimates are for the year 2000, we therefore rerun the negative binomial analysis excluding the years 1999 and 2000 and also for 2001-2016 (Tables 13 and 14). In both cases the coefficient on the less intense ($>$ 63km/hr) wind field remains positive but loses statistical significance. However, for more intense storms we find that the IM ratio in the impact area of $>$119 km/hr is large and highly statistically significant in all specifications (model (3) of Tables 12, 13 and 14). We also report OLS regression results for models comparable to Table 12 in Tables 15 and 16. Once again, while all estimates of the IM ratio are positive, they are only statistically significant for the more intense (> 119 km/hr) wind field.

C Supplementary Figures and Tables

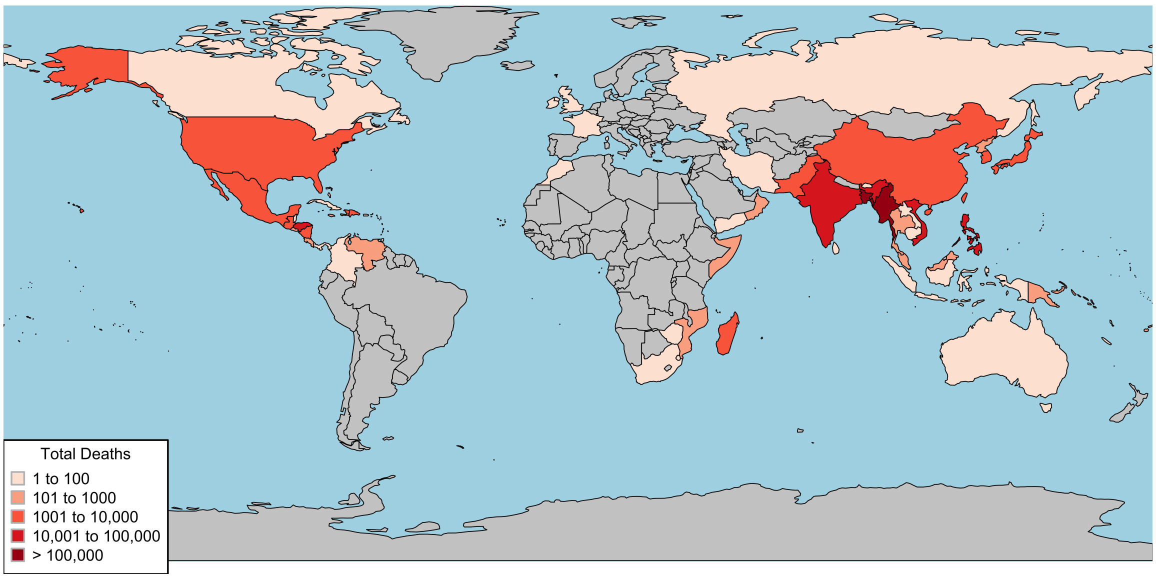

Figure 6: Cumulative deaths from tropical cyclone disasters, 1979 to 2016. Based on data from the EM-DAT (Guha-Sapir, 2018).

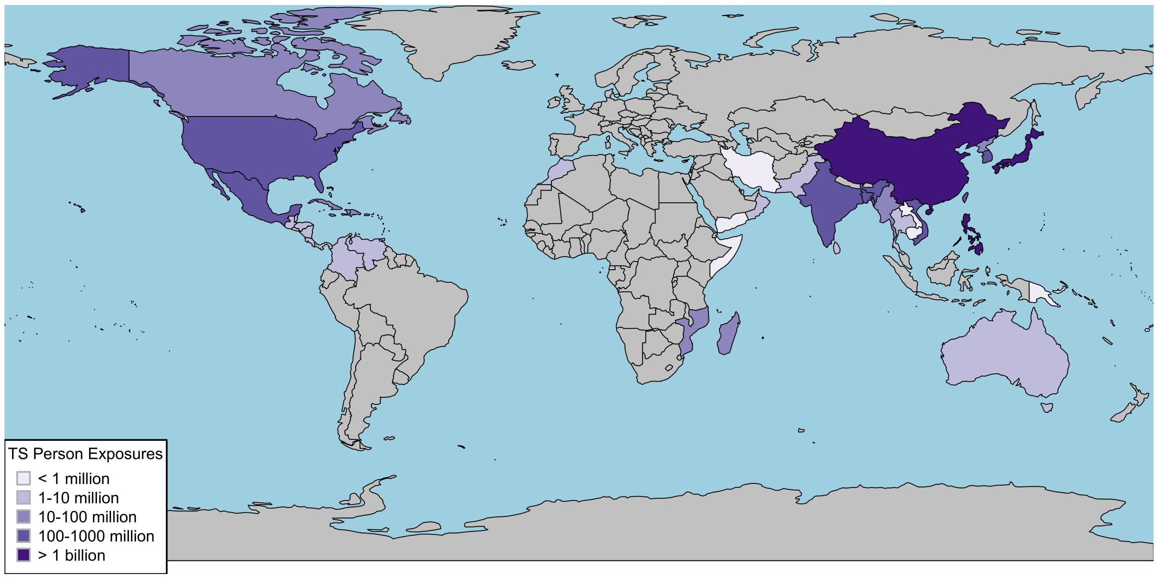

Figure 7: Cumulative population exposure to tropical storms and cyclones (sustained winds $>$ 63 km/hr) from 1979 to 2016. See Table 1 for a description of the population exposure variables. Based on source data from (CIESEN, 2017a,b; Knapp et al., 2010).

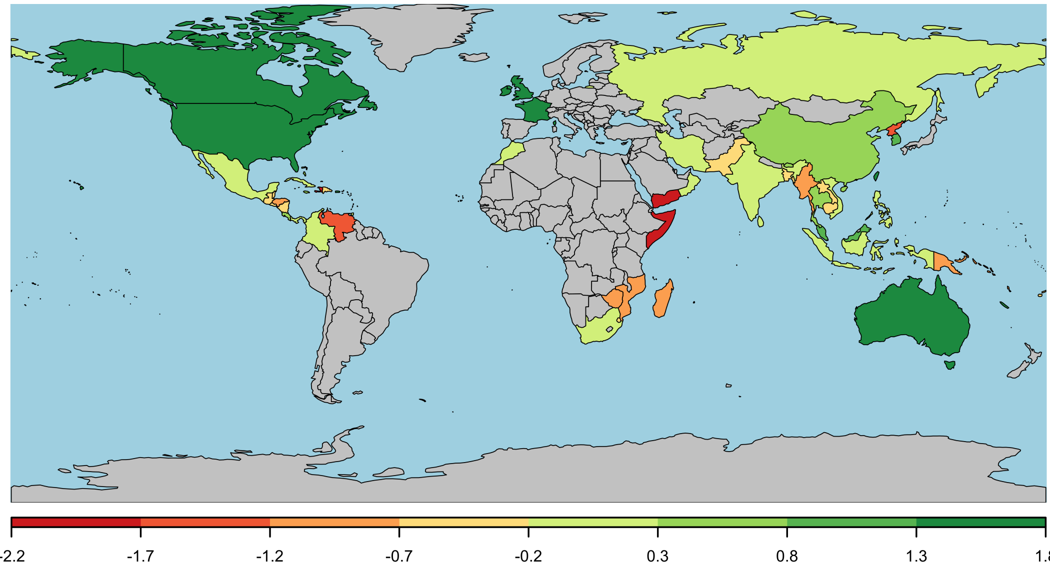

Figure 8: National government effectiveness scores for tropical cyclone affected countries, 2016. Higher scores indicate more effective governance. Countries are shaded in grey if 2016 WGI are not available or the country did not experience a deadly tropical cyclone disaster between 1979 and 2016. Source data from the EM-DAT (Guha-Sapir, 2018) and the World Governance Indicators (Kaufmann et al., 2010).

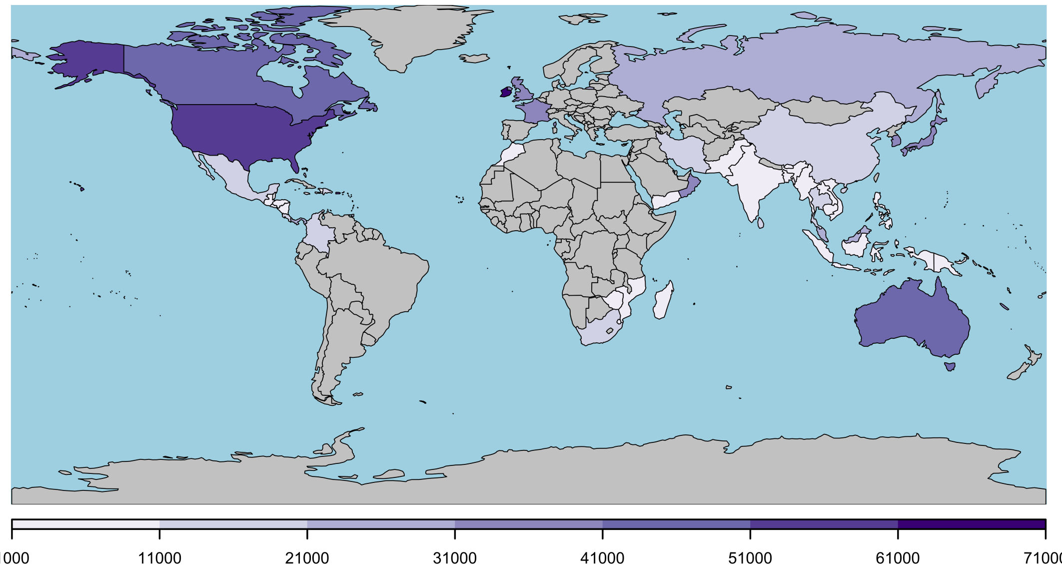

Figure 9: Real GDP per capita (2010$) for tropical cyclone affected countries, 2016. Countries are shaded in grey if GDP data are not available or the country did not experience a deadly tropical cyclone disaster between 1979 and 2016. Source data from the EM-DAT (Guha-Sapir, 2018) and the World Bank World Development Indicators, supplemented with data from Penn World Tables (WDI, 2018; Feenstra et al., 2015)

Table 1: Summary of hazard intensity and exposure variables

Variable	**Description**	**Source**
Pop. (millions) exposed to winds 63-118 km/hr	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 (CIESEN, 2017a,b). Spatial extent of wind field modeled using *stormwindmodel* (Anderson et al., 2017; Willoughby et al., 2006) and IBTrACS data (Knapp et al., 2010).
Pop. (millions) exposed to winds 119-153 km/hr	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.
Pop. (millions) exposed to winds > 153 km/hr	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). Population data from the the Center for International Earth Science Information Network (CIESEN, 2017a,b).

Table 2: Summary of socioeconomic variables

Variable	**Scale**	**Years**	**Description**	**Source**
Government effectiveness	country	1996-2016*	Government effectiveness	The World Governance Indicators (Kaufmann et al., 2010).
Real GDP per capita (ln)	country	1978-2016	The natural logarithm of Real GDP per capita (constant 2010 US$)	The World Development Indicators and Penn World Tables (WDI, 2018; Feenstra et al., 2015).
Infant mortality rate	country	1978-2016	Mortality rate, infant (per 1,000 live births)	The World Development Indicators (WDI, 2018)
Education	country	1979-2016	School enrollment, primary (% net)	The World Development Indicators (WDI, 2018).
Infant mortality ratio	subnational	2000	Population-weighted infant mortality rate (IMR) in wind field** / average national IMR	Center for International Earth Science Information Network (CIESIN), Columbia University (CIESEN, 2005; WDI, 2018).
Excluded ethnic group (% of wind field)**	subnational	1979-2016	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

Table 3: Descriptive statistics for national analysis dataset (1996-2016)

variable	min	max	median	mean	std.dev
Deaths	0.00	3682	5.00	45.52	231.0
Government effectiveness	-2.27	1.99	0.09	0.25	0.90
Real GDP per capita	467.7	53632	8593	16216	15076
National infant mortality rate	1.70	138.7	18.10	20.82	17.70
Primary school enrollment (% net)	55.58	99.94	94.91	93.06	6.09
Pop. (millions) exposed to winds 63-118 km/hr	0.00	92.68	0.28	6.09	13.22
Pop. (millions) exposed to winds 119-153 km/hr	0.00	25.51	0.00	0.35	1.46
Pop. (millions) exposed to winds $>$ 153 km/hr	0.00	3.15	0.00	0.04	0.21
Maximum rainfall exposure (mm)	0.00	1551	207.1	234.0	186.7

Table 4: Pairwise correlations for national analysis 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 enroll-ment (% 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	-0.095	-0.095	0.098	-0.068	0.013	0.097	0.038	0.061
Governance	-0.095	1.000	0.895	-0.688	0.415	0.213	0.124	0.019	0.188
RealGDPpc	-0.095	0.895	1.000	-0.655	0.397	0.173	0.093	0.044	0.107
IMR	0.098	-0.688	-0.655	1.000	-0.758	-0.204	-0.097	-0.045	-0.073
Education	-0.068	0.415	0.397	-0.758	1.000	0.092	-0.018	0.026	-0.054
ExpTS	0.013	0.213	0.173	-0.204	0.092	1.000	0.344	0.051	0.204
ExpTC1	0.097	0.124	0.093	-0.097	-0.018	0.344	1.000	0.237	0.194
ExpTC2	0.038	0.019	0.044	-0.045	0.026	0.051	0.237	1.000	0.070
MaxRain	0.061	0.188	0.107	-0.073	-0.054	0.204	0.194	0.070	1.000

Table 5: National determinants of TC mortality (1996-2016): Negative binomial regression with regional controls

	IRR (1)	IRR (2)	IRR (3)	IRR (4)	IRR (5)	IRR (6)	IRR (7)
Government Effectiveness	0.252 ***	-	-	-	0.497 **	0.508 *	0.393 *
	(0.034)	-	-	-	(0.129)	(0.135)	(0.151)
Ln real GDP per capita (t-1)	-	0.325 ***	-	-	0.514 **	0.535	0.710
	-	(0.046)	-	-	(0.126)	(0.188)	(0.296)
National infant mortality rate (t-1)	-	-	1.071 ***	-	-	1.004	0.994
	-	-	(0.006)	-	-	(0.012)	(0.020)
Primary school enrollment (% net)	-	-	-	0.946 ***	-	-	1.014
	-	-	-	(0.015)	-	-	(0.020)
Pop. (millions) exposed to winds 119-153 km/hr	1.468 ***	1.453 ***	1.441 ***	1.705 ***	1.448 ***	1.447 ***	1.664 ***
	(0.096)	(0.102)	(0.103)	(0.103)	(0.099)	(0.099)	(0.096)
Pop. (millions) exposed to winds > 153 km/hr	1.089	1.564	1.080	0.650	1.546	1.525	1.239
	(0.271)	(0.380)	(0.241)	(0.258)	(0.376)	(0.370)	(0.667)
Maximum rainfall exposure (mm)	1.002 ***	1.002 ***	1.002 **	1.001	1.002 ***	1.002 ***	1.002 **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time (years)	0.950 *	0.971	0.960	0.965 *	0.965	0.965	0.974
	(0.021)	(0.018)	(0.024)	(0.017)	(0.020)	(0.021)	(0.020)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	868	837	866	505	836	836	486

Negative binomial results are presented as Incident Rate Ratios (IRRs), obtained by exponentiating the estimated coefficients. Thus, we are testing the null hypothesis that IRR = 1. If the regression coefficient is negative the IRR < 1 and if the regression 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 6: Robustness of national determinants of TC mortality (1996-2016): Negative binomial regression with no geographic controls

	IRR (1)	IRR (2)	IRR (3)	IRR (4)	IRR (5)	IRR (6)	IRR (7)
Government effectiveness	0.348 ***	-	-	-	0.579 *	0.510 *	0.473 *
	(0.037)	-	-	-	(0.140)	(0.137)	(0.163)
Ln real GDP per capita (t-1)	-	0.412 ***	-	-	0.610 *	0.567	0.652
	-	(0.042)	-	-	(0.125)	(0.204)	(0.238)
National infant mortality rate (t-1)	-	-	1.053 ***	-	-	0.986	0.973
	-	-	(0.004)	-	-	(0.014)	(0.016)
Primary school enrollment (% net)	-	-	-	0.948 ***	-	-	0.998
	-	-	-	(0.012)	-	-	(0.020)
Pop. (millions) exposed to winds 119-153 km/hr	1.682 ***	1.617 ***	1.475 ***	1.548 ***	1.659 ***	1.680 ***	1.896 ***
	(0.102)	(0.107)	(0.085)	(0.083)	(0.106)	(0.110)	(0.108)
Pop. (millions) exposed to winds $>$ 153 km/hr	0.879	1.353	1.108	1.000	1.262	1.284	1.236
	(0.225)	(0.339)	(0.301)	(0.521)	(0.324)	(0.326)	(0.689)
Maximum rainfall exposure (mm)	1.002 ***	1.002 ***	1.002 ***	1.002 **	1.002 ***	1.002 ***	1.002 ***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Time (years)	0.943 *	0.957 *	0.942 *	0.955 **	0.953 *	0.951 *	0.963 *
	(0.024)	(0.020)	(0.027)	(0.016)	(0.022)	(0.023)	(0.018)
Geography	none	none	none	none	none	none	none
Observations	868	837	866	505	836	836	486

Negative binomial results are presented as Incident Rate Ratios (IRRs), obtained by exponentiating the estimated coefficients. Thus, we are testing the null hypothesis that IRR = 1. If the regression coefficient is negative the IRR $<$ 1 and if the regression 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 7: Robustness of national determinants of TC mortality (1996-2016): OLS regressions of log (deaths + 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government Effectiveness	-0.647 ***	-	-	-	-0.381 **	-0.395 **	-0.543 **
	(0.071)	-	-	-	(0.141)	(0.142)	(0.172)
Ln real GDP per capita (t-1)	-	-0.611 ***	-	-	-0.335 **	-0.221	-0.181
	-	(0.059)	-	-	(0.118)	(0.153)	(0.185)
National infant mortality rate (t-1)	-	-	0.033 ***	-	-	0.008	-0.004
	-	-	(0.005)	-	-	(0.007)	(0.009)
Primary school enrollment (% net)	-	-	-	-0.037 **	-	-	-0.002
	-	-	-	(0.011)	-	-	(0.014)
Pop. (millions) exposed to winds 119-153 km/hr	0.163 ***	0.165 ***	0.151 ***	0.154 ***	0.166 ***	0.165 ***	0.148 ***
	(0.032)	(0.034)	(0.031)	(0.042)	(0.034)	(0.033)	(0.039)
Pop. (millions) exposed to winds > 153 km/hr	0.331	0.431	0.440	0.588 *	0.415	0.404	0.715 *
	(0.311)	(0.415)	(0.322)	(0.237)	(0.405)	(0.400)	(0.321)
Maximum rainfall exposure (mm)	0.002 ***	0.002 ***	0.002 ***	0.001 ***	0.002 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	-0.040 ***	-0.028 **	-0.025 **	-0.038 **	-0.034 ***	-0.033 ***	-0.036 **
	(0.009)	(0.009)	(0.009)	(0.012)	(0.009)	(0.009)	(0.012)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	868	837	866	505	836	836	486

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

Table 8: Robustness of national determinants of TC mortality (1996-2016): OLS regressions of log (deaths)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government Effectiveness	-0.647 ***	-	-	-	-0.381 **	-0.395 **	-0.543 **
	(0.071)	-	-	-	(0.141)	(0.142)	(0.172)
Ln real GDP per capita (t-1)	-	-0.611 ***	-	-	-0.335 **	-0.221	-0.181
	-	(0.059)	-	-	(0.118)	(0.153)	(0.185)
National infant mortality rate (t-1)	-	-	0.033 ***	-	-	0.008	-0.004
	-	-	(0.005)	-	-	(0.007)	(0.009)
Primary school enrollment (% net)	-	-	-	-0.037 **	-	-	-0.002
	-	-	-	(0.011)	-	-	(0.014)
Pop. (millions) exposed to winds 119-153 km/hr	0.163 ***	0.165 ***	0.151 ***	0.154 ***	0.166 ***	0.165 ***	0.148 ***
	(0.032)	(0.034)	(0.031)	(0.042)	(0.034)	(0.033)	(0.039)
Pop. (millions) exposed to winds > 153 km/hr	0.331	0.431	0.440	0.588 *	0.415	0.404	0.715 *
	(0.311)	(0.415)	(0.322)	(0.237)	(0.405)	(0.400)	(0.321)
Maximum rainfall exposure (mm)	0.002 ***	0.002 ***	0.002 ***	0.001 ***	0.002 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time (years)	-0.040 ***	-0.028 **	-0.025 **	-0.038 **	-0.034 ***	-0.033 ***	-0.036 **
	(0.009)	(0.009)	(0.009)	(0.012)	(0.009)	(0.009)	(0.012)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	868	837	866	505	836	836	486

Disasters resulting in zero deaths are undefined and therefore excluded. Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: Logistic Regression: Inclusion of exposures (winds > 63 km/hr) in the EM-DAT

	(1)	(2)	(3)
Government Effectiveness	-0.892 ***	-	-0.398 *
	(0.081)	-	(0.171)
Ln real GDP per capita (t-1)	-	-0.794 ***	-0.484 **
	-	(0.070)	(0.150)
Time (years)	0.024 *	0.039 ***	0.033 **
	(0.012)	(0.012)	(0.012)
Pop. (millions) exposed to winds 63-118 km/hr	0.043 ***	0.043 ***	0.043 ***
	(0.008)	(0.008)	(0.008)
Pop. (millions) exposed to winds > 119 km/hr	0.321 *	0.335 *	0.330 *
	(0.142)	(0.144)	(0.143)
Average wind speed exposure (> 63 km/hr)	0.022 ***	0.022 ***	0.022 ***
	(0.003)	(0.003)	(0.003)
Maximum rainfall exposure (mm)	0.006 ***	0.005 ***	0.005 ***
	(0.001)	(0.001)	(0.001)
Observations	1231	1231	1231

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

Table 10: Descriptive statistics for subnational analysis dataset (1979-2016)

variable	min	max	median	mean	std.dev
Deaths	0.00	3682	9.00	57.30	204.7
Infant mortality ratio (wind field > 63 km/hr)	0.29	1.86	1.00	0.98	0.21
Infant mortality ratio (wind field > 119 km/hr)	0.30	1.83	1.00	1.02	0.23
Excluded ethnic group in (wind field > 63 km/hr)	0.00	1.00	0.00	0.14	0.26
Excluded ethnic group in (wind field > 119 km/hr)	0.00	1.00	0.00	0.08	0.24
National infant mortality rate	1.80	164.7	18.80	23.74	20.66
Real GDP per capita	345.1	53632	9225	15954	14665
Pop. (millions) exposed to winds 63-118 km/hr	0.00	92.68	2.44	8.53	14.20
Pop. (millions) exposed to winds 119-153 km/hr	0.00	25.51	0.00	0.50	1.64
Pop. (millions) exposed to winds > 153 km/hr	0.00	3.19	0.00	0.06	0.26
Maximum rainfall exposure (mm)	0.00	1551	229.5	262.5	170.1

Table 11: Pairwise correlations for subnational analysis 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	0.009	-0.001	0.141	-0.149	0.037	0.145	0.135	0.053
IMRratioTS	0.009	1.000	0.304	0.021	0.159	-0.463	-0.039	0.036	0.115
ExcludedTS	-0.001	0.304	1.000	-0.179	0.287	-0.163	-0.024	0.100	0.103
IMR	0.141	0.021	-0.179	1.000	-0.658	-0.174	-0.080	-0.002	-0.077
RealGDPpc	-0.149	0.159	0.287	-0.658	1.000	0.119	0.077	0.031	0.064
ExpTS	0.037	-0.463	-0.163	-0.174	0.119	1.000	0.306	0.006	0.136
ExpTC1	0.145	-0.039	-0.024	-0.080	0.077	0.306	1.000	0.214	0.166
ExpTC2	0.135	0.036	0.100	-0.002	0.031	0.006	0.214	1.000	0.009
MaxRain	0.053	0.115	0.103	-0.077	0.064	0.136	0.166	0.009	1.000

Table 12: Effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): NB2 incident rate ratios

	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)	2.936 *	2.913	-
	(1.524)	(1.777)	-
Excluded ethnic group in (wind field > 63 km/hr)	1.057	1.132	-
	(0.646)	(1.079)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	4.474 ***
	-	-	(1.885)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	1.630
	-	-	(0.601)
National infant mortality rate (t-1)	1.022 *	1.010	1.045 ***
	(0.011)	(0.021)	(0.014)
Ln real GDP per capita (t-1)	0.303 ***	0.260 ***	0.199 ***
	(0.068)	(0.086)	(0.058)
Pop. (millions) exposed to winds 63-118 km/hr	1.020 **	1.013	1.024 *
	(0.006)	(0.008)	(0.009)
Pop. (millions) exposed to winds > 119 km/hr	1.559 ***	-	1.511 ***
	(0.091)	-	(0.093)
Maximum rainfall exposure (mm)	1.001 *	1.001	-
	(0.001)	(0.001)	-
Time (years)	1.016	1.017	1.045 *
	(0.018)	(0.029)	(0.019)
Geography	countries	countries	countries
Observations	599	362	229

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 regression coefficient is negative the IRR < 1 and if the regression coefficient is positive the IRR > 1. The slight discrepency in number observations is due to storms with population exposure to sustained winds > 119 km/hr, but for which subnational IMR data was missing for the more intense wind field. 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 13: Robustness of subnational determinants of TC mortality (1979-2016, excluding 1999-2000): Negative binomial regression

	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)	2.879	2.817	-
	(1.577)	(1.842)	-
Excluded ethnic group in (wind field > 63 km/hr)	1.129	1.234	-
	(0.689)	(1.189)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	4.149 ***
	-	-	(1.782)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	1.738
	-	-	(0.670)
National infant mortality rate (t-1)	1.021 *	1.010	1.047 ***
	(0.011)	(0.021)	(0.014)
Ln real GDP per capita (t-1)	0.298 ***	0.254 ***	0.206 ***
	(0.067)	(0.084)	(0.060)
Pop. (millions) exposed to winds 63-118 km/hr	1.020 **	1.014	1.022 *
	(0.007)	(0.009)	(0.010)
Pop. (millions) exposed to winds > 119 km/hr	1.550 ***	-	1.497 ***
	(0.090)	-	(0.090)
Maximum rainfall exposure (mm)	1.001 *	1.001	-
	(0.001)	(0.001)	-
Time (years)	1.015	1.016	1.046 *
	(0.018)	(0.029)	(0.019)
Geography	countries	countries	countries
Observations	572	344	220

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 regression coefficient is negative the IRR < 1 and if the regression coefficient is positive the IRR > 1. The slight discrepency in number observations is due to storms with population exposure to sustained winds > 119 km/hr, but for which subnational IMR data was missing for the more intense wind field. 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 14: Robustness of subnational determinants of TC mortality (2001-2016): Negative binomial regression

	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)	3.185	1.478	-
	(2.410)	(1.264)	-
Excluded ethnic group in (wind field > 63 km/hr)	1.574	1.974	-
	(1.078)	(1.834)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	28.963 ***
	-	-	(22.804)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	1.168
	-	-	(0.746)
National infant mortality rate (t-1)	0.959	0.946	0.845 *
	(0.043)	(0.053)	(0.065)
Ln real GDP per capita (t-1)	0.036 ***	0.017 ***	0.026 **
	(0.030)	(0.017)	(0.036)
Pop. (millions) exposed to winds 63-118 km/hr	1.017	1.022	1.011
	(0.009)	(0.013)	(0.011)
Pop. (millions) exposed to winds > 119 km/hr	1.417 ***	-	1.323 ***
	(0.093)	-	(0.076)
Maximum rainfall exposure (mm)	1.001	1.002 *	-
	(0.001)	(0.001)	-
Time (years)	0.996	1.061	0.930
	(0.041)	(0.051)	(0.063)
Geography	countries	countries	countries
Observations	326	211	111

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 regression coefficient is negative the IRR < 1 and if the regression coefficient is positive the IRR > 1. The slight discrepency in number observations is due to storms with population exposure to sustained winds > 119 km/hr, but for which subnational IMR data was missing for the more intense wind field. 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 15: Robustness of subnational determinants of TC mortality (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)	0.509	0.300	-
	(0.378)	(0.440)	-
Excluded ethnic group in (wind field > 63 km/hr)	-0.208	-0.060	-
	(0.273)	(0.394)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.197 *
	-	-	(0.486)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	0.084
	-	-	(0.344)
National infant mortality rate (t-1)	0.019 *	0.020	0.016
	(0.009)	(0.013)	(0.013)
Ln real GDP per capita (t-1)	-1.146 ***	-1.358 ***	-1.340 ***
	(0.191)	(0.257)	(0.333)
Pop. (millions) exposed to winds 63-118 km/hr	0.032 ***	0.027 ***	0.031 ***
	(0.006)	(0.008)	(0.009)
Pop. (millions) exposed to winds > 119 km/hr	0.190 ***	-	0.173 ***
	(0.052)	-	(0.044)
Maximum rainfall exposure (mm)	0.002 ***	0.001 *	-
	(0.000)	(0.001)	-
Time (years)	0.001	0.023	0.001
	(0.011)	(0.017)	(0.016)
Geography	countries	countries	countries
Observations	599	362	229

The slight discrepency in number observations is due to storms with population exposure to sustained winds > 119 km/hr, but for which subnational IMR data was missing for the more intense wind field. 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 16: Robustness of subnational determinants of TC mortality (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)	0.181	0.034	-
	(0.373)	(0.427)	-
Excluded ethnic group in (wind field > 63 km/hr)	-0.109	0.065	-
	(0.301)	(0.439)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.157 *
	-	-	(0.496)
Excluded ethnic group in (wind field > 119 km/hr)	-	-	0.309
	-	-	(0.349)
National infant mortality rate (t-1)	0.016	0.006	0.026
	(0.009)	(0.012)	(0.014)
Ln real GDP per capita (t-1)	-0.689 ***	-0.752 **	-1.066 **
	(0.197)	(0.254)	(0.332)
Pop. (millions) exposed to winds 63-118 km/hr	0.026 ***	0.017 *	0.033 ***
	(0.006)	(0.007)	(0.008)
Pop. (millions) exposed to winds > 119 km/hr	0.185 ***	-	0.169 ***
	(0.050)	-	(0.043)
Maximum rainfall exposure (mm)	0.002 ***	0.001 *	-
	(0.000)	(0.001)	-
Time (years)	-0.010	-0.007	0.008
	(0.011)	(0.018)	(0.016)
Geography	countries	countries	countries
Observations	529	312	210

The slight discrepency in number observations is due to storms with population exposure to sustained winds > 119 km/hr, but for which subnational IMR data was missing for the more intense wind field. 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 * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.