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 physical exposure in an econometric analysis may result in imprecise and 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 average income and other socioeconomic conditions. Within countries, deaths are higher when strong winds are concentrated over areas of the country with elevated infant mortality rates, an indicator of institutional effectiveness through public service delivery. 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 and territories have lost their lives in tropical cyclone disasters.[1] However, there is substantial variation in the degree of harm. As recently as 2008, the Cyclone Nargis killed over 138,000 people in Myanmar. Nargis was a powerful Category 3 or 4 storm at landfall, but tropical cyclones with similar wind speeds struck several other countries that year with far fewer fatalities. Out of more than 4,000 tropical storms and cyclones recorded between 1979 and 2016, about 20% triggered humanitarian disasters and less than 5% resulted in more than 100 deaths. Understanding what drives this large variation in impacts may provide guidance on how we can prevent mortality from future storms, which will be of increasing importance as countries grapple with complex vulnerabilities to extreme weather events under climate change (IPCC, 2014).

This paper investigates relationships between tropical cyclone mortality and institutional, economic, and human development (collectively referred to as 'development'). We focus in particular on the role of institutional effectiveness, 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 locally elevated infant mortality rates (IMR) in the exposure zone are associated with increased tropical cyclone mortality. We interpret this as evidence that tropical cyclones are more deadly when they impact areas with weaker public services due to limited local institutional capacity or the failure of national programs to be inclusive of all vulnerable populations.

Natural hazards, including tropical cyclones, result in disasters only when vulnerable human systems are exposed to hazardous conditions. This can be represented as follows (e.g. Alexander, 1991; Blaikie et al., 2004; uni, 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 events of different types (i.e. earthquakes, storms, floods and heat waves) are not directly compa-

[1]The statistics presented in this paragraph are the authors' calculations based on data from (Guha-Sapir, 2018; Knapp et al., 2010, 2017).

rable. As a result, estimates of socioeconomic risk factors for vulnerability will be imprecise. Indeed, previous large-N empirical efforts that have pooled different types of hazards 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). Measures of democracy and the quality of institutions, including government effectiveness, 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. In Figure 1 we illustrate how from 1996 to 2016 countries with more effective governments had lower mortality from tropical cyclones even though more people within those countries were exposed to dangerous wind speeds. 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 and adaptation that include physical hazard observe that storms of similar intensity tend to result in fewer deaths when they strike countries with higher GDP per capita (Hsiang and Narita, 2012; Peduzzi et al., 2005). This may reflect higher levels of individual or collective investment in assets and activities that reduce risk. However, the effects of economic development on risk are not unambiguously positive; growth-targeting activities can also exacerbate or create new vulnerabilities (Adger et al., 2003; Blaikie et al., 2004; Denton et al., 2014). 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 GDP effect may 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, lower poverty rates, or better quality institutions (Adger et al., 2003; Blaikie et al., 2004; Pachauri and Mayer, 2015).

Institutional effectiveness and inclusivity at multiple scales may be particularly important for reducing mortality from natural hazards, such as tropical cyclones. The IPCC Fifth Assessment Report concludes with "very high confidence" that the quality of institutions and governance are enabling factors for adaptation and disaster risk reduction in the context of climate change (Pachauri and Mayer, 2015). The state plays a direct role in disaster preparedness and response, and further influences how conducive the national environment is to collective and individual adaptation (Adger, 2003). Government capacity may com-

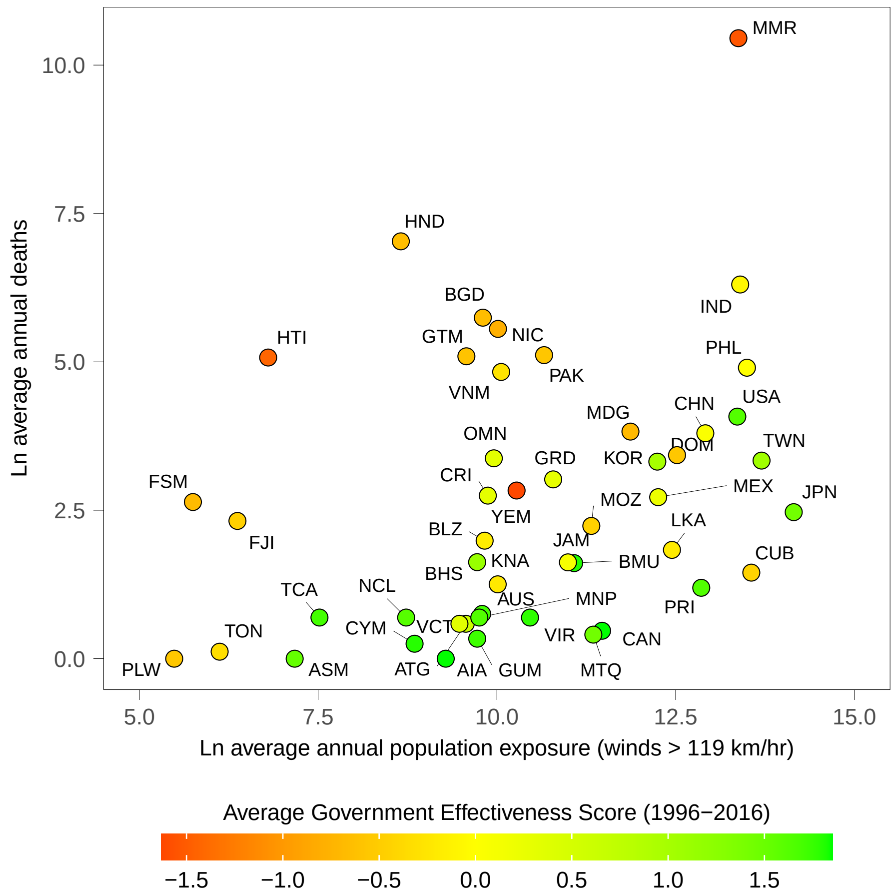

Figure 1: Governance, mortality and exposure for tropical-cyclone affected countries, 1996-2016. Average national government effectiveness scores from 1996 to 2016 are taken from the World Governance Indicators; higher scores indicate more effective governance (Kaufmann et al., 2010). Average annual 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. Exposure from tropical cyclones occurring in the Indian Ocean Basin may be underestimated due to missing storm tracks in the underlying data (see SI for details).

plement financial resources, particularly when the state acts as an intermediary in receiving and disbursing bilateral and multilateral aid (Eakin and Lemos, 2006). It is also important in its own right; economically less developed countries with high functioning states and civil societies have repeatedly demonstrated the capacity for adaptation to hazards (Adger et al., 2003; Adger, 2003). In contrast, government failures such as the lack of capacity, will, and resources 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). Government programs for managing tropical cyclone risk - including early warning systems, shelters and evacuation plans, and integrating disaster risk and development planning - require an effective central bureaucracy but also depend upon local institutions for implementation.

Within countries, who benefits from disaster risk reduction policies and investments is shaped by existing patterns of vulnerability and marginalization (Adger, 2006; Barbier and Hochard, 2018; Blaikie et al., 2004; Pelling, 1999). People and locales may be excluded from national protections against tropical cyclone hazard due to the uneven quality of local institutions, the political marginalization of certain groups, and other forms of social or economic inequality. If these inequalities and their effects are large, they are likely to contribute to within-country variation in tropical cyclone mortality when patterns of physical exposure are sufficiently varied. 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). However, 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 local institutional quality and socioeconomic conditions may differ from national averages in storm-affected regions. As a result, our understanding of the scales at which underdevelopment contributes to tropical cyclone vulnerability is limited. This constrains the ability of policy-makers to target their actions; for example, whether to focus on building the capacity of the federal bureaucracy, local institutions, or both.

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 nearly fifteen-hundred tropical cyclone disasters from 1979 to 2016. Our analysis is based on two subsets of this dataset, the first from 1996 to 2016 - where we test the relationship to national government effectiveness - and the second from 1979 to 2016 - where we test subnational indicators of institutional capacity and inclusion. 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, 2017; National Oceanic and Atmospheric Administration, 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. We draw on data and insights from the civil conflict, development economics, and public health literatures to characterize subnational heterogeneities in institutional effectiveness (e.g. Briggs, 2018; Pongou et al., 2017; von Uexkull et al., 2016). 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 allows us to observe the conditions under which tropical cyclone disaster is avoided.

2 Results

The effects of institutions, income, and human capital 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 characteristics on cyclone deaths using data from over nine-hundred events across 67 countries between 1996 and 2016. 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 disaster mortality using data from tropical cyclone disasters in 59 countries between 1979 and 2016. Socioeconomic conditions in the path of the storm are found to have a large effect

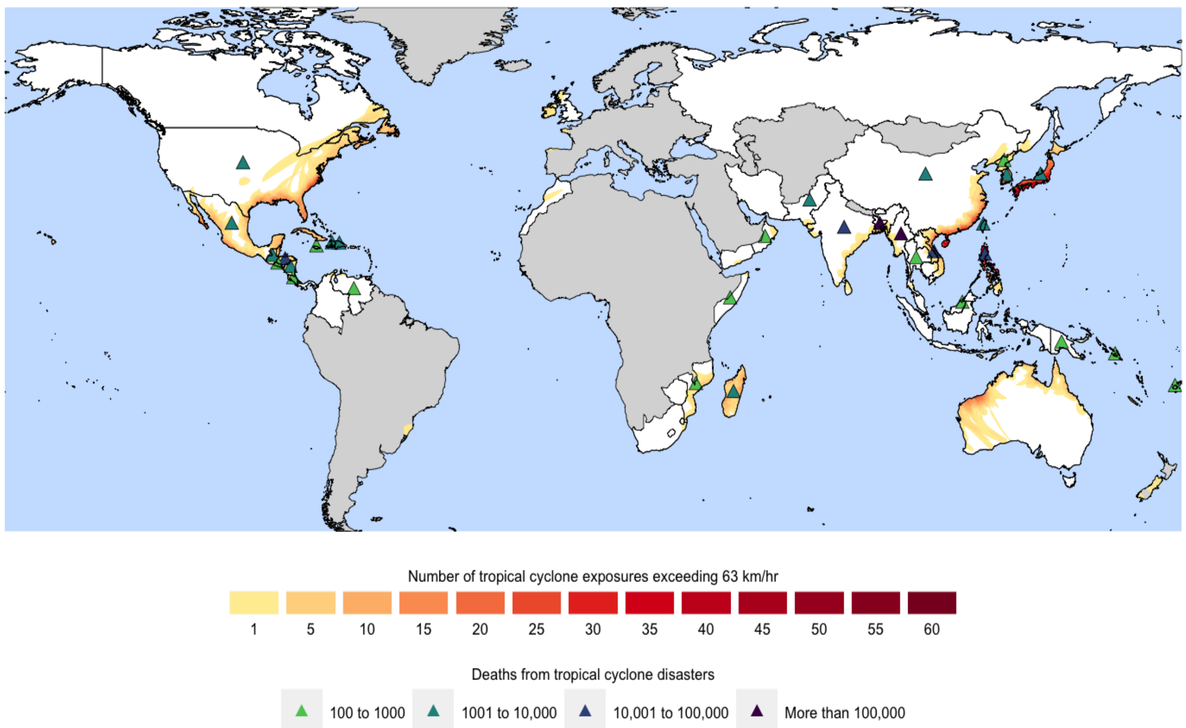

Figure 2: National tropical cyclone disaster deaths and subnational wind exposure (1979-2016). Total mortality is indicated by the shaded triangles for all countries with at least 100 total deaths from 1979-2016 (Guha-Sapir, 2018). Areas shaded in gray indicate countries that have not experienced tropical 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, 2017; 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).

on expected mortality. Importantly, we control for hazard exposure in both the national and subnational specifications.

National government effectiveness and socioeconomic conditions

Government effectiveness, real GDP per capita, infant mortality rates and primary school enrollment are all good predictors of cyclone mortality in a country-level model that controls for hazard exposure. When we include only one of these four development indicators at a time, each has a highly statistically significant association with 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 66% decrease in deaths in a model with no other socioeconomic variables. However, because institutions, income, health and education are highly correlated, the independent effects of these variables cannot be identified by models with only a single socioeconomic variable.

To parse these relationships, we test multiple aspects of national development in combination (Table 5 (5-7)). 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 71% decrease in deaths. As illustrated in Figure 3, when we add GDP per capita and infant mortality to the model, government effectiveness accounts for a 49% decrease in mortality per standard deviation - remaining practically and statistically significant. When we also include education this reduces the number of observations due to missing data, but the effect of governance remains large and statistically significant. The association between government effectiveness and lower tropical cyclone deaths is robust to a range of sensitivity analyses, including OLS estimation, as described in SI Section B (Tables 6-14).

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 66% to 44% when we add government effectiveness to the income-only model. The GDP per capita loses statistical significance with the addition of infant mortality and education to the model. The effects of infant mortality and education also lose statistical significance in the joint model with GDP per capita and government effectiveness.

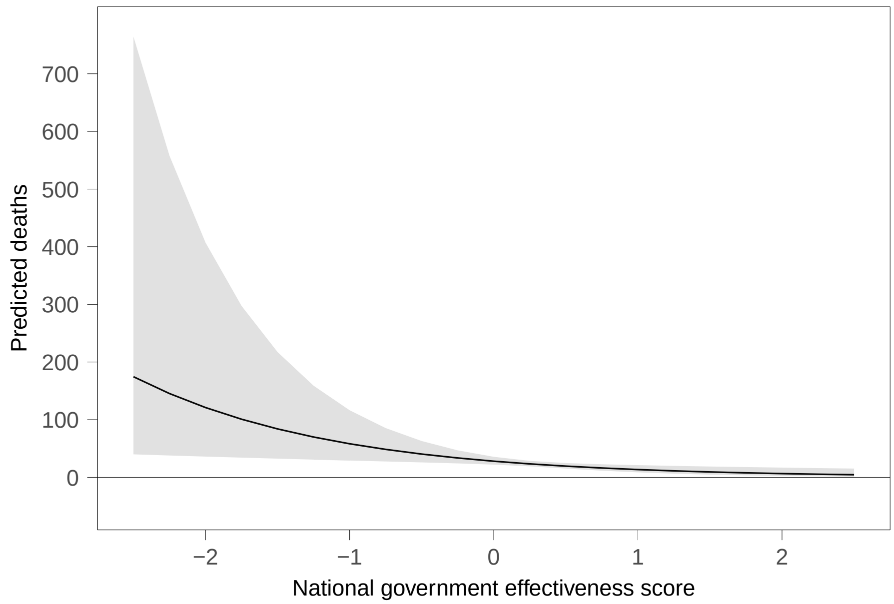

Figure 3: Predicted effects of national government effectiveness score on deaths, based on model (6) in Table 5. The shaded area represents the 95% confidence interval. Variables not shown, including real GDP per capita and infant mortality, are held at mean values for prediction.

2.0.1 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 reports from governments, UN-agencies and other non-governmental organizations. This raises two key concerns when the EM-DAT 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 have been discussed in the literature (see Peduzzi et al., 2012), but have 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 1996 to 2016 based on the IBTrACS dataset. We can then estimate a logistical regression model of the probability that an instance of tropical storm or 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 hazard exposure. Our results indicate that tropical storm or cyclone exposures that occur in wealthier countries with more effective governments are less likely to be included in the EM-DAT (see Table 15). 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.

Institutions and socioeconomic conditions in the cyclone wind field

We also investigate whether the protections afforded by effective national governments and other country-level attributes are inclusive of areas of the country with weaker institutions or marginalized groups. We select infant mortality rates and settlements of politically excluded ethnic groups as proxies for the quality and inclusiveness of institutions at the wind field level. Infant mortality rates are linked to the quality of institutions via their role in the provision of public services (Pongou et al., 2017; Sirag et al., 2017), such as health care, education, sanitation, and social safety nets that protect against food insecurity and malnutrition. Elevated infant mortality may reflect a lack of will or capacity in the provision of such services, or else that not all segments of the population benefit from them. The political exclusion of ethnic groups was selected to more specifically capture the effects of marginalization; we anticipate that death tolls will increase when governments lack accountability to portions of the affected population (Busby and von Uexkull, 2018). This could occur because areas settled by excluded groups receive fewer resources, group members have less trust in or access to them, or because marginalized groups are forced to settle in more physically vulnerable locations (Blaikie et al., 2004; Bretthauer, 2015). 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. The construction of the wind field variables is described in the Materials & Methods and further elaborated in SI Section A.

The main results of the subnational analysis are presented in Figure 4 and based on the negative binomial regression model estimated in Table 18. 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. For the tropical storm-strength wind field (sustained winds $>$ 63 km/hr), the model predicts an 11%

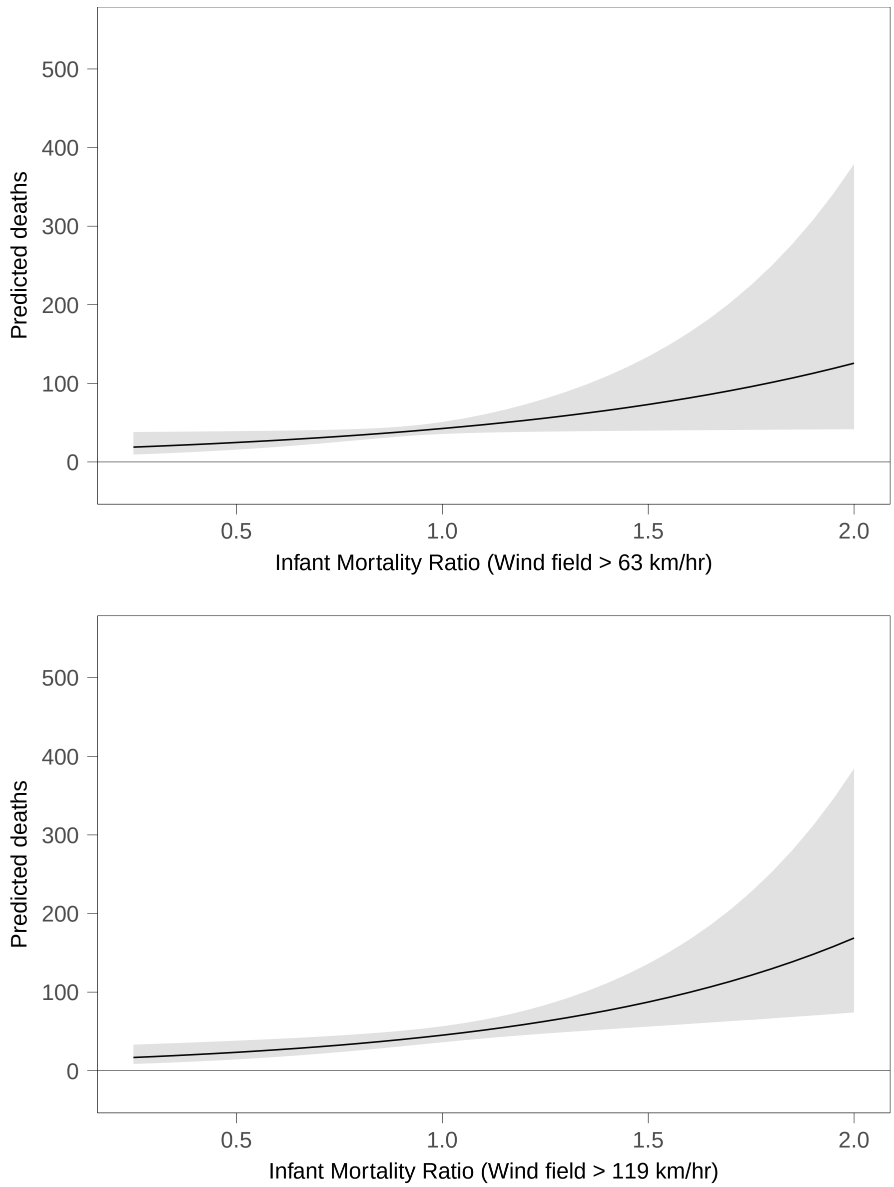

Figure 4: Predicted effects of the wind field infant mortality ratio (IM ratio) on deaths. The IM ratio is the ratio of the infant mortality rate in the storm wind field compared to the national average. The top panel represents the predicted effect of the IM ratio in the tropical storm exposure zone (sustained winds $>$ 63 km/hr). The bottom panel represents the expected effects of the IM ratio in the more intense tropical cyclone exposure zone (sustained winds $>$ 119 km/hr). Predictions are based on models (1) and (3) of Table 18, respectively. The shaded areas represent the 95% confidence intervals.

increase in storm deaths when local infant mortality rates are elevated by 10% above the national average. At higher wind speeds (sustained winds > 119 km/hr) the effect is more pronounced; a 10% increase in wind field infant mortality is associated with a 14% increase in storm mortality. The results for these more intense tropical cyclone wind fields are robust to various permutations of the model and the dataset, while the result for the weaker tropical storm wind fields lose statistically significance in some alternative specifications (SI Section B; Tables 19-29).

The statistical relationship between elevated infant mortality rates and disaster deaths may be interpreted in several ways. Infant mortality is a measure of public health and has also been employed as a proxy for overall well-being, poverty or inequality (e.g. Barbier and Hochard, 2018; Briggs, 2018; Esty et al., 1999; Hillesund et al., 2018), each of which is plausibly related to disaster deaths. However, the importance of within-country variation in infant mortality rates clearly demonstrates that disaster deaths are not only a function of the national context and hazard exposure. Local vulnerabilities are important, and particularly so in areas that are exposed to sustained wind speeds in excess of 119 km/hr, the "very dangerous" threshold for tropical cyclone winds (noa, 2020).

Our analysis of the effects of politically exclusive institutions on disaster mortality is not conclusive and highlights the need for further research on this topic. Following the EPR classifications, we consider groups to be excluded from executive political power if they are powerless, discriminated or self-excluded (Cederman et al., 2010; Vogt et al., 2015). By this measure, the effects of exclusion are not precisely estimated (Table 18). However, we find that very few tropical cyclones in our dataset actually impact areas settled by discriminated or self-excluded groups. Our measure of ethnic group exclusion therefore primarily captures the effects of powerless groups settled in the impact area (Table 30). Powerless groups, which lack representation, may be less likely to be excluded from national protections compared to groups that are actively discriminated against. Our indicators of exclusion also do not unpack potentially important heterogeneities in the density of ethnic group settlements and the *de facto* and *de jure* forms of political power sharing (Bormann, 2019; Busby, 2018; Strøm et al., 2017).

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 lend support for general theories of how effective and inclusive institutions can moderate vulnerability and foster resilience to a range of shocks and stressors.

We acknowledge several limitations of this work. First, we rely on data that includes only the direct, short-term disaster deaths. Our analysis does not capture how institutions may mediate longer-term mortality, for example through their role in mitigating economic hardship or re-establishing health care and other services in the aftermath of the storm (Anttila-Hughes and Hsiang, 2013; Kishore et al., 2018). Second, these results may be sensitive to the data sources used to operationalize the latent concept of institutional capacity. Our analysis relies on the World Governance Indicator's subjective government effectiveness scores. While to our knowledge a suitable alternative measure of government effectiveness is not publicly available at present, we encourage future research to test the robustness of these findings using new or proprietary data sources. Future work could also investigate the importance of other facets of governance, including polity and socio-political goals, for disaster mortality (Haddad, 2005; Lesnikowski et al., 2013). Third, 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, however, go beyond previous efforts by demonstrating that the association between national government effectiveness and tropical cyclone mortality cannot be fully explained by indicators of income, health or education. Finally, the trade-off of focusing on a single class of hazard is that it limits our ability to generalize these results to other types of natural disaster. However, our approach can be adapted to the study of additional hazards, scales and outcomes to gain further insight into the role of institutions and economic development in risk reduction.

Our findings are salient to current questions about the intersection of institutions, sustainable development and disaster risk; questions made more urgent under climate change. The intensity and rainfall of the strongest tropical cyclones are expected to increase under climate change (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 are amplified by uneven progress on eliminating poverty, hunger, disease, illiteracy, environmental degradation, and discrimination against women (IPCC, 2014; un2, 2015). Enhancing institutions may have wide-ranging benefits for disaster risk reduction as well as climate adaptation and sustainable development. This underscores the value of understanding relationships between institutions and disasters.

4 Materials and Methods

Disasters occur when a population is exposed to hazardous conditions and is unable to adapt or cope. Understanding mortality from tropical cyclones therefore requires information about the spatial intersection of physical hazard and socioeconomic systems. 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. Tables 1 and 2 summarize the hazard exposure variables and the socioeconomic variables; the source data and methods are described in further detail in SI Section A.

Dataset

Our approach recognizes the importance of accurately accounting not only for the intensity of the hazard, but also for the number of people exposed to hazardous conditions and the local socioeconomic conditions of the affected population. Basic statistics such as 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.

To translate from hazard to exposure, we develop a method to match storm tracks and rainfall to disaster data and then parametrically model the intensity and spatial extent of each storm. With the area of exposure spatially delineated, we can then determine the size and socioeconomic conditions of the population living there. In brief, this is done by first identifying the grid cells that fall within the storm's wind field, extracting the measures of interest for each of those grid cells (e.g. population, infant mortality), and then computing the average conditions in the wind field. Thus, while several variables in this analysis draw on subnational data specific to the area of the country impacted by the storm, these data are aggregated into country-storm measures. This allows for comparison with our principal outcome variable: the number of disaster deaths associated with each country-storm event. Our criteria for disaster are detailed in SI Section A and follow the Emergency Events Database (EM-DAT), the source of the disaster mortality data for this analysis (Guha-Sapir, 2018).

Measures of hazard intensity and exposure

Tropical cyclone data obtained from the Best Track Archive for Climate Stewardship (IBTrACS) Project (Knapp et al., 2010, 2017) do not share a common identifier with the EM-DAT disaster data. The observations were therefore matched using a spatial algorithm that, for each disaster, looks for the closest storm in space and time. Automated matches between the EM-DAT and IBTrACS were manually reviewed for accuracy by consulting additional sources, such as storm reports published by governments and meteorological agencies.

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 estimate the exposure. 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 (National Oceanic and Atmospheric Administration, 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, and to more recent years (1996+) for specifications including national government effectiveness scores. Indian Ocean tropical cyclones are excluded from our main specifications due to concerns about the quality and completeness of the data for this region during the study period. However, the main findings presented in this paper are robust to the inclusion or

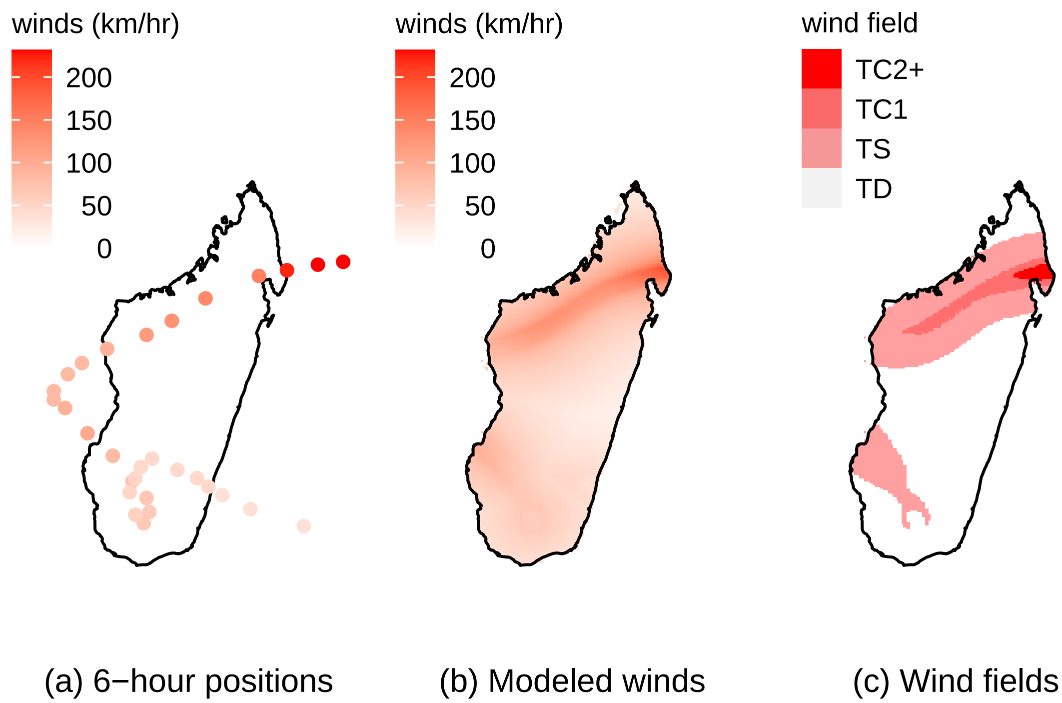

Figure 5: Modeling tropical cyclone wind fields for Cyclone Gafilo (2004) in Madagascar. I begin with (a) the 6-hourly wind speeds and locations (Knapp et al., 2010). Using a parametric wind speed model (Willoughby et al., 2006) implemented in the software R (Anderson et al., 2017), I then estimate (b)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

exclusion of any particular region, including the Indian Ocean Basin. See the SI for the sensitivity analyses and additional documentation of the Indian Ocean storms.

Socioeconomic variables

Country-level socioeconomic variables are matched to tropical cyclone events based on the year and the country. National indicators of income, health and education are taken from the World Development Indicators (WDI) (wdi, 2020) and other sources (Feenstra et al., 2020; csd, 2016; mhw, 2017). The GDP per capita and infant mortality rates are lagged by one year.

Following previous related work (e.g. Brooks et al., 2005; Peduzzi et al., 2012), we use the World Governance Indicators (WGI) to capture national government effectiveness, defined as the quality of public policies and service delivery by formal institutions (wgi, 2020; Kaufmann et al., 2010). The scores are based on surveys of public, private and NGO experts combined using an unobserved components model. While perception-based measures are unavoidably imprecise, an advantage of the WGI methodology is the explicit characterization of the uncertainty. This allows us to conclude that there is meaningful variation in governance scores across the countries in our dataset.

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 wind fields of multiple intensities (as illustrated in Figure 5). Both the infant mortality and political exclusion variables are weighted by the grid cell population (CIESEN, 2017a,b), and therefore are restricted to the over-land wind field. 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 models, as the resolution of the infant mortality data varies by country. Given that the underlying subnational IMR data are time-invariant (for the year 2000), one concern is that infant mortality might be elevated in parts of the country due to the direct or indirect impacts of tropical cyclones. However, when we exclude the years 1999-2000 or only include the years 2001-2016 as a robustness check, the estimated effect of locally elevated IMR on disaster deaths remains consistently positive and, for the tropical cyclone strength wind fields, highly statistically significant (Tables 19 & 20).

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. However, the excluded ethnic group settlements that overlap with the tropical cyclones are primarily classified as powerless rather than discriminated or self-excluded. See SI Section B for a discussion of the implications.

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

One drawback of the negative binomial model is that it is not well suited to handle large outlier events. We therefore exclude events with more than 5,000 deaths from the negative binomial specifications. These outlier events are few in number,[2] but catastrophic in their humanitarian impacts. We therefore estimate comparable ordinary least squares

[2] Our criteria exclude Thelma (1991) and Haiyan (2013) in the Philippines and Mitch (1998) in Honduras. See SI for additional Indian Ocean storms that exceed 5,000 deaths.

(OLS) models with a transformed dependent variable to accommodate these high-mortality events as a robustness check. As described in SI Section B, the main results are robust to OLS estimation with and without the outlier events.

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A Dataset

Dependent variable: tropical cyclone mortality

Here, we discuss the tropical cyclone mortality data used in this analysis, the potential sources of bias, and the implications for the analysis.

The tropical cyclone mortality data 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 disasters, including the total deaths associated with each event. 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 these criteria for disasters, and is further limited to events of the subtype 'tropical cyclone' in the EM-DAT database.

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 the reports of 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. By design, the database therefore excludes events in which physical exposure did not lead to a disastrous outcome, possibly due to the interventions of effective and well-endowed institutions. Alternatively, instances of hazard that do not correspond to an EM-DAT disaster may indicate missing observations, for example due to under-reporting in countries with weaker capacity or corruption. 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 a disaster that corresponds to a 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 15. In sum, we find that tropical cyclone events are more likely to be included in the EM-DAT when people in countries with weaker government effectiveness and lower GDP per capita are exposed. 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.

As noted in the main text, tropical cyclones deaths are highly skewed with a few large outliers, which can complicate statistical analyses with trade-offs between different approaches. Tropical cyclone disasters have precipitated over 418,000 deaths from 1979 to 2016.[3] Fatal tropical cyclone disasters occurred in 72 countries (85 countries and territories, which includes dependencies). However, of those deaths 95% were concentrated in just 10 countries. Figure 6 maps total deaths by country over the 1979 to 2016 study period. In order from most to least tropical cyclone deaths by country 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 (2,818). Just two disaster events 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). We discuss our treatment of these high-mortality events later in this section, and test the robustness of those decisions in SI Section B).

Control variables: hazard intensity and exposure

Our approach to constructing the hazard intensity and exposure variables is described in the main text. This section revisits the 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 & 16 for the national and subnational datasets, respectively. The cumulative population exposure from 1979 to 2016 is mapped at the country level in Figure 7.

[3]The tropical cyclone mortality statistics presented in this section are author calculations based on data including the EM-DAT (Guha-Sapir, 2018).

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. The event mortality data is reported by country-storm event. The country-storm event is also our unit of analysis. In contrast, the tropical cyclone data consist of maximum sustained wind speeds geo-referenced (with a latitude and longitude) at 6-hour intervals, obtained from the Best Track Archive for Climate Stewardship (IBTrACS) Project (Knapp et al., 2010, 2017). 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 that is broadly similar to Peduzzi and co-authors (Peduzzi et al., 2005, 2012) to match storm and disaster event records. The EM-DAT disasters and IBTrACs storms were matched using a spatial algorithm that, for each disaster, looks for the storm records that best match in space and time. The automated match was then manually reviewed for accuracy. The basic steps of this process are as follows:

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.

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 exposed to the storm. Tropical cyclone maximum sustained wind speeds were modeled for all tropical cyclones in the IBTrACS from 1979-2016 using a parametric wind speed model.

The storm track data was obtained from the IBTrACS Project (Version: v03r10) downloaded from the website on October 8, 2017 (Knapp et al., 2010, 2017).[4] 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+ (or 1996+ for some specifications) and allows for a linear time trend. The IBTrACS does not presently correct for differences in agency data collection and processing methods; instead, IBTrACS provides an average of the 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. This helps 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 (eAt, 2018) it was evident that tropical cyclone disasters

[4] We note that Version 4 of the IBTrACS is now available.

recorded 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. The main results of the analysis appear to be robust to the decision to exclude the Indian Ocean basin from this analysis (see SI Section B and Tables 7, 11, 12, 26, and 27); however, due to the concerns enumerated above, we emphasize that these estimates are intended as a robustness check only.

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 translate the storm tracks into estimates of maximum sustained wind speed suitable for spatial matching with gridded population and socioeconomic data. Because a comprehensive global dataset including information on 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 (e.g. IBTrACS). 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). This is another reason why we include regional or country-level controls in our main specifications. 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 (v0.1.0-global available at https://github.com/liztennant/stormwindmodel). One limitation of this software 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. This two-step procedure decreases total computation time. 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.

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, tropical cyclone, and intense tropical cyclone 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 (National Oceanic and Atmospheric Administration, 2018). While rainfall data are already available in spatial grid format, they are not linked to specific storm events. For each country-storm event, we 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, our 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 more sophisticated rainfall hazard and exposure metrics in future research efforts.

Independent variables: institutions, income, and human development

Country-level socioeconomic variables are matched to tropical cyclone events based on the year and the country in which the disaster occurred. National 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; wgi, 2020). National data on income, health and education are taken from the World Development Indicators (WDI) (wdi, 2020). Within countries, local institutional quality and inclusion are proxied using subnational infant mortality rates (IMR) and spatial data on the political exclusion of ethnic groups.

National variables: 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)

Figure 8, which maps government effectiveness in 2016 for countries that experienced tropical cyclone deaths between 1979 and 2016, illustrates the wide range of scores across tropical cyclone affected countries. The WGI are available biannually from 1996 to 2002 and then annually (Kaufmann et al., 2010). For events occurring in 1997, 1999, and 2001 – before the WGI data was annual – we use the nearest governance score to the storm date. For example, a January 1997 storm is matched to the 1996 government effectiveness estimate; a November 1997 storm to the 1998 estimate. 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).

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 (wdi, 2020; Feenstra et al., 2015, 2020). Infant mortality rates are also primarily taken from the WDI (wdi, 2020), supplemented by data from the Hong Kong Census and Statistics Department and the Taiwan Ministry of Health and Welfare (csd, 2016; mhw, 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, we designate the relevant 'national' government based on responsibility for disaster management in that territory. We emphasize that these designations are specific to disaster management and are not assessments of the overall sovereignty or diplomatic status of these territories. For example, 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.

Socioeconomic conditions in the impact zone

We construct two types of wind-field level socioeconomic variable: one based on local infant mortality rates and the other on spatial polygons of politically excluded ethnic groups. As described above and in the main text, for each storm we have identified the areas of the country exposed to tropical storm and tropical cyclone strength winds. These wind fields are the basis for both the infant mortality and political exclusion variables.

The infant mortality ratio (IM ratio) is a ratio of the IMR in the storm wind field compared to the national IMR. We first calculate the local IMR for the event by summing infant deaths for all grid cells in the wind-field and dividing by the sum of wind-field births. The IM ratio is then computed by dividing the local IMR by the national IMR. We use 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, we include country controls in all models containing the infant mortality ratio variables. We also address the possible endogeneity issue posed by the time-invariant nature of the subnational IMR data in our robustness checks (see SI Section B).

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). The EPR dataset provides annual assessments of 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. 1331)

The observations in our dataset are dominated by the exposure of *powerless*, versus *discriminated* or *self-excluded*, groups to tropical cyclones. A powerless ethnic group is present in 42% of the weaker tropical storm wind fields and 14% of the stronger tropical cyclone wind fields. In contrast, discriminated ethnic groups were present in less than 1% of tropical storm wind fields and none of the stronger tropical cyclone wind fields. Self-excluded groups were also rare in both tropical storm (2%) and tropical cyclone (less than 1%) wind fields. As discussed in further detail in SI Section B, it is therefore unsurprising that tests for all excluded groups (Table 18) and only powerless groups (Table 30) yield similar results; the coefficients are positive, but the results are not precisely estimated.

In Table 2 we describe the key socioeconomic variables and the sources they are drawn from. See Tables 3 & 16 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 18. These are discussed in the main text; this section focuses primarily on robustness checks to the preferred specifications. Statistical tables are presented in SI Section C.

As discussed in the main text, one drawback of the negative binomial model is that it cannot accommodate large outlier events. We handle this by excluding events that exceed 5,000 deaths. For the main dataset this includes three country-storm events: the 1991 Hurricane Mitch in Honduras (14,600 deaths), the 2013 Typhoon Haiyan or Yolanda in the Philippines (7,354 deaths), and the 1991 Tropical Storm Thelma or Uring in the Philippines (5,956 deaths). If we include Indian Ocean observations in the dataset additional outliers would be the 1991 Bangladesh cyclone (138,866 deaths), the 2008 Cyclone Nargis in Myanmar (138,366 deaths), a 1985 cyclone in Bangladesh (15,000 deaths), and a 1999 cyclone in India (9,843 deaths). Death statistics are taken from the EM-DAT (Guha-Sapir, 2018).

These outlier events are few in number, but catastrophic in their humanitarian impacts. In this section we therefore present an alternative model that can accommodate these events; an ordinary least squares (OLS) models with a transformation of the dependent variable, deaths. Our preferred alternative model is an OLS regression of the inverse hyperbolic sine of y on $\mathbf{x}_i$. The inverse hyperbolic sine transformation

$$\sinh^{-1}(y_{it}) = \ln(y_{it} + \sqrt{y_{it}^2 + 1}) \tag{5}$$

is approximately equal to $\ln(2y_{it})$ unless y_{it} is very small, and the coefficients can therefore be interpreted as semi-elasticities (Burbidge et al., 1988; Eyer and Wichman, 2018). The inverse hyperbolic sine has the advantage that it is defined at zero values of y. In contrast, because $\ln(y)$ is undefined when $y = 0$ a natural logarithm model requires either that the dependent variable be further transformed, for example to $\ln(deaths + 1)$, or else that zero death events be excluded from the analysis. For both the inverse hyperbolic sine and natural logarithm models, interpretation is less useful compared to the negative binomial because our primary interest is in the count variable deaths. While our preferred OLS specification is the inverse hyperbolic sine, we estimate models with all three transformations of the dependent variable for comparison: $\sinh^{-1}(y)$, $\ln(y + 1)$, and $\ln(y)$. The results are discussed in the following sections; in preview, the main findings are robust to OLS estimation with and without the inclusion of the outlier events.

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

In this section we investigate the robustness of our findings to our choice of econometric model, geography, and treatment of outliers. We find the main results of the national analysis - in particular the association between government effectiveness and lower tropical cyclone deaths - to be robust.

First, we test the sensitivity of the results to our choice of a negative binomial versus OLS regression model. We estimate OLS models of the inverse hyperbolic sine of deaths (Table 9) and the natural logarithm of deaths (+ 1) (Table 13) that are comparable (using the same data set and independent variables) to the main negative binomial results in Table 5. As in the negative binomial regression results, government effectiveness has a large and statistically significant association with lower mortality in all OLS specifications tested in Tables 9 and 13. When government effectiveness is the only socioeconomic variable in the OLS model, a one unit increase in the governance score is associated with a 75% decrease in deaths (Table 9 (1)). When we add real GDP per capita and infant mortality to the model, a one unit increase in government effectiveness is associated with approximately a 47% decrease in deaths (Table 9 (6)). The coefficients are slightly smaller in magnitude in the OLS model of $\ln(deaths + 1)$, but remain practically and statistically significant (Table 13). If we exclude zero death events from the dataset, the model of $\ln(deaths)$ yields slightly larger coefficients than the inverse hyperbolic sine models (Table 14 (1) and (6)).

One advantage of the OLS models is that they can better accommodate the outlier events that are excluded from the main analysis. In the multi-variate OLS model of the inverse hyperbolic sine of deaths, a one unit increase in governance is associated with a 47% (46%) decrease in deaths when we exclude (include) the outlier events (Tables 9 and 10). If we add the Indian Ocean Basin events including the *most* deadly storms (as discussed above), the estimated effect increases very slightly to 50% (Table 11). For reasons discussed in Section A, we urge caution in interpreting results that include the Indian Ocean observations. However, to further test the robustness of the main results to our decision to exclude the Indian Ocean Basin, we also estimate both NB2 (Table 7) and OLS (Table 12) models *with* the Indian Ocean observations but *excluding* events with more than 5,000 deaths. The findings hold under these alternative specifications.

While the results are shown to be robust to the inclusion or exclusion of the Indian Ocean Basin, one might still be concerned that the results are driven by a particular region and therefore lack general validity. The dataset does not allow us to precisely estimate a multivariate model for individual regions due to the limited number of observations for most categories. The number of observations by region in the 1996 to 2016 dataset is: Asia (439), Latin America and the Caribbean (246), Northern America (70), Oceania (65), Africa (62), and Europe (36). Note that Europe includes island territories of European nations, for example the Cayman Islands and Réunion.[5] To ensure that the results are not driven by a single region we exclude one region at a time from the dataset. Regardless of which region is removed from the dataset, we find a statistically significant association between higher government effectiveness scores and lower tropical cyclone deaths in a model that controls for real GDP per capita (see Table 8). However, if we add additional variables (i.e. infant mortality rates and education), which reduces the starting number of observations, the negative binomial model does not converge when we remove Asia from the dataset. Further, while the main results do not appear to be driven by observations from a single region, the magnitude of the effect may indeed vary substantially by region.

These results are sensitive to the choice of regions as our geographic control. 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 in the dataset from 1996-2016. It is due to the insufficient variation in within country government effectiveness that we include regional but not country geographic controls in the preferred specifications (Table 5). Excluding the regional controls has a modest effect on the coefficients and standard errors, but the main results hold (see Table 6).

As discussed in the main text, model standard errors for the NB2 model 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.

B.2 Institutions and socioeconomic conditions in the cyclone wind-field: robustness checks

We test the robustness of the association between elevated infant mortality rates and disaster deaths, addressing endogeneity concerns, the treatment of outliers, the choice of models, and the geographic scope of the dataset. We find that the relationship between locally elevated infant mortality in the tropical cyclone-force wind field ($>$ 119 km/hr) and increased disaster mortality is highly robust. However, when the wind field is defined at a lower intensity ($>$ 63

[5] The regional classifications are based on the Unites Nations Statistics Division (UNSD) Standard country or area codes for statistical use (M49).

km/hr) estimates remain positive but lose statistical significance in some of the specifications in the sensitivity analyses.

One potential concern specific to this portion of the analysis 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 19 and 20). 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 18, 19 and 20). However, while in both cases the coefficient on the less intense (> 63km/hr) wind field remains positive it loses statistical significance when the dataset is restricted to 2001-2016.

As in the national analysis, we estimate OLS regressions of the inverse hyperbolic sine of deaths and the natural logarithm of deaths (+ 1) using the same data and independent variables as in the main results. The results are reported in Tables 24 and 28. All estimates of the IM ratio are positive; however, they are only statistically significant for the more intense (> 119 km/hr) wind field. The OLS model of the natural logarithm of deaths, excluding zero death events (as ln(0) is undefined), yields a similar result (Table 29).

Using the OLS model of the inverse hyperbolic sine of deaths, which is better able to handle large outliers than the negative binomial model, we test alternative versions of the dataset that include outliers (Table 25), include the Indian Ocean Basin and outliers (Table 26), and include the Indian Ocean Basin but exclude outliers (Table 27). Similar to estimates based on the main dataset, in each case we see a large, statistically significant effect for infant mortality rates in the more intense tropical cyclone wind field (>119 km/hr). For the weaker tropical storm wind fields the results are consistently positive, but not statistically significant.

Next we address the concern that the results may be driven by observations from a single region, and therefore lack general validity. As with the national analysis, there are insufficient observations for individual regions to precisely estimate the results based on regional datasets. The number of observations by region in the 1979 to 2016 dataset used for this portion of the analysis is: Asia (505), Latin America and the Caribbean (207), Northern America (89), Oceania (48), Africa (65), and Europe (including small island territories of European nations) (43). Similar to other sensitivity analyses in this section, the main results for the stronger tropical cyclone wind fields are more robust than for the weaker tropical storm wind fields (Tables 22 and 23). In both cases, we see a large increase in the coefficient when the most represented region, Asia, is excluded. This may indicate that the association between locally elevated infant mortality and storm deaths is less pronounced, or different, in Asia.[6]

B.3 Institutions and socioeconomic conditions in the cyclone wind-field: Powerless and excluded ethnic groups

In order to test the hypothesis that ethnic marginalization in the wind field increases mortality, for each storm we estimate the population-weighted percentage of the storm wind field that is settled by an excluded ethnic group. The direction of the coefficients for excluded settlements on cyclone mortality are consistent with this hypothesis in our main specifications, but are not precisely estimated (Table 18). Further, the coefficients on the excluded ethnic group indicators vary in sign and magnitude across the alternative datasets and models tested (Tables 18 - 29). Although not in keeping with our initial hypothesis, previous work has 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. The excluded groups, although not represented politically, may still benefit from national initiatives related to cyclone preparedness, evacuation and response. This is plausible given the geography of tropical cyclone exposure in relation to politically excluded groups. Following the EPR classification, the *excluded* designation includes all ethnic groups "excluded from executive state power" (Vogt et al., 2015, p. 1331). However, as described in SI Section A, our observations of excluded groups settled within tropical cyclone wind fields are heavily dominated by *powerless* - versus *discriminated* or *self-excluded* - ethnic groups. It is therefore unsurprising that an alternative specification that replaces all excluded groups with only settlements of powerless ethnic groups yields very similar (null) results (Table 30). With so few observations available, our data are not suitable for testing the arguably stronger hypothesis that tropical cyclones are more deadly when *discriminated* ethnic group settlements are exposed to natural hazards. Additionally, our estimates of exclusion are an imperfect indicator of the actual size of the excluded population: we capture only the spatial extent of ethnic group settlements, not the density or degree of exclusion. Further, the outcome variable deaths is not disaggregated by ethnic group; we have no data on whether mortality is higher or lower amongst members of an excluded group. There may also be heterogeneities that are not captured by our estimates of average effects; a binary indicator of exclusion does not capture the multiple forms and on-the-ground realities of political powersharing arrangements (Busby, 2018; Strøm et al., 2017). The effect may also work in multiple directions: exclusion from national government protections being compensated for by some other factor, such as indigenous knowledges and institutions or strong social capital at the local level.

[6] Asia excludes the Indian Ocean Basin events, which primarily affect countries in Southern Asia.

C Supplementary Figures and Tables

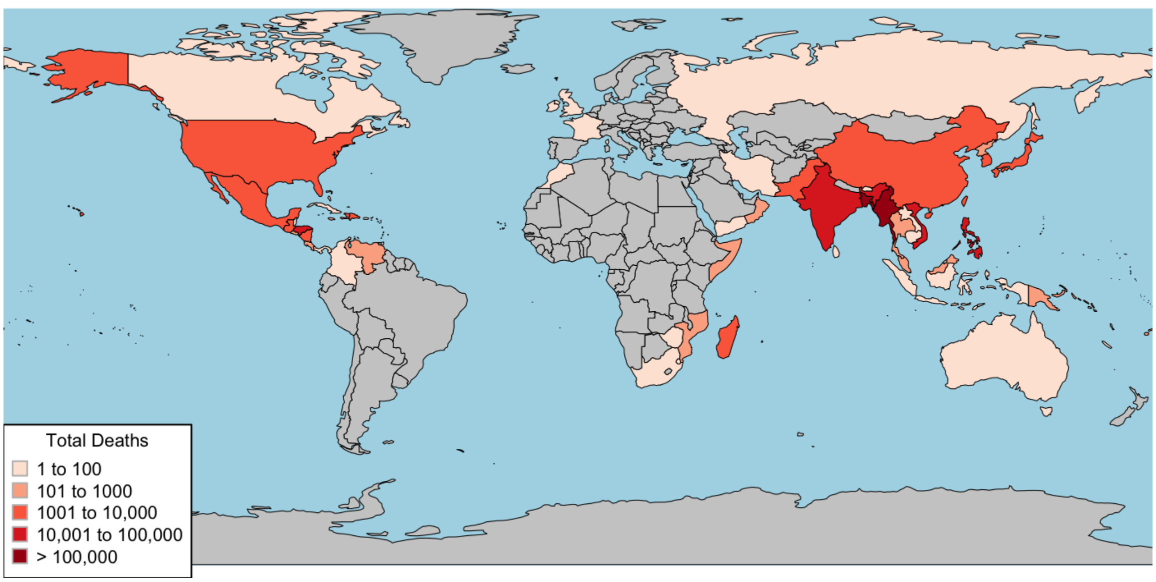

Figure 6: Cumulative deaths from tropical cyclone disasters, 1979 to 2016. Based on data from the EM-DAT (Guha-Sapir, 2018).

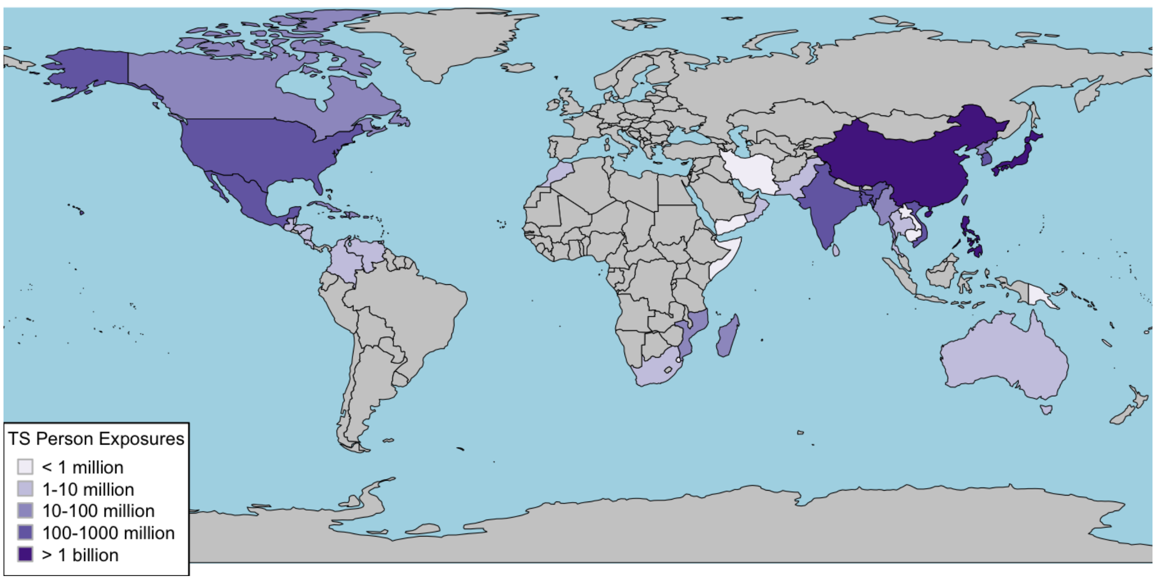

Figure 7: Cumulative population exposure to tropical storms and cyclones (sustained winds $>$ 63 km/hr) from 1979 to 2016. See Table 1 for a description of the population exposure variables. Author calculations based on source data and models by (Anderson et al., 2017; CIESEN, 2017a,b; Knapp et al., 2010; Willoughby et al., 2006).

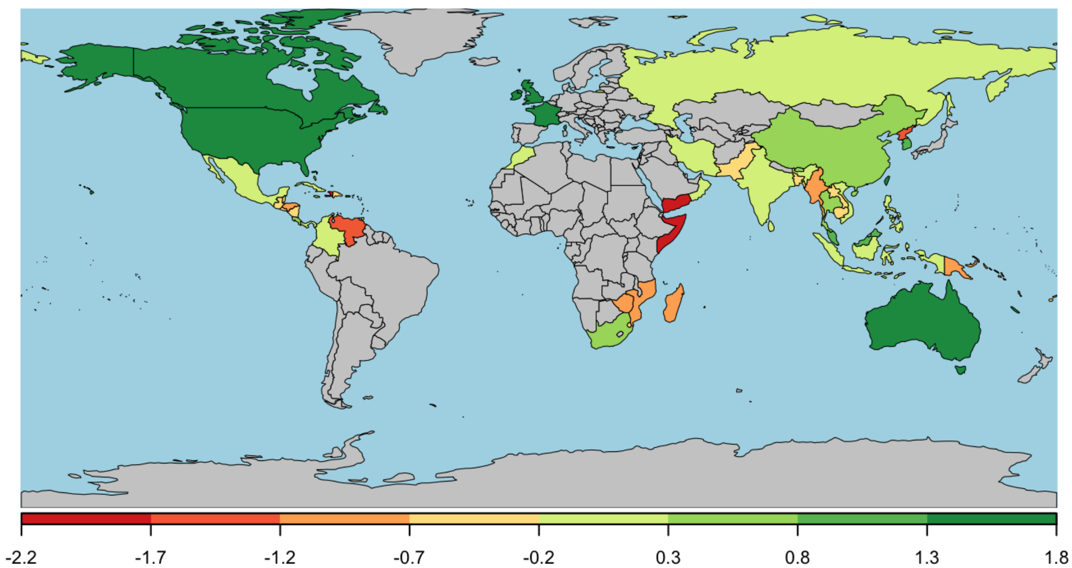

Figure 8: National government effectiveness scores for tropical cyclone affected countries, 2016. Higher scores indicate more effective governance. Countries are shaded in grey if 2016 WGI are not available or the country did not experience a deadly tropical cyclone disaster between 1979 and 2016. Source data from the World Governance Indicators (Kaufmann et al., 2010; wgi, 2020).

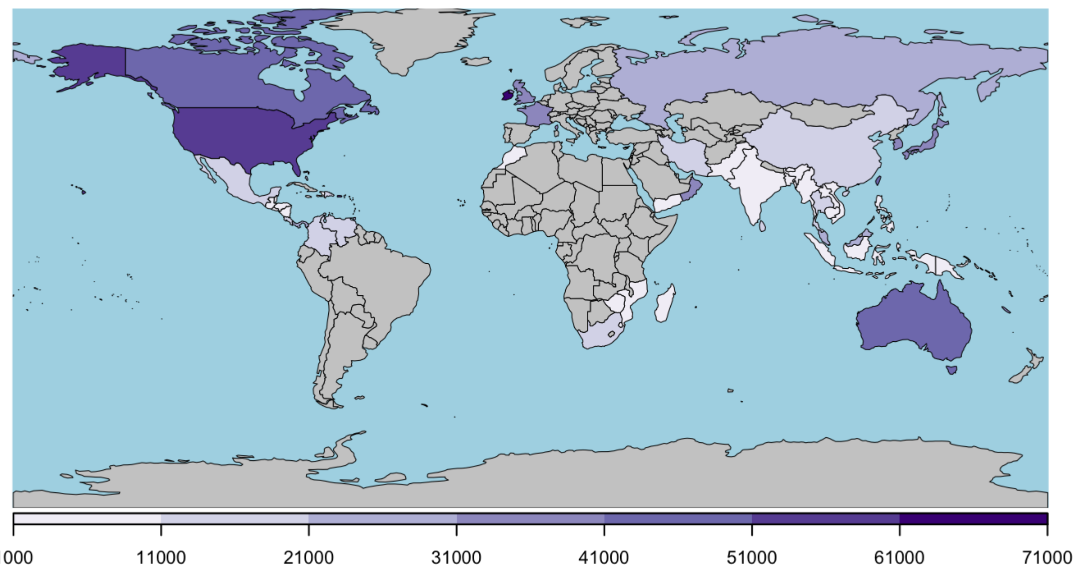

Figure 9: Real GDP per capita (2010$) for tropical cyclone affected countries, 2016. Countries are shaded in grey if GDP data are not available or the country did not experience a deadly tropical cyclone disaster between 1979 and 2016. Source data from the World Bank World Development Indicators, supplemented with data from Penn World Tables (wdi, 2020; Feenstra et al., 2015, 2020)

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 Saffir-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 Saffir-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 (National Oceanic and Atmospheric Administration, 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; wgi, 2020).
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, 2020; Feenstra et al., 2015, 2020).
Infant mortality rate	country	1978-2016	Mortality rate, infant (per 1,000 live births)	The World Development Indicators (wdi, 2020)
Education	country	1979-2016	School enrollment, primary (% net)	The World Development Indicators (wdi, 2020).
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, 2020).
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; for storms occurring in 1997, 1999 and 2001 the nearest estimate (by date) is matched to the storm.
** Variable calculated for multiple wind thresholds, i.e. 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	508.3	53632	8627	16395	15158
National infant mortality rate	1.70	138.7	18.10	20.82	17.70
Primary school enrollment (% net)	56.92	99.95	94.78	92.66	6.46
Pop. (millions) exposed to winds 63-118 km/hr	0.00	86.36	0.37	6.11	13.04
Pop. (millions) exposed to winds 119-153 km/hr	0.00	25.51	0.00	0.32	1.37
Pop. (millions) exposed to winds $>$ 153 km/hr	0.00	2.65	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 effectiveness	Real GDP per capita	National infant mortality rate	Primary school enrollment (% net)	Pop. (millions) exposed to winds 63-118 km/hr	Pop. (millions) exposed to winds 119-153 km/hr	Pop. (millions) exposed to winds > 153 km/hr	Maximum rainfall exposure (mm)
Deaths	1.000	-0.095	-0.097	0.098	-0.057	0.014	0.105	0.038	0.061
Governance	-0.095	1.000	0.895	-0.688	0.338	0.206	0.110	0.017	0.188
RealGDPpc	-0.097	0.895	1.000	-0.654	0.335	0.169	0.091	0.038	0.113
IMR	0.098	-0.688	-0.654	1.000	-0.708	-0.198	-0.086	-0.044	-0.073
Education	-0.057	0.338	0.335	-0.708	1.000	0.004	-0.030	0.058	-0.061
ExpTS	0.014	0.206	0.169	-0.198	0.004	1.000	0.335	0.043	0.206
ExpTC1	0.105	0.110	0.091	-0.086	-0.030	0.335	1.000	0.262	0.189
ExpTC2+	0.038	0.017	0.038	-0.044	0.058	0.043	0.262	1.000	0.073
MaxRain	0.061	0.188	0.113	-0.073	-0.061	0.206	0.189	0.073	1.000

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

	Dependent variable: *Deaths*						
	IRR (1)	IRR (2)	IRR (3)	IRR (4)	IRR (5)	IRR (6)	IRR (7)
Government effectiveness	0.250 ***	-	-	-	0.463 **	0.481 **	0.371 *
	(0.033)	-	-	-	(0.117)	(0.129)	(0.156)
Ln real GDP per capita (t-1)	-	0.340 ***	-	-	0.559 *	0.584	0.684
	-	(0.046)	-	-	(0.135)	(0.212)	(0.282)
National infant mortality rate (t-1)	-	-	1.070 ***	-	-	1.005	0.989
	-	-	(0.006)	-	-	(0.013)	(0.018)
Primary school enrollment (% net)	-	-	-	0.960 **	-	-	1.000
	-	-	-	(0.014)	-	-	(0.021)
Pop. (millions) exposed to winds 119-153 km/hr	1.418 ***	1.395 ***	1.430 ***	1.615 ***	1.397 ***	1.433 ***	1.596 ***
	(0.103)	(0.112)	(0.112)	(0.086)	(0.107)	(0.109)	(0.080)
Pop. (millions) exposed to winds > 153 km/hr	1.096	1.506	1.055	0.665	1.460	1.401	1.190
	(0.286)	(0.397)	(0.249)	(0.298)	(0.380)	(0.367)	(0.723)
Maximum rainfall exposure (mm)	1.003 ***	1.003 ***	1.002 ***	1.001	1.003 ***	1.003 ***	1.002 **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time (years)	0.951 *	0.968	0.960	0.965	0.962 *	0.965	0.969
	(0.019)	(0.017)	(0.024)	(0.018)	(0.018)	(0.020)	(0.022)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	916	885	892	452	884	862	433

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

	Dependent variable: *Deaths*						
	IRR (1)	IRR (2)	IRR (3)	IRR (4)	IRR (5)	IRR (6)	IRR (7)
Government effectiveness	0.351 ***	-	-	-	0.590 *	0.514 *	0.417 *
	(0.037)	-	-	-	(0.142)	(0.141)	(0.159)
Ln real GDP per capita (t-1)	-	0.421 ***	-	-	0.613 *	0.566	0.630
	-	(0.045)	-	-	(0.133)	(0.210)	(0.235)
National infant mortality rate (t-1)	-	-	1.052 ***	-	-	0.985	0.967 *
	-	-	(0.004)	-	-	(0.014)	(0.014)
Primary school enrollment (% net)	-	-	-	0.965 **	-	-	0.987
	-	-	-	(0.012)	-	-	(0.018)
Pop. (millions) exposed to winds 119-153 km/hr	1.610 ***	1.544 ***	1.455 ***	1.623 ***	1.584 ***	1.645 ***	2.075 ***
	(0.110)	(0.117)	(0.091)	(0.080)	(0.116)	(0.121)	(0.119)
Pop. (millions) exposed to winds > 153 km/hr	0.929	1.355	1.107	0.914	1.267	1.240	0.826
	(0.244)	(0.357)	(0.310)	(0.495)	(0.340)	(0.333)	(0.476)
Maximum rainfall exposure (mm)	1.003 ***	1.003 ***	1.002 ***	1.002 **	1.003 ***	1.003 ***	1.002 ***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Time (years)	0.942 *	0.955 *	0.942 *	0.950 **	0.951 *	0.952 *	0.969
	(0.023)	(0.019)	(0.027)	(0.017)	(0.021)	(0.022)	(0.021)
Geography	none	none	none	none	none	none	none
Observations	916	885	892	452	884	862	433

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): Negative binomial regression including Indian Ocean Basin

	Dependent variable: *Deaths*						
	IRR (1)	IRR (2)	IRR (3)	IRR (4)	IRR (5)	IRR (6)	IRR (7)
Government effectiveness	0.236 ***	-	-	-	0.547 *	0.557 *	0.427 *
	(0.031)	-	-	-	(0.134)	(0.138)	(0.156)
Ln real GDP per capita (t-1)	-	0.316 ***	-	-	0.462 ***	0.582	0.701
	-	(0.042)	-	-	(0.108)	(0.193)	(0.249)
National infant mortality rate (t-1)	-	-	1.063 ***	-	-	1.017	0.998
	-	-	(0.005)	-	-	(0.011)	(0.014)
Primary school enrollment (% net)	-	-	-	0.958 ***	-	-	0.994
	-	-	-	(0.012)	-	-	(0.019)
Pop. (millions) exposed to winds 119-153 km/hr	1.412 ***	1.410 ***	1.462 ***	1.581 ***	1.409 ***	1.456 ***	1.628 ***
	(0.103)	(0.112)	(0.110)	(0.087)	(0.108)	(0.109)	(0.082)
Pop. (millions) exposed to winds > 153 km/hr	0.896	1.161	0.892	0.754	1.115	1.045	0.919
	(0.182)	(0.263)	(0.177)	(0.205)	(0.243)	(0.230)	(0.304)
Maximum rainfall exposure (mm)	1.002 ***	1.002 ***	1.002 **	1.001	1.002 ***	1.003 ***	1.002 **
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time (years)	0.937 ***	0.964 *	0.959	0.966	0.958 *	0.964	0.972
	(0.018)	(0.015)	(0.023)	(0.018)	(0.016)	(0.019)	(0.022)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	973	942	949	482	941	919	463

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 8: Robustness of national determinants of TC mortality (1996-2016): Regional sensitivity of negative binomial regression results

	Dependent variable: *Deaths*						
	Main Dataset IRR (1)	Exclude Africa IRR (2)	Exclude Asia IRR (3)	Exclude Europe IRR (4)	Exclude LAC IRR (5)	Exclude N. America IRR (6)	Exclude Oceania IRR (7)
Government effectiveness	0.463 **	0.470 **	0.579 *	0.432 **	0.514 **	0.530 *	0.457 **
	(0.117)	(0.137)	(0.149)	(0.120)	(0.130)	(0.133)	(0.132)
Ln real GDP per capita (t-1)	0.559 *	0.556 *	0.329 ***	0.583 *	0.605	0.519 **	0.566 *
	(0.135)	(0.158)	(0.080)	(0.147)	(0.168)	(0.124)	(0.145)
Pop. (millions) exposed to winds 119-153 km/hr	1.397 ***	1.399 ***	2.644 ***	1.396 ***	1.402 ***	1.095 *	1.393 ***
	(0.107)	(0.108)	(0.387)	(0.107)	(0.109)	(0.043)	(0.107)
Pop. (millions) exposed to winds > 153 km/hr	1.460	1.320	0.740	1.447	1.673	2.844 **	1.460
	(0.380)	(0.358)	(0.222)	(0.378)	(0.527)	(0.987)	(0.382)
Maximum rainfall exposure (mm)	1.003 ***	1.003 ***	1.004 ***	1.003 ***	1.002 ***	1.003 ***	1.003 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time (years)	0.962 *	0.960 *	1.014	0.961 *	0.959 *	0.959 *	0.958 *
	(0.018)	(0.019)	(0.027)	(0.019)	(0.019)	(0.019)	(0.019)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	884	825	452	848	657	814	824

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 9: Robustness of national determinants of TC mortality (1996-2016): OLS regressions of the inverse hyperbolic sine of deaths

	Dependent variable: $\sinh^{-1}(Deaths)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government effectiveness	-0.752 ***	-	-	-	-0.483 **	-0.484 **	-0.588 **
	(0.079)	-	-	-	(0.163)	(0.166)	(0.215)
Ln real GDP per capita (t-1)	-	-0.680 ***	-	-	-0.337 *	-0.198	-0.171
	-	(0.063)	-	-	(0.132)	(0.173)	(0.215)
National infant mortality rate (t-1)	-	-	0.038 ***	-	-	0.011	-0.003
	-	-	(0.005)	-	-	(0.008)	(0.011)
Primary school enrollment (% net)	-	-	-	-0.028 *	-	-	-0.003
	-	-	-	(0.012)	-	-	(0.015)
Pop. (millions) exposed to winds 119-153 km/hr	0.173 ***	0.174 ***	0.161 ***	0.173 ***	0.176 ***	0.174 ***	0.165 ***
	(0.034)	(0.036)	(0.035)	(0.047)	(0.036)	(0.038)	(0.044)
Pop. (millions) exposed to winds > 153 km/hr	0.369	0.463	0.493	0.567 *	0.439	0.427	0.678
	(0.324)	(0.417)	(0.340)	(0.245)	(0.407)	(0.419)	(0.349)
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)	-0.046 ***	-0.034 ***	-0.027 *	-0.035 *	-0.041 ***	-0.037 ***	-0.038 *
	(0.010)	(0.010)	(0.010)	(0.015)	(0.010)	(0.011)	(0.015)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	916	885	892	452	884	862	433

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

Table 10: Robustness of national determinants of TC mortality (1996-2016): OLS regressions of the inverse hyperbolic sine of deaths including outliers

	Dependent variable: $\sinh^{-1}(Deaths)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government effectiveness	-0.764 ***	-	-	-	-0.460 **	-0.462 **	-0.588 **
	(0.080)	-	-	-	(0.164)	(0.167)	(0.215)
Ln real GDP per capita (t-1)	-	-0.696 ***	-	-	-0.369 **	-0.243	-0.171
	-	(0.064)	-	-	(0.134)	(0.176)	(0.215)
National infant mortality rate (t-1)	-	-	0.038 ***	-	-	0.010	-0.003
	-	-	(0.005)	-	-	(0.008)	(0.011)
Primary school enrollment (% net)	-	-	-	-0.028 *	-	-	-0.003
	-	-	-	(0.012)	-	-	(0.015)
Pop. (millions) exposed to winds 119-153 km/hr	0.169 ***	0.169 ***	0.157 ***	0.173 ***	0.170 ***	0.169 ***	0.165 ***
	(0.034)	(0.036)	(0.035)	(0.047)	(0.036)	(0.038)	(0.044)
Pop. (millions) exposed to winds > 153 km/hr	0.632	0.764	0.738	0.567 *	0.748	0.745	0.678
	(0.404)	(0.484)	(0.403)	(0.245)	(0.483)	(0.496)	(0.349)
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)	-0.047 ***	-0.035 ***	-0.028 **	-0.035 *	-0.041 ***	-0.037 ***	-0.038 *
	(0.010)	(0.010)	(0.011)	(0.015)	(0.010)	(0.011)	(0.015)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	918	887	894	452	886	864	433

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

Table 11: Robustness of national determinants of TC mortality (1996-2016): OLS regressions of the inverse hyperbolic sine of deaths including the Indian Ocean Basin and outliers

	Dependent variable: $\sinh^{-1}(Deaths)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government effectiveness	-0.848 ***	-	-	-	-0.498 **	-0.551 **	-0.820 **
	(0.083)	-	-	-	(0.175)	(0.177)	(0.253)
Ln real GDP per capita (t-1)	-	-0.764 ***	-	-	-0.415 **	-0.078	0.046
	-	(0.063)	-	-	(0.135)	(0.176)	(0.228)
National infant mortality rate (t-1)	-	-	0.040 ***	-	-	0.021 **	0.007
	-	-	(0.004)	-	-	(0.007)	(0.011)
Primary school enrollment (% net)	-	-	-	-0.031 *	-	-	0.000
	-	-	-	(0.012)	-	-	(0.015)
Pop. (millions) exposed to winds 119-153 km/hr	0.160 ***	0.167 ***	0.159 ***	0.176 ***	0.167 ***	0.168 ***	0.170 ***
	(0.032)	(0.036)	(0.035)	(0.050)	(0.035)	(0.037)	(0.048)
Pop. (millions) exposed to winds > 153 km/hr	0.784 ***	0.821 ***	0.734 ***	0.606 **	0.820 ***	0.762 **	0.606 *
	(0.235)	(0.236)	(0.211)	(0.228)	(0.238)	(0.236)	(0.274)
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)	-0.053 ***	-0.037 ***	-0.025 *	-0.030 *	-0.045 ***	-0.037 ***	-0.036 *
	(0.010)	(0.010)	(0.010)	(0.014)	(0.010)	(0.011)	(0.015)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	977	946	953	483	945	923	464

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

Table 12: Robustness of national determinants of TC mortality (1996-2016): OLS regressions of the inverse hyperbolic sine of deaths including Indian Ocean Basin

	Dependent variable: $\sinh^{-1}(Deaths)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government effectiveness	-0.810 ***	-	-	-	-0.440 **	-0.490 **	-0.653 **
	(0.077)	-	-	-	(0.157)	(0.157)	(0.202)
Ln real GDP per capita (t-1)	-	-0.737 ***	-	-	-0.429 ***	-0.110	-0.085
	-	(0.061)	-	-	(0.128)	(0.159)	(0.194)
National infant mortality rate (t-1)	-	-	0.039 ***	-	-	0.020 **	0.003
	-	-	(0.004)	-	-	(0.007)	(0.011)
Primary school enrollment (% net)	-	-	-	-0.029 *	-	-	-0.002
	-	-	-	(0.012)	-	-	(0.015)
Pop. (millions) exposed to winds 119-153 km/hr	0.166 ***	0.171 ***	0.162 ***	0.173 ***	0.172 ***	0.172 ***	0.168 ***
	(0.032)	(0.036)	(0.035)	(0.047)	(0.035)	(0.037)	(0.046)
Pop. (millions) exposed to winds > 153 km/hr	0.368	0.427	0.432	0.484 **	0.408	0.367	0.481 *
	(0.241)	(0.289)	(0.250)	(0.162)	(0.283)	(0.284)	(0.201)
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)	-0.052 ***	-0.036 ***	-0.025 *	-0.030 *	-0.044 ***	-0.035 ***	-0.034 *
	(0.010)	(0.010)	(0.010)	(0.014)	(0.010)	(0.010)	(0.015)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	973	942	949	482	941	919	463

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 national determinants of TC mortality (1996-2016): OLS regressions of ln (deaths + 1)

	Dependent variable: $\ln(Deaths + 1)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government effectiveness	-0.665 ***	-	-	-	-0.399 **	-0.400 **	-0.485 **
	(0.069)	-	-	-	(0.139)	(0.142)	(0.182)
Ln real GDP per capita (t-1)	-	-0.606 ***	-	-	-0.322 **	-0.210	-0.178
	-	(0.056)	-	-	(0.114)	(0.151)	(0.185)
National infant mortality rate (t-1)	-	-	0.033 ***	-	-	0.009	-0.004
	-	-	(0.005)	-	-	(0.007)	(0.009)
Primary school enrollment (% net)	-	-	-	-0.024 *	-	-	-0.002
	-	-	-	(0.011)	-	-	(0.013)
Pop. (millions) exposed to winds 119-153 km/hr	0.157 ***	0.158 ***	0.148 ***	0.168 ***	0.160 ***	0.160 ***	0.161 ***
	(0.029)	(0.031)	(0.030)	(0.044)	(0.031)	(0.033)	(0.042)
Pop. (millions) exposed to winds $>$ 153 km/hr	0.311	0.409	0.421	0.428	0.389	0.381	0.533
	(0.287)	(0.370)	(0.299)	(0.222)	(0.362)	(0.373)	(0.329)
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)	-0.041 ***	-0.031 ***	-0.025 **	-0.032 *	-0.037 ***	-0.033 ***	-0.035 **
	(0.009)	(0.009)	(0.009)	(0.013)	(0.009)	(0.009)	(0.013)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	916	885	892	452	884	862	433

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 national determinants of TC mortality (1996-2016): OLS regressions of ln (deaths)

	Dependent variable: ln($Deaths$)*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Government effectiveness	-0.822 ***	-	-	-	-0.590 ***	-0.593 ***	-0.591 *
	(0.079)	-	-	-	(0.158)	(0.161)	(0.231)
Ln real GDP per capita (t-1)	-	-0.648 ***	-	-	-0.246	-0.262	-0.269
	-	(0.065)	-	-	(0.127)	(0.174)	(0.215)
National infant mortality rate (t-1)	-	-	0.033 ***	-	-	-0.002	-0.007
	-	-	(0.005)	-	-	(0.008)	(0.010)
Primary school enrollment (% net)	-	-	-	-0.001	-	-	0.022
	-	-	-	(0.012)	-	-	(0.015)
Pop. (millions) exposed to winds 119-153 km/hr	0.140 ***	0.135 ***	0.127 ***	0.179 ***	0.137 ***	0.141 ***	0.172 ***
	(0.026)	(0.026)	(0.026)	(0.047)	(0.026)	(0.028)	(0.047)
Pop. (millions) exposed to winds > 153 km/hr	0.352	0.572	0.500	0.150	0.536	0.546	0.296
	(0.272)	(0.328)	(0.267)	(0.229)	(0.320)	(0.339)	(0.345)
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)	-0.029 **	-0.019	-0.013	-0.029 *	-0.026 *	-0.026 *	-0.030 *
	(0.010)	(0.010)	(0.010)	(0.014)	(0.010)	(0.011)	(0.015)
Geography	regions	regions	regions	regions	regions	regions	regions
Observations	703	686	685	345	686	668	334

Robust standard errors are reported in parentheses. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Zero death events are excluded from the dataset as ln(0) is undefined.

Table 15: Logistic Regression: Inclusion of exposures (winds > 63 km/hr) in the EM-DAT

	(1)	(2)	(3)
Government effectiveness	-0.906 ***	-	-0.544 **
	(0.078)	-	(0.166)
Ln real GDP per capita (t-1)	-	-0.759 ***	-0.343 *
	-	(0.066)	(0.141)
Time (years)	0.028 *	0.043 ***	0.035 **
	(0.011)	(0.011)	(0.011)
Pop. (millions) exposed to winds 63-118 km/hr	0.048 ***	0.049 ***	0.048 ***
	(0.008)	(0.008)	(0.008)
Pop. (millions) exposed to winds > 119 km/hr	0.643 **	0.668 **	0.656 **
	(0.205)	(0.206)	(0.206)
Average wind speed exposure (> 63 km/hr)	0.024 ***	0.022 ***	0.024 ***
	(0.003)	(0.003)	(0.003)
Maximum rainfall exposure (mm)	0.005 ***	0.004 ***	0.005 ***
	(0.000)	(0.000)	(0.000)
Observations	1365	1365	1365

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

Table 16: Descriptive statistics for subnational analysis dataset (1979-2016)

variable	min	max	median	mean	std. dev
Deaths	0.00	3682	9.00	55.78	200.2
Infant mortality ratio (wind field > 63 km/hr)	0.29	1.86	1.00	0.99	0.20
Infant mortality ratio (wind field > 119 km/hr)	0.30	1.83	1.00	1.02	0.22
Excluded ethnic group (wind field > 63 km/hr)	0.00	1.00	0.00	0.13	0.25
Excluded ethnic group (wind field > 119 km/hr)	0.00	1.00	0.00	0.08	0.23
National infant mortality rate	1.80	172.4	18.80	24.42	22.14
Real GDP per capita	346.4	53632	9381	16167	14785
Pop. (millions) exposed to winds 63-118 km/hr	0.00	86.36	2.27	8.17	13.82
Pop. (millions) exposed to winds 119-153 km/hr	0.00	25.51	0.00	0.45	1.52
Pop. (millions) exposed to winds > 153 km/hr	0.00	3.19	0.00	0.06	0.25
Maximum rainfall exposure (mm)	0.00	1551	231.5	264.8	171.7

Table 17: Pairwise correlations for subnational analysis dataset (1979-2016)

	Deaths	IMRatioTS	ExcludedTS	IMR	RealGDPpc	ExpTS	ExpTC1	ExpTC2+	MaxRain
	Deaths	Infant mortality ratio (wind field > 63 km/hr)	Excluded ethnic group (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	0.000	0.132	-0.152	0.044	0.158	0.138	0.050
IMRatioTS	0.009	1.000	0.297	0.031	0.144	-0.466	-0.040	0.033	0.126
ExcludedTS	0.000	0.297	1.000	-0.179	0.285	-0.152	-0.014	0.101	0.081
IMR	0.132	0.031	-0.179	1.000	-0.650	-0.165	-0.071	-0.009	-0.050
RealGDPpc	-0.152	0.144	0.285	-0.650	1.000	0.107	0.068	0.024	0.063
ExpTS	0.044	-0.466	-0.152	-0.165	0.107	1.000	0.300	0.005	0.124
ExpTC1	0.158	-0.040	-0.014	-0.071	0.068	0.300	1.000	0.233	0.151
ExpTC2+	0.138	0.033	0.101	-0.009	0.024	0.005	0.233	1.000	0.004
MaxRain	0.050	0.126	0.081	-0.050	0.063	0.124	0.151	0.004	1.000

Table 18: Effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): Negative binomial regression results

	Winds > 63 km/hr	Winds 63-119 km/hr	Winds > 119 km/hr
	IRR (1)	IRR (2)	IRR (3)
Infant mortality ratio (wind field > 63 km/hr)	2.954 *	3.414 *	-
	(1.526)	(2.127)	-
Excluded ethnic group (wind field > 63 km/hr)	1.194	1.102	-
	(0.762)	(1.070)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	3.732 **
	-	-	(1.548)
Excluded ethnic group (wind field > 119 km/hr)	-	-	1.803
	-	-	(0.771)
National infant mortality rate (t-1)	1.012	1.009	1.027
	(0.010)	(0.014)	(0.016)
Ln real GDP per capita (t-1)	0.321 ***	0.266 ***	0.224 ***
	(0.071)	(0.082)	(0.067)
Pop. (millions) exposed to winds 63-118 km/hr	1.022 ***	1.014	1.026 **
	(0.006)	(0.008)	(0.010)
Pop. (millions) exposed to winds > 119 km/hr	1.544 ***	-	1.510 ***
	(0.091)	-	(0.096)
Maximum rainfall exposure (mm)	1.001	1.001	-
	(0.001)	(0.001)	-
Time (years)	1.003	1.015	1.020
	(0.017)	(0.027)	(0.022)
Geography	countries	countries	countries
Observations	629	378	242

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 19: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016, excluding 1999-2000): Negative binomial regression results

	Dependent variable: *Deaths*		
	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)	2.828 *	3.144	-
	(1.486)	(1.985)	-
Excluded ethnic group (wind field > 63 km/hr)	1.282	1.205	-
	(0.818)	(1.186)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	3.619 **
	-	-	(1.521)
Excluded ethnic group (wind field > 119 km/hr)	-	-	1.916
	-	-	(0.851)
National infant mortality rate (t-1)	1.013	1.010	1.033 *
	(0.009)	(0.014)	(0.017)
Ln real GDP per capita (t-1)	0.314 ***	0.256 ***	0.224 ***
	(0.068)	(0.079)	(0.067)
Pop. (millions) exposed to winds 63-118 km/hr	1.021 **	1.015	1.025 *
	(0.007)	(0.008)	(0.010)
Pop. (millions) exposed to winds > 119 km/hr	1.535 ***	-	1.497 ***
	(0.091)	-	(0.092)
Maximum rainfall exposure (mm)	1.001	1.001	-
	(0.001)	(0.001)	-
Time (years)	1.004	1.017	1.025
	(0.017)	(0.027)	(0.023)
Geography	countries	countries	countries
Observations	600	359	233

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 20: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (2001-2016): Negative binomial regression results

	Dependent variable: *Deaths*		
	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)	2.687	1.765	-
	(1.966)	(1.434)	-
Excluded ethnic group (wind field > 63 km/hr)	1.928	2.038	-
	(1.352)	(1.928)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	16.134 ***
	-	-	(12.156)
Excluded ethnic group (wind field > 119 km/hr)	-	-	1.234
	-	-	(0.899)
National infant mortality rate (t-1)	0.949	0.936 *	0.927
	(0.031)	(0.028)	(0.067)
Ln real GDP per capita (t-1)	0.027 ***	0.015 ***	0.039 *
	(0.022)	(0.014)	(0.052)
Pop. (millions) exposed to winds 63-118 km/hr	1.017 *	1.021	1.008
	(0.009)	(0.012)	(0.011)
Pop. (millions) exposed to winds > 119 km/hr	1.412 ***	-	1.339 ***
	(0.090)	-	(0.077)
Maximum rainfall exposure (mm)	1.001	1.002	-
	(0.001)	(0.001)	-
Time (years)	1.005	1.055	0.972
	(0.040)	(0.050)	(0.065)
Geography	countries	countries	countries
Observations	342	220	118

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 21: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): Negative binomial regression including Indian Ocean Basin

	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)	3.068 *	3.723 *	-
	(1.438)	(2.152)	-
Excluded ethnic group (wind field > 63 km/hr)	1.127	0.973	-
	(0.683)	(0.893)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	3.267 **
	-	-	(1.287)
Excluded ethnic group (wind field > 119 km/hr)	-	-	1.858
	-	-	(0.806)
National infant mortality rate (t-1)	1.014	1.014	1.025
	(0.009)	(0.013)	(0.015)
Ln real GDP per capita (t-1)	0.308 ***	0.256 ***	0.227 ***
	(0.066)	(0.077)	(0.067)
Pop. (millions) exposed to winds 63-118 km/hr	1.018 **	1.009	1.021 *
	(0.006)	(0.007)	(0.010)
Pop. (millions) exposed to winds > 119 km/hr	1.516 ***	-	1.462 ***
	(0.091)	-	(0.095)
Maximum rainfall exposure (mm)	1.001	1.001	-
	(0.001)	(0.001)	-
Time (years)	1.004	1.020	1.019
	(0.017)	(0.027)	(0.022)
Geography	countries	countries	countries
Observations	674	409	256

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 22: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): Regional sensitivity of negative binomial regression with TS+ wind fields (sustained winds > 63 km/hr)

	Dependent variable: *Deaths*						
	Main Dataset IRR (1)	Exclude Africa IRR (2)	Exclude Asia IRR (3)	Exclude Europe IRR (4)	Exclude LAC IRR (5)	Exclude N. America IRR (6)	Exclude Oceania IRR (7)
Infant mortality ratio (wind field > 63 km/hr)	2.954 *	2.895	9.022 ***	2.954 *	2.510	2.872	2.821 *
	(1.526)	(1.648)	(5.819)	(1.526)	(1.454)	(1.565)	(1.451)
Excluded ethnic group (wind field > 63 km/hr)	1.194	1.241	0.462 *	1.194	1.429	1.209	1.139
	(0.762)	(0.808)	(0.150)	(0.762)	(1.109)	(0.947)	(0.730)
National infant mortality rate (t-1)	1.012	1.018	1.007	1.012	1.008	1.004	1.017
	(0.010)	(0.018)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)
Ln real GDP per capita (t-1)	0.321 ***	0.336 ***	0.373	0.321 ***	0.269 ***	0.345 ***	0.311 ***
	(0.071)	(0.079)	(0.204)	(0.071)	(0.063)	(0.077)	(0.070)
Pop. (millions) exposed to winds 63-118 km/hr	1.022 ***	1.022 ***	1.053 ***	1.022 ***	1.022 ***	1.021 ***	1.021 ***
	(0.006)	(0.006)	(0.012)	(0.006)	(0.007)	(0.006)	(0.006)
Pop. (millions) exposed to winds > 119 km/hr	1.544 ***	1.525 ***	2.228 ***	1.544 ***	1.492 ***	1.298 ***	1.551 ***
	(0.091)	(0.092)	(0.356)	(0.091)	(0.093)	(0.051)	(0.090)
Maximum rainfall exposure (mm)	1.001	1.001	1.002 *	1.001	1.000	1.001	1.001 *
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time (years)	1.003	1.005	0.984	1.003	1.012	0.986	1.011
	(0.017)	(0.021)	(0.016)	(0.017)	(0.017)	(0.019)	(0.019)
Geography	countries	countries	countries	countries	countries	countries	countries
Observations	629	577	271	629	506	563	599

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 23: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): Regional sensitivity of negative binomial regression with TC wind fields (sustained winds > 119 km/hr)

	Dependent variable: *Deaths*						
	Main Dataset IRR (1)	Exclude Africa IRR (2)	Exclude Asia IRR (3)	Exclude Europe IRR (4)	Exclude LAC IRR (5)	Exclude N. America IRR (6)	Exclude Oceania IRR (7)
Infant mortality ratio (wind field > 119 km/hr)	3.732 **	3.637 **	18.822 ***	3.732 **	3.372 *	2.740 *	3.767 **
	(1.548)	(1.562)	(12.758)	(1.548)	(1.729)	(1.403)	(1.571)
Excluded ethnic group (wind field > 119 km/hr)	1.803	1.937	0.822	1.803	2.034	1.991	1.745
	(0.771)	(0.831)	(0.386)	(0.771)	(1.145)	(1.324)	(0.692)
National infant mortality rate (t-1)	1.027	1.053 *	1.007	1.027	1.015	0.989	1.048 **
	(0.016)	(0.023)	(0.021)	(0.016)	(0.019)	(0.015)	(0.017)
Ln real GDP per capita (t-1)	0.224 ***	0.258 ***	0.373	0.224 ***	0.192 ***	0.345 **	0.206 ***
	(0.067)	(0.081)	(0.482)	(0.067)	(0.061)	(0.116)	(0.060)
Pop. (millions) exposed to winds 63-118 km/hr	1.026 **	1.026 **	1.063 ***	1.026 **	1.026 **	1.020 *	1.024 **
	(0.010)	(0.009)	(0.019)	(0.010)	(0.010)	(0.009)	(0.009)
Pop. (millions) exposed to winds > 119 km/hr	1.510 ***	1.493 ***	2.500 ***	1.510 ***	1.478 ***	1.162 ***	1.498 ***
	(0.096)	(0.093)	(0.423)	(0.096)	(0.099)	(0.040)	(0.090)
Maximum rainfall exposure (mm)	-	-	-	-	-	-	-
Time (years)	1.020	1.036	0.988	1.020	1.022	0.969	1.049 *
	(0.022)	(0.025)	(0.033)	(0.022)	(0.023)	(0.026)	(0.023)
Geography	countries	countries	countries	countries	countries	countries	countries
Observations	242	224	136	242	189	198	221

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 24: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): OLS regression of the inverse hyperbolic sine of deaths

	Dependent variable: $\sinh^{-1}(Deaths)$		
	Winds > 63 km/hr	Winds 63-119 km/hr	Winds > 119 km/hr
	(1)	(2)	(3)
Infant mortality ratio (wind field > 63 km/hr)	0.519	0.358	-
	(0.421)	(0.495)	-
Excluded ethnic group (wind field > 63 km/hr)	-0.195	-0.048	-
	(0.315)	(0.448)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.216 *
	-	-	(0.518)
Excluded ethnic group (wind field > 119 km/hr)	-	-	0.018
	-	-	(0.409)
National infant mortality rate (t-1)	0.017 *	0.023 *	0.001
	(0.008)	(0.011)	(0.015)
Ln real GDP per capita (t-1)	-1.267 ***	-1.507 ***	-1.357 ***
	(0.204)	(0.275)	(0.350)
Pop. (millions) exposed to winds 63-118 km/hr	0.036 ***	0.031 ***	0.034 ***
	(0.006)	(0.008)	(0.009)
Pop. (millions) exposed to winds > 119 km/hr	0.201 ***	-	0.178 ***
	(0.056)	-	(0.047)
Maximum rainfall exposure (mm)	0.002 ***	0.001 *	-
	(0.000)	(0.001)	-
Time (years)	-0.002	0.027	-0.013
	(0.012)	(0.019)	(0.017)
Geography	countries	countries	countries
Observations	629	378	242

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

Table 25: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): OLS regression of the inverse hyperbolic sine of deaths, including outliers

	Dependent variable: $\sinh^{-1}(Deaths)$		
	Winds > 63 km/hr	Winds 63-119 km/hr	Winds > 119 km/hr
	(1)	(2)	(3)
Infant mortality ratio (wind field > 63 km/hr)	0.477	0.346	-
	(0.421)	(0.494)	-
Excluded ethnic group (wind field > 63 km/hr)	-0.243	-0.090	-
	(0.317)	(0.449)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.283 *
	-	-	(0.518)
Excluded ethnic group (wind field > 119 km/hr)	-	-	-0.184
	-	-	(0.423)
National infant mortality rate (t-1)	0.017 *	0.021 *	0.002
	(0.008)	(0.011)	(0.015)
Ln real GDP per capita (t-1)	-1.275 ***	-1.503 ***	-1.401 ***
	(0.205)	(0.276)	(0.351)
Pop. (millions) exposed to winds 63-118 km/hr	0.035 ***	0.030 ***	0.033 ***
	(0.006)	(0.008)	(0.009)
Pop. (millions) exposed to winds > 119 km/hr	0.213 ***	-	0.194 ***
	(0.063)	-	(0.055)
Maximum rainfall exposure (mm)	0.002 ***	0.001 *	-
	(0.000)	(0.001)	-
Time (years)	-0.002	0.024	-0.009
	(0.012)	(0.019)	(0.017)
Geography	countries	countries	countries
Observations	632	379	244

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

Table 26: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): OLS regression of the inverse hyperbolic sine of deaths, including Indian Ocean Basin and outliers

	Dependent variable: $\sinh^{-1}(Deaths)$		
	Winds > 63 km/hr	Winds 63-119 km/hr	Winds > 119 km/hr
	(1)	(2)	(3)
Infant mortality ratio (wind field > 63 km/hr)	0.654	0.401	-
	(0.392)	(0.455)	-
Excluded ethnic group (wind field > 63 km/hr)	-0.413	-0.139	-
	(0.319)	(0.420)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.498 **
	-	-	(0.503)
Excluded ethnic group (wind field > 119 km/hr)	-	-	-0.300
	-	-	(0.429)
National infant mortality rate (t-1)	0.020 *	0.023 *	0.006
	(0.008)	(0.010)	(0.015)
Ln real GDP per capita (t-1)	-1.230 ***	-1.475 ***	-1.474 ***
	(0.208)	(0.275)	(0.356)
Pop. (millions) exposed to winds 63-118 km/hr	0.032 ***	0.028 ***	0.029 **
	(0.006)	(0.008)	(0.010)
Pop. (millions) exposed to winds > 119 km/hr	0.246 ***	-	0.239 ***
	(0.070)	-	(0.070)
Maximum rainfall exposure (mm)	0.002 ***	0.001 *	-
	(0.000)	(0.001)	-
Time (years)	-0.002	0.024	-0.006
	(0.012)	(0.019)	(0.017)
Geography	countries	countries	countries
Observations	680	410	261

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

Table 27: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): OLS regression of the inverse hyperbolic sine of deaths, including Indian Ocean Basin

	Dependent variable: $\sinh^{-1}(Deaths)$		
	Winds > 63 km/hr	Winds 63-119 km/hr	Winds > 119 km/hr
	(1)	(2)	(3)
Infant mortality ratio (wind field > 63 km/hr)	0.524	0.415	-
	(0.383)	(0.455)	-
Excluded ethnic group (wind field > 63 km/hr)	-0.240	-0.102	-
	(0.300)	(0.419)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.160 *
	-	-	(0.491)
Excluded ethnic group (wind field > 119 km/hr)	-	-	-0.005
	-	-	(0.409)
National infant mortality rate (t-1)	0.018 *	0.025 *	-0.000
	(0.007)	(0.010)	(0.015)
Ln real GDP per capita (t-1)	-1.252 ***	-1.480 ***	-1.373 ***
	(0.203)	(0.274)	(0.347)
Pop. (millions) exposed to winds 63-118 km/hr	0.032 ***	0.028 ***	0.029 **
	(0.006)	(0.008)	(0.010)
Pop. (millions) exposed to winds > 119 km/hr	0.202 ***	-	0.187 ***
	(0.054)	-	(0.050)
Maximum rainfall exposure (mm)	0.002 ***	0.002 **	-
	(0.000)	(0.001)	-
Time (years)	-0.001	0.028	-0.013
	(0.011)	(0.019)	(0.017)
Geography	countries	countries	countries
Observations	674	409	256

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

Table 28: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): OLS regression of ln (deaths + 1)

	Dependent variable: $\ln(Deaths + 1)$		
	Winds > 63 km/hr	Winds 63-119 km/hr	Winds > 119 km/hr
	(1)	(2)	(3)
Infant mortality ratio (wind field > 63 km/hr)	0.435	0.298	-
	(0.376)	(0.440)	-
Excluded ethnic group (wind field > 63 km/hr)	-0.168	-0.030	-
	(0.280)	(0.398)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.106 *
	-	-	(0.482)
Excluded ethnic group (wind field > 119 km/hr)	-	-	0.029
	-	-	(0.371)
National infant mortality rate (t-1)	0.016 *	0.020 *	0.003
	(0.007)	(0.009)	(0.014)
Ln real GDP per capita (t-1)	-1.125 ***	-1.331 ***	-1.266 ***
	(0.184)	(0.244)	(0.322)
Pop. (millions) exposed to winds 63-118 km/hr	0.031 ***	0.027 ***	0.031 ***
	(0.006)	(0.008)	(0.009)
Pop. (millions) exposed to winds > 119 km/hr	0.190 ***	-	0.169 ***
	(0.051)	-	(0.043)
Maximum rainfall exposure (mm)	0.002 ***	0.001 *	-
	(0.000)	(0.001)	-
Time (years)	-0.002	0.023	-0.010
	(0.010)	(0.017)	(0.015)
Geography	countries	countries	countries
Observations	629	378	242

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

Table 29: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): OLS regression of ln (deaths)

	Dependent variable: 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)	0.110	0.047	-
	(0.373)	(0.431)	-
Excluded ethnic group (wind field > 63 km/hr)	-0.062	0.024	-
	(0.308)	(0.445)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	1.075 *
	-	-	(0.493)
Excluded ethnic group (wind field > 119 km/hr)	-	-	0.289
	-	-	(0.382)
National infant mortality rate (t-1)	0.012	0.011	0.008
	(0.007)	(0.009)	(0.014)
Ln real GDP per capita (t-1)	-0.680 ***	-0.753 **	-1.005 **
	(0.191)	(0.244)	(0.323)
Pop. (millions) exposed to winds 63-118 km/hr	0.026 ***	0.017 *	0.034 ***
	(0.006)	(0.007)	(0.008)
Pop. (millions) exposed to winds > 119 km/hr	0.185 ***	-	0.166 ***
	(0.049)	-	(0.043)
Maximum rainfall exposure (mm)	0.002 ***	0.001 *	-
	(0.000)	(0.001)	-
Time (years)	-0.014	-0.002	-0.009
	(0.011)	(0.017)	(0.016)
Geography	countries	countries	countries
Observations	553	327	218

*Zero death events are excluded as ln(0) is undefined. Robust standard errors are reported in parentheses.
Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 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.

Table 30: Robustness of effects of wind field socioeconomic conditions on cyclone deaths (1979-2016): Negative binomial regression results for powerless ethnic groups

	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)	2.896 *	3.392 *	-
	(1.493)	(2.110)	-
Powerless ethnic group (wind field > 63 km/hr)	1.261	1.128	-
	(0.816)	(1.100)	-
Infant mortality ratio (wind field > 119 km/hr)	-	-	3.685 **
	-	-	(1.529)
Powerless ethnic group (wind field > 119 km/hr)	-	-	1.866
	-	-	(0.800)
National infant mortality rate (t-1)	1.012	1.009	1.028
	(0.010)	(0.014)	(0.016)
Ln real GDP per capita (t-1)	0.322 ***	0.267 ***	0.225 ***
	(0.070)	(0.081)	(0.067)
Pop. (millions) exposed to winds 63-118 km/hr	1.022 ***	1.014	1.026 **
	(0.006)	(0.008)	(0.010)
Pop. (millions) exposed to winds > 119 km/hr	1.540 ***	-	1.507 ***
	(0.091)	-	(0.096)
Maximum rainfall exposure (mm)	1.001	1.001	-
	(0.001)	(0.001)	-
Time (years)	1.002	1.015	1.020
	(0.017)	(0.027)	(0.022)
Geography	countries	countries	countries
Observations	629	378	242

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