Poverty, institutions, and tropical cyclone deaths in the Philippines

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Abstract

Tropical cyclones in the Philippines are frequent, deadly, and devastating. Between 2006 and 2016, eighty-five storms have caused over eleven thousand fatalities in the country. Many of the areas affected by tropical cyclones also suffer from chronic poverty and weak government capacity. How to address the dual challenges of underdevelopment and risk from natural hazards is an important policy question. In this paper, I investigate whether short-term changes in local poverty rates and government fiscal capacity impact tropical cyclone mortality. I construct and analyze a panel dataset of tropical cyclone mortality, poverty rates, and local government financial flows for 78 provinces from 2005-2016 and 1,468 municipalities from 2007-2016. I also include local, time-variant measures of physical exposure to tropical cyclone winds and rainfall in the analysis. This improves precision of the estimates and corrects for biases that would otherwise be introduced by the correlation of poverty and exposure in the data. I find evidence that short-term changes in the share of people living in poverty impact tropical cyclone mortality risk at the municipal level. Relationships between local fiscal capacity and tropical cyclone risk are not precisely estimated.

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1 Introduction

That the poor are disproportionately vulnerable to natural hazards is frequently emphasized throughout the development, disaster risk reduction, and climate change literatures. In the case of tropical cyclones, the evidence supports an association between levels of socioeconomic development and risk at multiple scales. Tropical cyclones of similar intensity tend to have higher death tolls when they affect countries with weaker governments and lower GDP per capita (Hsiang and Narita, 2012; Peduzzi et al., 2012; Tennant, 2019), and for a given storm the poorer residents of a community or region may suffer disproportionately high impacts, particularly in terms of injury and deaths (e.g. Akter and Mallick, 2013; Aldrich, 2012; Carter et al., 2007; Cutter et al., 2006; Faber, 2015; Hossain, 2015).

How best to address the dual challenges of underdevelopment and vulnerability to climatic hazards is an important policy question, particularly in light of climate change. Some argue for a 'soft' or 'general' approach to climate adaptation, which in the near term would focus on building institutional capacity and boosting socioeconomic development so that governments and individuals are better equipped to deal with a range of current and future hazards (e.g. Ayers et al., 2014; Fankhauser and Burton, 2011). Others are skeptical of 'mainstreaming' adaptation to climatic hazards into existing development efforts, emphasizing the need for more transformative policies that address the underlying power structures and long-standing inequalities that produce both poverty and vulnerability (Adger, 2003; Bankoff, 1999; Pelling, 1999).

This question of approach in part depends on the mechanisms that underlie the overlap of poverty, weak institutions, and hazard risk. If direct causal mechanisms link socioeconomic conditions and vulnerability, we would expect that incremental efforts to reduce the poverty headcount and build institutional capacity would also benefit risk reduction. For example, a non-poor individual may be less likely to go out fishing under a tropical cyclone warning because they are better able to forego the days' income. In contrast, if longer-term structural processes are dominant, then progress against poverty might have little impact on hazard risk in the short-term. While a range of mechanisms are documented in the theoretical and case study literature, their relative importance and the spatial and temporal scales at which they operate are not well documented in the empirical literature.

This paper investigates whether short-term changes in socioeconomic conditions and local government capacity have a measurable impact on tropical cyclone mortality at the municipal and provincial scale. A new multi-level dataset compiled from death records and local fiscal data in the Philippines allows me to provide novel evidence of the nested scales of vulnerability to tropical cyclones. To my knowledge, this is the first representative study of tropical cyclone mortality outcomes to include the municipal level, for the Philippines or any country. I demonstrate that aggregate statistics at the national and even provincial scales can obscure large heterogeneities in socioeconomically produced vulnerabilities.

Studies of disaster vulnerability are often confounded by large spatial and temporal variations in hazard exposure, which make it difficult to precisely estimate relationships between socioeconomic risk factors and disaster impacts. Further, failure to control for correlation between exposure and socioeconomic conditions, across places but also over time, may result in biased estimates of the socioeconomic determinants of cyclone risk. I therefore include local, time-variant measures of hazard (winds and rainfall) and exposure (population) in all models. This corrects for potential biases and improves precision in the estimates.

I find strong evidence of a link between tropical cyclone mortality and changes in municipal (but not provincial) poverty rates over time. I do not find evidence of a relationship between government fiscal capacity and fatality rates at the municipal or provincial scale. However, there is some evidence that provincial (but not municipal) government expenditure may be associated with lower storm deaths. I find evidence of a decreasing trend in mortality over time in the Philippines (conditional on exposure), possibly due to advances in technology, national disaster preparedness and response, or other macro trends.

2 Background and Relation to the Literature

The impacts of a tropical cyclone are jointly determined by the hazard and the vulnerability of the human system exposed. While some definitions of vulnerability encompass the probability of hazard exposure, when studying the socioeconomic production of risk it is useful to define vulnerability purely as a function of place (e.g. Gallopín, 2006). In this paper vulnerability is defined as the susceptibility of a province or municipality to tropical cyclone mortality, conditional on hazard and exposure.

Tropical cyclones are a regular occurrence in the Philippines, with an average of 8 to 9 storms passing over the country each year (PAGASA, 2019). Over the past decade over eleven thousand deaths have been attributed to cyclone disasters in the Philippines (2007-2016) (NDRRMC, n.d.). Yet death tolls from these storms are highly variable from year to year (see Figure 1), and this variation is even more pronounced at the local level. This is at least in part a function of the extreme variability in the number of people exposed to winds and rainfall of different intensities (see Figure 2).

Controlling for hazard exposure is therefore critical to measuring tropical cyclone vulnerability. Given dramatic fluctuations in hazard and exposure, attempts to estimate relationships between socioeconomic patterns and mortality that do not account for storm exposure and intensity will be imprecise and possibly biased. This is particularly so when data is only available for a limited time period or a subset of years, as is the case for the poverty-mortality dataset analyzed in this paper. A key feature of this analysis is that I include time-variant measures of tropical cyclone exposure at the administrative unit level (province or municipality) throughout this analysis.

2.1 Socioeconomic development and vulnerability

There is evidence in the literature that poverty, weak institutions, and hazard risk are correlated at multiple scales. Less-developed countries with weaker institutions tend to have higher death tolls from tropical cyclones and other natural hazards (Hsiang and Narita, 2012; Kahn, 2005; Peduzzi et al., 2012; Tennant, 2019). Yet national protections are not necessarily inclusive; within countries, storms tend to be more deadly when they impact areas with relatively weaker institutions and socioeconomic conditions (Tennant, 2019). In a study of the socio-economic impacts of typhoons in the Philippines, Anttila-Hughes and Hsiang (2013) find evidence of large and enduring storm impacts on all-cause female infant mortality rates. This observed increase in infant deaths is largest amongst the poorest households. Based on findings from a province-level study of tropical disaster impacts in the Philippines, Yonson et al. (2018) argue that socioeconomic development and local government capacity reduce fatalities. To my knowledge, no existing representative studies of tropical cyclone vulnerability include the municipal (or second level administrative unit) scale.

At the local level, tropical cyclones pose a serious risk to communities and households across the income spectrum. However, there is evidence from single-event studies that the poorer residents of a community or region sometimes suffer disproportionately high impacts from tropical cyclone events. For example, Akter and Mallick (2013) find that the poor suffered more severe economic, physical, and structural damages from Cyclone Aila in affected coastal communities of Bangladesh. Carter et al. (2007) found that wealthier households in Honduras were actually more likely to experience loss of productive assets, but that the average percentage of household assets lost was highest in the poorest households. Poverty, race, and social inequality are frequently cited as important root causes of the

Hurricane Katrina disaster, a storm notorious for the level of death and destruction it caused in poor and disadvantaged neighborhoods of a wealthy, democratic country (Aldrich, 2012; Cutter et al., 2006).

This overlap of underdevelopment and cyclone vulnerability raises concerns that those most in need of adaptive measures will lack the resources, institutions and social capital to effectively implement solutions (Gupta et al., 2010; Denton et al., 2014). What gains in risk reduction can be made through development, such as interventions designed to reduce poverty and build institutional capacity? This depends in part upon the causal mechanisms that underlie the relationship between socioeconomic development and hazard risk. The poor may be more vulnerable because of their poverty; because their houses are poorly built, their health is more fragile, or their coping resources fewer. Patterns of vulnerability might also be, at least in part, a legacy of the disruption and devastation wrought by tropical cyclones themselves (e.g. Anttila-Hughes and Hsiang (2013); Hsiang and Jina (2014)). Long-standing inequalities in wealth and power are also frequently cited in the co-production of poverty and vulnerability to environmental hazards (e.g. Blaikie et al. (2004); Bankoff (1999); Pelling (1999).

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

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

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

Vulnerability produced through historical processes that have shaped the location of settlements in relation to physical vulnerability and hazard exposure imply a relatively indirect link between poverty and vulnerability. One would expect to see spatial correlation between poverty and physical risk factors, such as settlement in low-lying coastal areas or on unstable slopes. However, we would not necessarily expect modest income gains to have large impacts on risk in the near-term. In contrast, if more direct and immediate mechanisms link socioeconomic conditions and vulnerability there may be strong synergies between poverty reduction, instutution and capacity building, and disaster risk reduction. The existing state of the empirical evidence on this topic is insufficient to distinguish the relative importance of short- and long-term mechanisms, or the scales at which they may be most relevant.

3 Model

In order to test whether short-term gains in institutional capacity and socioeconomic development are associated with changes in tropical cyclone risk at the local level, I construct and analyze a panel dataset of 78 provinces (2005-2016) and 1,468 municipalities (2007-2015). Using standard panel data methods, I model the inverse hyperbolic sine ihs of tropical cyclone mortality y for province (or municipality) i and in time period t using the following linear fixed effects regression model,

$$ihs(y_{it}) = \alpha_i + \gamma_t + \mathbf{v}'_{it}\boldsymbol{\beta}_1 + \mathbf{h}'_{it}\boldsymbol{\beta}_2 + \varepsilon_{it} \tag{1}$$

where α_i is the place fixed effect, γ_t the time fixed effect, $\mathbf{v}_{it}$ is a vector of local institutional and poverty regressors, and $\mathbf{h}_{it}$ represents the control variables for local hazard exposure (i.e., wind, rainfall and population). The time fixed effect is included to account for covariate shocks and trends, such as trends or shifts in national disaster preparedness and response, technology and other macro trends. Poverty rates are generally decreasing over time for most provinces and municipalities. However, this approach also risks absorbing annual variation in hazard exposure as well as causal variation in socioeconomic conditions into the time dummies. For comparison, I also present an alternative set of specifications where a linear time trend replaces the time fixed effect. This controls for steady improvement in technology, national response capacity, and other macro trends without absorbing random variation in hazard.

The inverse hyperbolic sine transformation $ihs(y_{it}) = \ln(y_{it} + \sqrt{y_{it}^2 + 1})$ allows us to utilize a linear model with a dependent variable, tropical cyclone deaths, that includes true zero values. In some cases, this type of 'count data' can also be modeled using Poisson or negative binomial models. However, a Poisson model would be inconsistent in this case due to overdispersion in the data: $E[y_i \mid \mathbf{x}_i] \ll Var[y_i \mid \mathbf{x}_i]$ (Greene, 2012). The negative binomial model relaxes the equidispersion principle, but available methods either do not offer a true fixed effect or tend to underestimate standard errors (Allison and Waterman, 2002). Further, I find negative binomial panel data methods to be computationally untenable for many specifications (particularly at the municipal level) due to the large number of local government units (Allison, 2009).

The analysis of fixed effects in this paper provides novel evidence of how improvements (or deterioration) in a locality's socioeconomic conditions and fiscal capacity can impact mortality from a tropical cyclone. However, a limitation of the fixed effects approach is that we are losing all of the between-unit variation in our data, which can render the estimates inefficient. This is a common problem with the fixed effects model, which can result in the underestimation of coefficients (Angrist and Pischke, 2009).

In order to exploit the between variation in the dataset, I also estimate comparable random effects and pooled OLS models. However, there is strong theoretical and empirical evidence for unobserved heterogeneity across the provinces and municipalities of the Philippines. Differences in the historical and geographic characteristics of localities are likely to impact both their long-term development trajectories as well as vulnerability to tropical cyclones. This is confirmed by statistical tests, which indicate inconsistency in the random effects and pooled OLS estimates.[1]

Parameterizing these models requires spatially and temporally matching observations

[1] I find strong evidence of unobserved heterogeneity using the Lagrange Multiplier test for individual effects. I also find that the strict exogeneity assumption for random effects is violated. Thus, I reject the null hypotheses that the random effects and pooled OLS models are consistent.

from socio-economic, disaster mortality, and physical storm data sources. In the following section I describe both the underlying data sources as well as the methods used to compile the dataset.

4 The Data

I construct and analyze a panel dataset that captures the socioeconomic conditions, intensity of exposure, and death tolls from tropical cyclones in the Philippines at the province (2005-2016) and municipal scales (2007-2016). Descriptions of the key hazard exposure and socioeconomic variables for this analysis can be found in Tables 1 and 2, respectively. Summary statistics are presented in Tables 3 and 5.

4.1 Hazard exposure

Over the 1979 to 2016 period, the Philippines have been exposed to more tropical storms and cyclones than any other country.[2] While all regions of the Philippines are periodically exposed to tropical cyclones, exposure is highly variable in intensity and frequency over space and time (see Figure 2). Further, exposure has historically been higher in the more affluent, northern regions of the country. In order to control for bias and reduce imprecision introduced by fluctuations in tropical cyclone exposure, I construct time-variant province and municipal exposure metrics. These variables include the intensity of wind and rainfall, and are summarized in Table 1.

Wind speeds are modeled using a parametric wind speed model developed by Willoughby et al. (2006). The model is implemented using the *stormwindmodel* software in R, developed by Anderson et al. (2017) and adapted by the author for global use.[3] I begin with a 15 arc-minute modeling of all storms recorded by the Best Track Archive for Climate Stewardship (IBTrACS) Project from 1979 to 2016 globally. Storms that generate sustained winds of 18 km/hr over the Philippines in this model are then modeled at a 2.5 arc-minute (approximately 5km at the equator) resolution. These raster wind fields are then overlain with municipal and provincial boundaries to estimate a maximum sustained wind speed variable. The annual maximum wind speed for an administrative unit is the strongest sustained wind speed experienced by that province or municipality for any storm

[2]Author calculations based on data and methods by Anderson et al. (2017); Knapp et al. (2010); Willoughby et al. (2006)

[3]The adapted software is open source and available at github.com/liztennant/stormwindmodel.

occurring in that year.

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

4.2 Mortality

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

According to NDRRMC records, a total of 13,108 deaths were attributed to tropical cyclones occurring between 2005 and 2016. Of these, 12,653 deaths occurred in the 78 provinces included in this analysis. The National Capital Region, including Metropolitan Manila, is not a part of any province and therefore excluded from this analysis. Three additional provinces and several municipalities were excluded due to missing data or administrative changes that render them incomparable over the study period. Second level administrative units classified as cities are not included in the municipal analysis, leaving 1,468 municipalities.

NDRRMC casualty reports include a data field that sometimes contains remarks on the cause or circumstances of the death. The field is often missing, particularly for the most heavily impacted locales and the strongest storms. A remark of some kind is included for only 34% (3,752) of deaths tabulated for 2007 to 2015. When remarks are included they do not follow a consistent coding scheme and are therefore not well suited to quantitative analysis. For example, entries such as "trauma" and "hit by a falling tree" could describe very different or very similar events. While clearly not representative, these data a provide a useful exploratory look at a range of causes and circumstances of tropical cyclone mortality. The word cloud in Figure 3 tabulates the frequency of the 100 words most frequently used to describe the cause or circumstances of death. 'Drowning' or 'drowned' stand out as a common cause of death, which may result from a range of physical hazards including storm surge, rain fed flooding, hazardous conditions at sea and more. Landslides and being 'hit' by various flying debris, falling trees and collapsed structures are also common. This limited information about cause of death indicates that wind and rainfall measures are suitable but incomplete proxies for exposure; we would ideally have data on the depth and extent of flooding and storm surge as well.

4.3 Institutional and socioeconomic conditions

Annual socioeconomic data at the province and municipal levels is compiled to test the effects of local government financial flows and poverty on tropical cyclone mortality. Details of the key socioeconomic variables in this analysis are summarized in Table 2.

The Family Income and Expenditure Survey (FIES) is the primary source of sub-national income data in the Philippines. This household survey is conducted every three years, and province-level poverty and income data published from the 2006, 2009, 2012 and 2015 surveys was obtained from the Philippines Statistical Authority (PSA) (FIES, 2018). At the municipal level, the FIES data are combined with census data from the same year to provide high-quality estimates of local poverty rates using a technique known as Small Area Estimation (Elbers et al., 2003). These small area poverty estimates are published by the Philippines Statistics Authority drawing on projects by the PSA, World Bank and other partners (PSA, 2016). Poverty in these estimates is defined in accordance with the Social Reform and Poverty Alleviation Act (Republic Act 8425): "families and individuals whose income fall below the poverty threshold and who cannot afford to provide for their minimum basic needs in a sustained manner." (PSA, 2016). Income data is not available at the municipal level, and is not available at the province scale for the year 2015.

The constraint of three-year poverty estimates is an important limitation in this analysis, as it limits the panel to 4 waves (3 if we include income). Particularly in the municipal results, where we have a large number of observations but limited time periods, this may result in inconsistent estimates of α_i. However, historical mortality records are limited and, to my knowledge, sub-nationally representative poverty data is simply not systematically collected on an annual basis for the Philippines. The Annual Poverty Indicators Survey

(APIS) that has recently been implemented (from 2013) is designed to be representative only at the national level.

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

5 Results & Discussion

During the study period annual tropical cyclone deaths were, on average, lower in poorer provinces of the Philippines. However, once we control for the negative correlation between poverty and hazard exposure, evidence of a positive relationship between poverty and cyclone deaths emerges. At the municipal scale, evidence from a two-way fixed effects model supports a positive relationship between poverty rates and tropical cyclone deaths. Comparable models do not yield statistically significant results at the provincial scale. Overall, relationships between local government fiscal capacity and tropical cyclone mortality are not precisely estimated. However, there is some evidence that provincial government expenditure may be associated with lower cyclone deaths. These findings and all of the results presented below are based on models that control for tropical cyclone hazard and exposure at the local level, unless specifically noted otherwise for purposes of comparison.

5.1 Poverty

The main results of the poverty and income models are presented in Tables 7 and 8. I find robust and statistically significant evidence of an association between municipal poverty rates and tropical cyclone mortality. This is slightly attenuated but remains practically and statistically significant if we control for provincial poverty incidence (Table 8 (3)). While fluctuations in poverty are likely to be correlated with trends in income and other measures of socioeconomic development which I do not control for, these results represent new evidence that short-term changes in socioeconomic conditions can measurably impact disaster mortality at the local level.

At the province level, the effects of poverty and income on tropical cyclone deaths are not precisely estimated. However, the sign of the point estimates are generally consistent with the hypotheses that tropical cyclone deaths are lower in provinces with lower poverty rates or higher incomes (Table 7 (1 & 2)). Province level poverty rates are statistically significant determinants of municipal deaths in a model that also contains municipal poverty measures (Tables 8 (3)), consistent with province-level correlation in temporal changes of socioeconomic conditions.

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

5.2 Local government capacity and expenditure

I next test for a relationship between tropical cyclone mortality and provincial and municipal fiscal capacity proxied by locally generated revenues. I do not find statistically significant evidence of a relationship between tropical cyclone mortality and fiscal capacity in the province or municipal two-way fixed effects models (Tables 9 & 10), either for local revenue per capita or the share of total income raised locally.

Overall, we do not see clear evidence of a link between tropical cyclone mortality and fiscal capacity at the provincial or local level. This may be because the capacity to levy taxes and fees is not sufficiently correlated with the particular attributes of governance necessary for reducing vulnerability to disaster mortality. Features such as public trust in government and civic engagement are not well captured by financial flows. Further, to the extent that general administrative capacity is required for both revenue collection and the types of planning and public works necessary for disaster risk reduction, there may be other limiting factors such as lack of disaster-specific knowledge and authority. This would be consistent with the centralized governance of disaster management in the Philippines, or with the particularly active role that non-governmental organizations (NGOs) play in the Philippines (Bankoff and Hilhorst, 2009; Brower and Magno, 2011).

Province-level expenditure, however, is associated with lower tropical cyclone deaths in the subsequent period (Table 9). This effect holds independent of local revenues, so may be less indicative of local fiscal capacity and more-so of the effects of government spending on public goods and services. The municipal level model does not indicate a relationship between municipal government expenditure and tropical cyclone mortality (Table 10).

5.3 Physical controls

Throughout this analysis, estimated coefficients for wind speed are large and highly statistically significant. They also prove important to identifying the relationships of interest; note that a model excluding hazard (Table 8 (1)) does not reproduce the finding that municipal poverty rates are associated with and cyclone deaths (Table 8 (2 & 3)). This contrasts the findings of Yonson et al. (2018), who do not find statistically significant evidence of an association between wind speed and fatalities at the provincial scale in the Philippines. However, our findings are consistent with theory and the broader literature on this topic, which indicate that wind speed is a useful control for the destructive potential of a storm (Anttila-Hughes and Hsiang, 2013; Hsiang and Narita, 2012; Peduzzi et al., 2012; Pugatch, 2019; Tennant, 2019).

The use of rainfall in addition to wind speed to proxy hazard exposure from tropical cyclones is less common in the literature (exceptions include Tennant (2019); Yonson et al. (2018)). In this analysis, the estimated effect of rainfall on mortality in models also including wind speed is consistently positive but not always statistically significant (particular when the number of observations is small). This indicates modest support for the use of rainfall as an additional control for storm exposure in subnational analyses of tropical cyclone impacts. Improving the sophistication of this measure, for example with higher resolution data (as available) or by interacting rainfall with surface hydrology models, might improve its explanatory power.

5.4 Robustness of results

I explore multiple sources of potential sensitivity for these results, including the years of analysis and the choice of a two-way fixed effects model versus a linear time trend. The main finding of an association between municipal poverty rates and cyclone mortality is robust to multiple alternative specifications and analytical choices. The observed relationship between provincial government expenditure and tropical cyclone deaths is more sensitive.

As previously discussed, poverty data are only available every three years with a total of 4 measurements available. This substantially reduces the years and therefore number of storm events upon which this portion of the analysis is based. As an alternative to the annual panel model, I construct a dataset with three year periods (so poverty in 2006 is compared to storm exposure and mortality in 2007-2009). The results at the municipal scale are in general robust to this alternative construction of the dataset. While standard errors increase, the coefficient on poverty increases in magnitude and remains statistically significant ($p < 0.05$). At the provincial level, relationships between tropical cyclone mortality and provincial poverty and income are not precisely estimated under this alternative construction of the dataset, as is the case in the main model (see Table 11).

The preferred specifications include administrative unit and year fixed effects, the latter accounting for shocks and trends that impact tropical cyclone vulnerability across the Philippines. This might include shifts in the technology, capacity and resources devoted to disaster preparedness and response at the national level. However, these year fixed effects will also absorb some of the average annual hazard intensity and exposure (see Figure 1). We therefore also report an alternative specification with year or time period as a continuous variable. While linearity is a strong assumption, it can capture incremental improvements in technology, national (or international) capacity for disaster risk reduction, and other macro trends without absorbing stochastic year-to-year variation in hazard exposure. The coefficients on the time variable generally support the hypothesis that deaths are decreasing over time, controlling for hazard exposure and local socioeconomic conditions (though the effect is not always precisely estimated) (see Tables 13 - 16).

The municipal results testing the relationship between poverty, government financial flows, and tropical cyclones are robust to this decision (see Tables 14 & 16). However, once again the province-level results are more sensitive to the use of a linear time trend. The coefficients on provincial expenditure remain negative in Table 15 (2 & 4), but are slightly attenuated and no longer statistically significant. Further, in Table 13 the association between higher incomes and lower deaths is statistically significant ($p < 0.05$) in model (3) but not in model (2).

6 Conclusions

The Philippines is amongst the most tropical cyclone affected countries in the world. Over the past decade 85 storms have caused over eleven thousand fatalities (2007-2016) (NDRRMC, n.d.). Yet tropical cyclones are just one of many natural hazards faced by the people of the Philippines. According to the Emergency Events Database (EM-DAT), from 1979 to 2016 the Philippines experienced disaster brought on by various forms of natural hazard including tropical cyclones (232 events), floods (133), landslides (28), earthquakes (18), volcanic activity (17) and drought (8) (Guha-Sapir, 2018). The Philippines also faces chronic poverty and underdevelopment, conflict and terrorism. Given finite resources and the battery of potential social, economic, and environmental shocks that developing countries such as the Philippines must cope with, policy-makers need tools to identify at-risk populations and to better understand how vulnerability is produced and perpetuated. In particular, one important policy question is whether short-term gains in general socioeconomic conditions and government capacity can reduce vulnerability to natural hazards, such as tropical cyclones.

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

I present novel evidence of a relationship between the share of people living in poverty at the municipal level and tropical cyclone mortality risk. Using a municipal fixed effects model, I find that an increase of 1% in the poverty rate is associated with a 0.25% decrease in tropical cyclone mortality. This result controls for tropical cyclone hazard and exposure, and is highly statistically significant and robust to a range of analytical choices. This does not necessarily indicate that poverty is the only or dominant causal mechanism underlying this result, as poverty rates tend to be highly correlated with income and other socioeconomic variables. However, these results do provide robust evidence that short-term fluctuations in local socioeconomic conditions are associated with changes in the mortality risk from tropical cyclones. At the provincial level relationships between poverty rates and tropical cyclone deaths are not precisely estimated.

From a policy perspective, these results suggest that development gains - perhaps especially at the bottom of the distribution - may have short-term payoffs for disaster risk reduction. The results are also consistent with the presence of highly localized mechanisms for poverty-driven vulnerability to cyclone risk in the Philippines.

In contrast, the the evidence does not indicate a relationship between local fiscal capacity and tropical cyclone mortality rates. One explanation for these results may be that local government fiscal capacity is not sufficiently correlated with the types of capacity needed for disaster risk reduction. Locally representative data on qualities such as trust in governance, civic engagement, and disaster-specific knowledge and capacity are not readily available for the Philippines. Alternatively, it may be that general administrative abilities are not currently the binding constraint on local governments' efficacy in disaster risk management. In a country with historically centralized governance of disasters like the Philippines it is credible that, in addition to general administrative capacity, local governments are in need of risk-specific specific knowledge, skills and accountability to promote effective engagement in this sphere.

However, this analysis does have a number of limitations which might be addressed in future research. For example, we consider only the immediate deaths directly attributed to tropical cyclone disasters, possibly underestimating the full effects of tropical cyclone disasters on mortality by an order of magnitude or more (Anttila-Hughes and Hsiang, 2013). If these additional deaths are mediated by institutionally driven factors (i.e. the provision of medical care) and individual economic hardship (Anttila-Hughes and Hsiang, 2013; Kishore et al., 2018), this analysis may underestimate the differential vulnerability of places with weaker institutional capacity and higher poverty rates. Second, I demonstrate that including wind speed and rainfall improve the unbiasedness and precision of the estimates. However, differential exposure is likely still a source of bias and imprecision in this analysis. Data on the depth and extent of storm surge in particular would improve our estimates of local hazard exposure. Higher resolution rainfall data, ideally interacted with surface hydrology, would also improve hazard exposure models. As physical models and both physical and socioeconomic data availability improve, so will our ability to accurately identify the processes that connect poverty, governance and hazard risk.

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A Figures

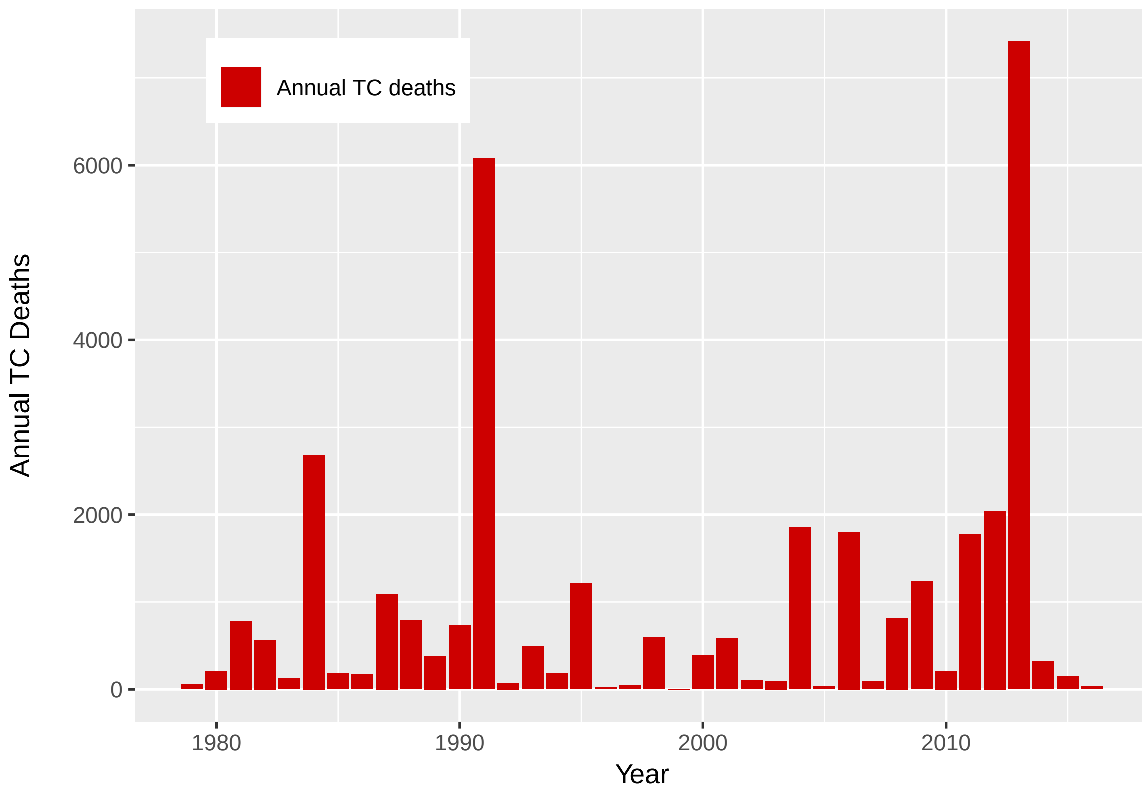

Figure 1: Annual deaths from tropical cyclone events in the Philippines, 1979-2016. Source data: the EM-DAT (Guha-Sapir, 2018).

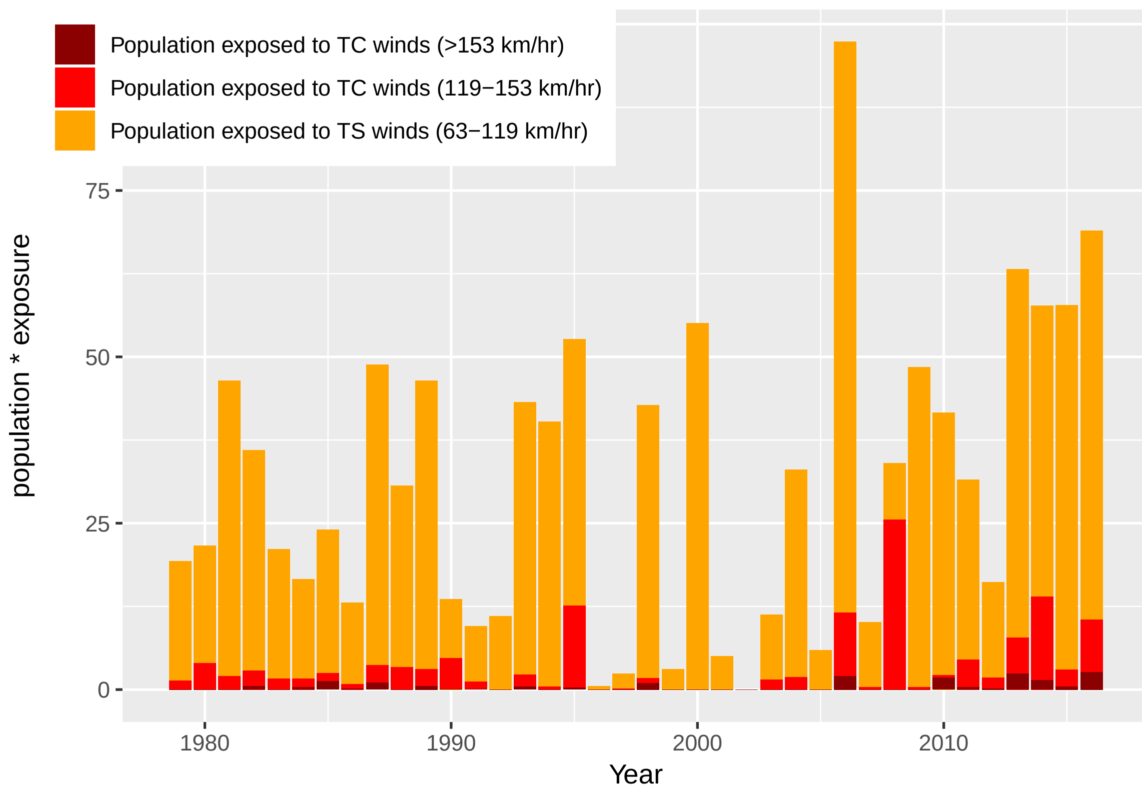

Figure 2: Annual population exposure to tropical cyclone events in the Philippines, 1979-2016. Source data: IBTrACS (Knapp et al. 2010) and CIESIN (2017a & 2017b).

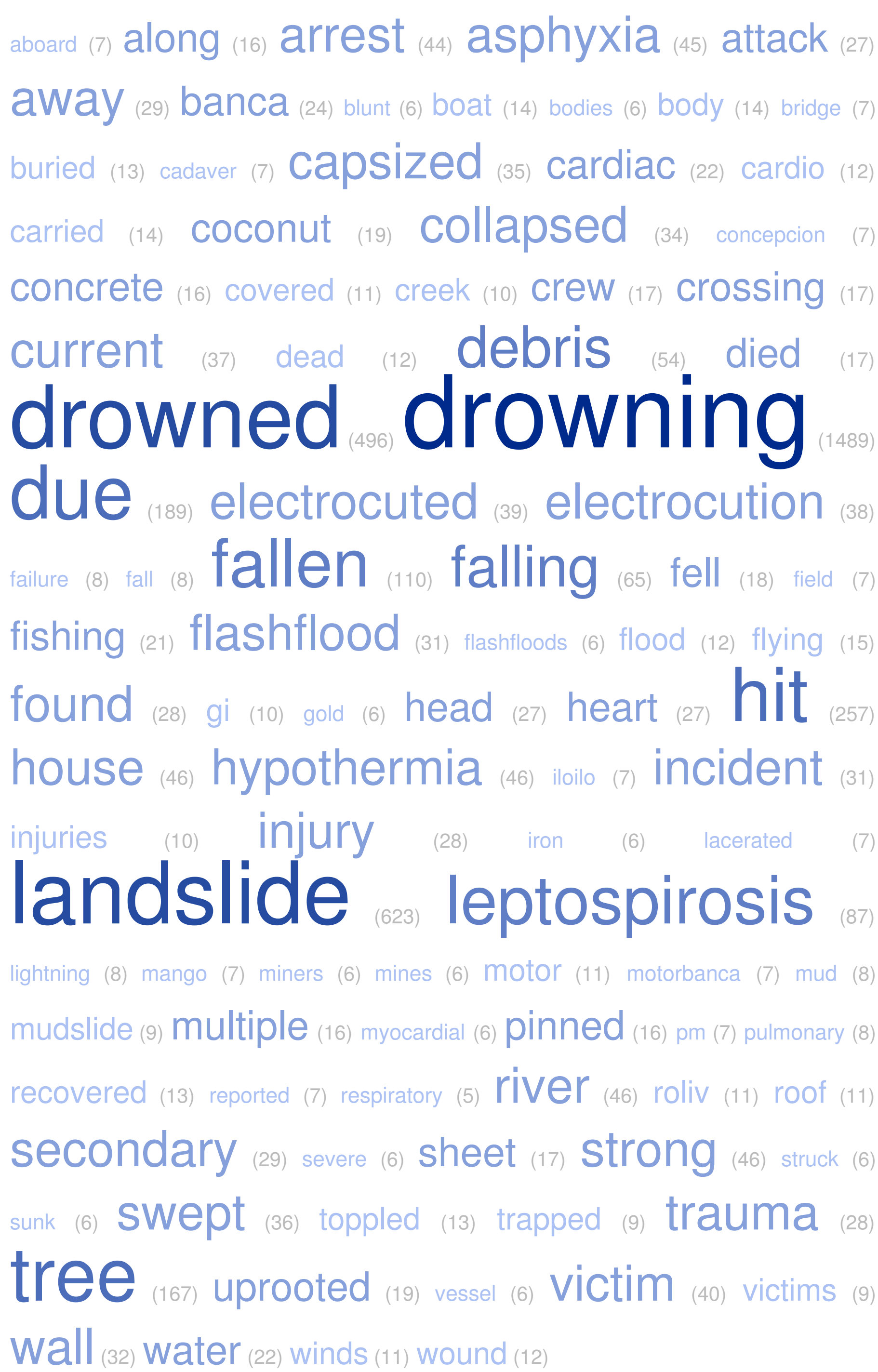

Figure 3: Tabulation of the 100 most commonly used words used to describe the cause or circumstances of tropical cyclone death, from NDRRMC tropical cyclone casualty reports, 2007 to 2015. Word cloud generated using the TagCrowd.com online tool.

A Tables

Table 1: Summary of hazard exposure variables

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

Table 2: Summary of socioeconomic variables

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

Table 3: Descriptive statistics for Provinces in the Philippines, 2004-2016

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

Table 4: Pairwise correlations in province dataset (2004-2016)

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

Table 5: Descriptive statistics for Municipalities in the Philippines, 2004-2015

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

Table 6: Pairwise correlations in municipal dataset (2004-2016)

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

Table 7: Province fixed effects regression results for poverty and income (2007, 2010, 2013, 2016)

	(1)	(2)	(3)
province poverty rate (t-1)	0.006	-	-0.008
	(0.010)	-	(0.016)
ln province income (pesos) (t-1)	-	-1.133	-1.289
	-	(0.769)	(0.836)
Total rainfall (cm)	0.006	0.003	0.003
	(0.007)	(0.009)	(0.009)
Wind speed (km/hr)	0.067 ***	0.084 ***	0.085 ***
	(0.009)	(0.012)	(0.012)
ln population	-0.457	-0.127	-0.205
	(0.722)	(1.250)	(1.264)
Geography	province	province	province
n	78	78	78
T	4	3	3
N	312	234	234
R-squared	0.209	0.263	0.264

Notes: The dependent variable is the inverse hyperbolic sine of tropical cyclone deaths. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Municipality fixed effects regression results for poverty (2007, 2010, 2013, 2016)

	(1)	(2)	(3)
municipal poverty rate (t-1)	0.001	0.003 **	0.004 ***
	(0.001)	(0.001)	(0.001)
province poverty rate (t-1)	-	-	0.000
	-	-	(0.002)
ln province income (pesos) (t-1)	-	-	-0.023
	-	-	(0.087)
Wind speed (km/hr)	-	0.022 ***	0.031 ***
	-	(0.001)	(0.001)
ln population	0.037	-0.051	0.068
	(0.055)	(0.051)	(0.089)
Geography	municipality	municipality	municipality
n	1468	1468	1468
T	4	4	3
N	5872	5872	4404
R-squared	0	0.161	0.231

Notes: The dependent variable is the inverse hyperbolic sine of tropical cyclone deaths. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: Province fixed effects regression results for government financial flows (2005-2016)

	(1)	(2)	(3)	(4)
ln local revenue per capita (t-1)	-0.024	-	-	0.020
	(0.089)	-	-	(0.091)
ln local expenditure per capita (t-1)	-	-0.476 *	-	-0.487 *
	-	(0.216)	-	(0.221)
local share revenue (t-1)	-	-	-0.001	-
	-	-	(0.004)	-
Total rainfall (cm)	0.020 ***	0.019 ***	0.020 ***	0.019 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Wind speed (km/hr)	0.051 ***	0.050 ***	0.051 ***	0.050 ***
	(0.005)	(0.005)	(0.005)	(0.005)
ln population	-0.073	-0.626	-0.062	-0.627
	(0.528)	(0.583)	(0.526)	(0.584)
Geography	province	province	province	province
n	73	73	73	73
T	12	12	12	12
N	876	876	876	876
R-squared	0.17	0.175	0.17	0.175

Notes: The dependent variable is the inverse hyperbolic sine of tropical cyclone deaths. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: Municipality fixed effects regression results for government financial flows (2007-2016)

	(1)	(2)	(3)	(4)
ln local revenue per capita (t-1)	0.008	-	-	0.009
	(0.010)	-	-	(0.010)
ln local expenditure per capita (t-1)	-	-0.003	-	-0.007
	-	(0.023)	-	(0.023)
local share revenue (t-1)	-	-	0.144	-
	-	-	(0.087)	-
Wind speed (km/hr)	0.013 ***	0.013 ***	0.013 ***	0.013 ***
	(0.000)	(0.000)	(0.000)	(0.000)
ln population	-0.039	-0.047	-0.047	-0.046
	(0.042)	(0.048)	(0.042)	(0.048)
Geography	municipality	municipality	municipality	municipality
n	1421	1421	1421	1421
T	10	10	10	10
N	14210	14210	14210	14210
R-squared	0.054	0.054	0.055	0.054

Notes: The dependent variable is the inverse hyperbolic sine of tropical cyclone deaths. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 11: Province fixed effects regression results for poverty and income (3-year periods: 2007-2009, 2010-2012, 2013-2015),

	(1)	(2)	(3)
province poverty rate (t-1)	-0.013	-	-0.017
	(0.018)	-	(0.019)
ln province income (pesos) (t-1)	-	-0.500	-0.602
	-	(0.588)	(0.599)
Total rainfall (cm)	0.027 ***	0.026 ***	0.026 ***
	(0.006)	(0.006)	(0.006)
Wind speed (km/hr)	0.069 ***	0.070 ***	0.071 ***
	(0.011)	(0.011)	(0.011)
ln population	0.444	1.196	1.066
	(1.343)	(1.470)	(1.479)
Geography	province	province	province
n	76	76	76
T	3	3	3
N	228	228	228
R-squared	0.278	0.279	0.283

Notes: The dependent variable is the inverse hyperbolic sine of tropical cyclone deaths. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 12: Municipality fixed effects regression results for poverty and income (3-year periods: 2007-2009, 2010-2012, 2013-2015)

	(1)	(2)	(3)
municipal poverty rate (t-1)	0.002	0.004 *	0.004 *
	(0.002)	(0.002)	(0.002)
province poverty rate (t-1)	-	-	-0.002
	-	-	(0.003)
Wind speed (km/hr)	-	0.020 ***	0.021 ***
	-	(0.001)	(0.001)
ln population	0.349 *	0.067	0.105
	(0.140)	(0.137)	(0.141)
Geography	municipality	municipality	municipality
n	1468	1468	1468
T	3	3	3
N	4404	4404	4404
R-squared	0.002	0.066	0.067

Notes: The dependent variable is the inverse hyperbolic sine of tropical cyclone deaths. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 13: Province fixed effects regression results for poverty and income with linear time trend (2007, 2010, 2013, 2016)

	(1)	(2)	(3)
province poverty rate (t-1)	0.007	-	-0.014
	(0.010)	-	(0.017)
ln province income (pesos) (t-1)	-	-1.456	-1.730 *
	-	(0.803)	(0.869)
Total rainfall (cm)	0.016 *	0.012	0.012
	(0.007)	(0.009)	(0.009)
Wind speed (km/hr)	0.074 ***	0.087 ***	0.088 ***
	(0.009)	(0.012)	(0.012)
ln population	-0.383	0.087	-0.058
	(0.757)	(1.311)	(1.324)
year	-0.060 **	0.020	0.034
	(0.023)	(0.064)	(0.067)
Geography	province	province	province
n	78	78	78
T	4	3	3
N	312	234	234
R-squared	0.276	0.326	0.329

Notes: The dependent variable is the inverse hyperbolic sine of tropical cyclone deaths. Statistical significance is indicated by * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 14: Municipality fixed effects regression results for poverty with linear time trend (2007, 2010, 2013, 2016)

	(1)	(2)	(3)
municipal poverty rate (t-1)	0.001	0.002 **	0.004 ***
	(0.001)	(0.001)	(0.001)
province poverty rate (t-1)	-	-	-0.001
	-	-	(0.002)
ln province income (pesos) (t-1)	-	-	-0.111
	-	-	(0.083)
Wind speed (km/hr)	-	0.023 ***	0.032 ***
	-	(0.001)	(0.001)
ln population	0.046	-0.057	0.044
	(0.057)	(0.051)	(0.089)
year	0.004 *	-0.018 ***	-0.023 ***
	(0.002)	(0.002)	(0.006)
Geography	municipality	municipality	municipality
n	1468	1468	1468
T	4	4	3
N	5872	5872	4404
R-squared	0.002	0.196	0.265

Notes: The dependent variable is the inverse hyperbolic sine of tropical cyclone deaths. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 15: Province fixed effects regression results for government financial flows with linear time trend (2005-2016)

	(1)	(2)	(3)	(4)
ln local revenue per capita (t-1)	0.018	-	-	0.047
	(0.091)	-	-	(0.093)
ln local expenditure per capita (t-1)	-	-0.317	-	-0.341
	-	(0.221)	-	(0.226)
local share revenue (t-1)	-	-	-0.001	-
	-	-	(0.005)	-
Total rainfall (cm)	0.026 ***	0.026 ***	0.026 ***	0.026 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Wind speed (km/hr)	0.054 ***	0.053 ***	0.054 ***	0.053 ***
	(0.005)	(0.005)	(0.005)	(0.005)
ln population	-0.012	-0.400	-0.026	-0.399
	(0.552)	(0.608)	(0.549)	(0.608)
year	-0.035 *	-0.025	-0.034 *	-0.029
	(0.017)	(0.015)	(0.014)	(0.017)
Geography	province	province	province	province
n	73	73	73	73
T	12	12	12	12
N	876	876	876	876
R-squared	0.222	0.224	0.222	0.224

Notes: The dependent variable is the inverse hyperbolic sine of tropical cyclone deaths. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 16: Municipality fixed effects regression results for government financial flows with linear time trend (2007-2016)

	(1)	(2)	(3)	(4)
ln local revenue per capita (t-1)	0.012	-	-	0.012
	(0.010)	-	-	(0.010)
ln local expenditure per capita (t-1)	-	0.006	-	0.001
	-	(0.023)	-	(0.023)
local share revenue (t-1)	-	-	0.183 *	-
	-	-	(0.087)	-
Wind speed (km/hr)	0.013 ***	0.013 ***	0.013 ***	0.013 ***
	(0.000)	(0.000)	(0.000)	(0.000)
ln population	-0.031	-0.032	-0.042	-0.030
	(0.043)	(0.048)	(0.042)	(0.048)
year	-0.009 ***	-0.009 ***	-0.009 ***	-0.009 ***
	(0.001)	(0.002)	(0.001)	(0.002)
Geography	municipality	municipality	municipality	municipality
n	1421	1421	1421	1421
T	10	10	10	10
N	14210	14210	14210	14210
R-squared	0.061	0.061	0.062	0.061

Notes: The dependent variable is the inverse hyperbolic sine of tropical cyclone deaths. Statistical significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.