# Adaptation to Cyclone Risk: Evidence from the Global Cross-Section

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*Abstract*: Understanding the feasibility and cost of adaptation is essential to management of the global climate. Unfortunately, we lack general estimates of adaptive responses to almost all climatological processes. To address this for one phenomenon, we estimate the extent of adaption to tropical cyclones (TCs) using the global cross-section of countries. We reconstruct every TC observed during 1950-2008 to parameterize countries' TC climate and year-to-year TC exposure. We then look for evidence of adaptation by comparing deaths and damages from physically similar TC events across countries with different TC climatologies. We find that countries with more intense TC climates suffer lower marginal losses from an actual TC event, indicating that adaption to this climatological risk occurs but it is costly. Overall, there is strong evidence that it is both feasible and cost-effective for countries with intense TC climatologies to invest heavily in adaptation. However, marginal changes from countries' current TC climates generate persistent losses, of which only ~3% is "adapted away" in the long run. These findings are consistent with the Envelope Theorem (Nordhaus, 2010).

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## 1. Introduction

A central question in climate change economics is how humans adapt to their climate. Adaptive adjustments limit the negative effects of individual weather events, whose occurrence are stochastic and described by a probability distribution that we call the climate. Changes in the climate may enhance the probability of costly weather events, but losses to those events could be partly offset by populations' compensatory efforts to protect themselves. These adaptive adjustments might be, for example, *ex ante* investments in defensive measures or *ex post* changes in behavior, depending on the cost of technology and the availability of information. Because there are numerous possible adaptive adjustments that populations might employ, it is difficult to speculate what the cumulative efficacy of these adjustments will be. Yet, collectively, these adjustments may dramatically influence the social impact of weather events and thereby influence the cost of climatic changes. To date, we have almost no empirical estimates for the total feasibility, cost or adoption of modern adaptive adjustments to climate, a fact that severely limits our ability to estimate the social cost of future climate changes (Tol, 2009, Patt et al. 2009, de Bruin et al, 2009).

Using a global cross-section, we estimate the extent of adaptation to a specific climatological risk: tropical cyclones. Tropical cyclones (TCs) are the family of phenomena that are known as hurricanes and tropical storms in the Atlantic Ocean, typhoons in the Pacific Ocean, or simply cyclones in the Indian Ocean; and they are a feature of the global climate that is expected to respond to future warming. Recent research suggests that the probability distribution of TC events, i.e. the TC climate, will shift toward higher intensities[1] in a warming world (Knutson et al., 2010).

Here we produce the first empirical estimates of how much populations around the world actually adapt to changes in their TC climate. We first merge data on population's physical exposure to actual TC events with the losses they suffer as a result. We then compare the extent of adaptation across populations by comparing how different societies fare when they are exposed to physically identical events. If we observe that one population suffers smaller losses relative to another population, then we infer that the former has protected themselves better, i.e. they are more adapted to TCs.

Our ability to characterize patterns of adaptation rests entirely on our ability to compare physical exposure to TCs across countries. Thus, the key innovation for our

[1] Knutson et al. (2010), a recent review of this topic, conclude

> [F]uture projections based on theory and high-resolution dynamical models consistently indicate that greenhouse warming will cause the globally averaged intensity of tropical cyclones to shift towards stronger storms, with intensity increases of 2–11% by 2100. Existing modeling studies also consistently project decreases in the globally averaged frequency of tropical cyclones, by 6–34%. Balanced against this, higher resolution modelling studies typically project substantial increases in the frequency of the most intense cyclones, and increases of the order of 20% in the precipitation rate within 100 km of the storm centre. (p. 157)

Thus the entire distribution of TC events is expected to shift on average, with fewer low intensity storms but more frequent high intensity storms. However, there remains extensive uncertainty and the relationship between TCs and warming is an area of active research.

econometric identification of adaptation is our physical model of TCs. This physical model, first developed and presented in Hsiang (2010), allows us to summarize a socially relevant measure of TC exposure using scale-free, i.e. intensive, statistics. Our construction of intensive measures of TC exposure is the core reason why we can objectively compare TC exposure across countries of different sizes, populations and geographies is meaningful way. Having verified the econometric utility of these measures (Hsiang, 2010) we exploit them fully by reconstructing all 6,712 storms observed on the planet during 1950-2008 and characterizing the TC exposure of 233 countries.

Consistent with economic theory, we infer that countries exposed to relatively greater TC risk are more adapted to TC exposure because they display differentially smaller losses when exposed to an actual TC event. For example, in the case of economic damages we find that exposure to TC winds that are an additional 1 m/s faster increases damages by 20.3%; however, a 1 m/s increase in climatological (average) TC exposure decreases these marginal damages to 19.6%. While this "adaptation effect" seems small for this marginal change, it becomes large for countries with intense TC climatologies[2]. Overall, we find strong evidence that it is both feasible and cost-effective for countries with intense climatologies to invest heavily in adaptation. However, consistent with predictions of the Envelope Theorem (Nordhaus, 2010), we find that marginal changes from countries' current TC climates induce only very small changes in adaptive investments. This suggests that when forecasting the costs of future changes to TC climates, the "dumb farmer" assumption that populations will not adapt in response to these changes is a reasonable first approximation.

*Prior Art*

Empirical measurements of adaptation to climate are sparse compared to the breadth of the problem. For example, a small number of historical analyses document *ex post* responses to new climate conditions (e.g. Olmstead and Rhode, 2011, Hornbeck, forthcoming). However, these efforts focus on understanding specific responses to particular events, in these cases the westward expansion of North American wheat and the Dust Bowl, that are difficult to map onto modern global conditions. More generally, empirical research has remained conceptually focused on understanding the mechanisms through which populations adapt to climate conditions, for a variety of examples see chapters in Libecap and Steckel (2011). Unfortunately, this approach requires that analyses be so specific that their results are difficult or impossible to generalize globally. This absence of a more general picture of adaptation has hobbled integrated assessments of global change (Tol, 2009), forcing modelers to make sweeping assumptions about the feasibility, cost and adoption of adaptive adjustments (Patt et al. 2009; de Bruin et al, 2009). This study adopts a fully global perspective in an effort to inform planetary-scale evaluations, but in doing so we admittedly sacrifice our ability to observe which specific strategies adapting populations employ. Nonetheless, our reduced-form findings conform to basic microeconomic theory, a fact that, in our view, bolsters their credibility.

[2] Taiwan has the most intense TC climate with average annual wind exposure of 27.7 m/s.

In this study, we empirically estimate how the expectation of future TC events influences populations' investment in protection. To do this, we extend and fuse approaches developed by previous studies of TCs and natural disasters generally. In particular, our study could be viewed as the child of Khan (2005) and Nordhaus (2010).

Khan (2005) uses a global cross-sectional model to understand determinants of natural disaster[3] death tolls. Khan concludes that societies respond differently to natural disasters, with income, democracy and institutions being important determinants of losses – in other words, his study hints that the adaptive capacity of societies may differ according to their socioeconomic conditions. This basic notion, and his global cross-sectional model, is the starting point for our study. Unfortunately, his study suffered from its simple treatment of disasters. In particular, for lack of an alternative, he assumed that the reported incidence of disasters is exogenous to all other determinants of disaster losses. This "exogeneity assumption" remains prevalent in economic studies of natural disasters despite demonstrations that it is false (Gall et al., 2009, World Bank and the United Nations, 2010) and the recognition that physical models of natural hazards could make it obsolete[4] (Noy, 2009).

In contrast to Khan's cross-country approach that omitted variables for disaster physics, Nordhaus (2010) restricted his analysis to the United States and explicitly focused on how TC properties at landfall influenced their economic damage[5]. Nordhaus found strong evidence that storm physics were important for damages, but because he was only examining TCs that struck the United States his sample contained limited variation in TC climatology, making it difficult to discern whether different populations adapted to their different TC climates.

Our study uses the strengths of these two studies to overcome their respective weaknesses. Following Nordhaus, we use a physical model of TCs to parameterize both TC exposure and TC risk. Following Khan, we extend this model globally to 233 countries, providing us with strong variations in TC climatologies. In the spirit of Khan, we then use our estimates of TC risk to understand global cross-sectional patterns of adaptation. However, having learned from Nordhaus, we avoid Khan's "exogeneity assumption" by using a physical model to identify country-specific TC-loss functions.

Finally, it is worth noting that the direct economic impacts of TCs have themselves attracted interest in climate change economics. Climate models suggest that the distribution of TCs may intensify in a globally warmed world (IPCC, 2007, Knutson et al., 2010) leading some to speculate that losses to enhanced TCs will constitute an

[3] Khan examines a large number of disaster types, which includes TCs as a subcategory.

[4] In 2009, Noy noted, "[T]he exogeneity issue can potentially be fully overcome by producing an index of disaster intensity that depends only on the physical characteristics of the disaster… The collection of such data from primary sources and the construction of a comprehensive index for the all the different disaster types are beyond the scope of this paper but may be worth pursing in future research."

[5] Nordhaus' original work was presented in a 2006 working paper. Similar studies that followed include Mendelsohn et al. (2010) and Hsiang (2010).

important economic cost of climate change (Stern, 2007, ISDR, 2009, World Bank and the United Nations, 2010). Integrated economic assessments of enhanced TC damage under climate change have since examined these claims more closely (Cline, 1992; Fankhauser, 1995; Pielke, 2007; Narita et al., 2009; Mendelsohn et al., 2010; Nordhaus, 2010) however none have been able to draw on empirical and global estimates of TC loss-functions. Thus, while our focus is to understand global patterns of adaptation, an ancillary benefit of this work is to estimate the first globally general loss-function for direct TC exposure.

The paper is organized as follows. In Section 2, we develop a simple theory of optimal adaptation to TC risk and an approach for estimating it empirically when actual adaptive investments are not observed. Section 3 describes the data, estimates a general model of TC losses and tests whether populations have adapted to their climates. Section 4 discusses our results, with a focus on adaptation to future climate changes.

## 2. Theoretical Framework

The aim of this study is to examine the role of TC risk on the size of TC losses when agents can invest in the protection of their lives and assets. To motivate and clarify our empirical analysis, we first examine how the risks posed by a TC climate should influence costly adaptive investments in theory. Our model, which is a TC-specific refinement of Mendelsohn (2000), predicts this key feature of the data: when exposed to physically similar events, populations with high TC risk and/or high capital densities should suffer relatively low loses because they have a greater incentive to invest in protection.

*Setup*

The economy is closed and consists of one agent who makes an investment decision in adaptation in the first period to mitigate losses from a possible TC in the second period.[6] The cost of investment is $I(e)$, where $e \in [0,1)$ is the level of protection achieved via adaptive effort. $I(.)\geq 0$, $I'(.)\geq 0$, $I''(.) > 0$, and $I(0)=I'(0)=0$.

The economy's capital endowment is $K_0$, the density of capital spread over a single unit of land. Adaptation mitigates the expected reduction in the second period capital density $K$:

(1) $$E[K] = K_0[1 - P(1-e)]$$

Here, $P$ is the probability that a unit of capital is destroyed in a TC event in the second period. $P$ can be decomposed into $p$, the probability that a TC strikes, and $d$, the probability of capital destruction conditional on a strike occurring. Let $p=p(x)$ and

[6] Although the general features of the model are applicable in broader cases, for simplicity of discussion we here assume that adaptation measures are just discovered or developed at the beginning of the first period, and that any adaptation measures have not been taken prior to the first period.

$d$=$d$($x$) for a TC event of intensity $x$.[7] Note that $p(x)$ is a probability density function over TC intensities while no restrictions are placed on $d(x)$. Since TCs of various intensities hit with different probabilities of arrival and the probability of capital destruction depends on the intensity of the TC, $P$ is the summary statistic

$$(2) \qquad P = \int_0^\infty p(x)d(x)dx.$$

In a particularly useful and realistic case, if cyclones of intensity $x$ arrive according to the negative exponential probability distribution function

$$(3) \qquad p(x) = \lambda \exp[-\lambda x]$$

then $x_{mean}=1/\lambda$. Furthermore, if their destruction is described by a positive exponential function

$$(4) \qquad d(x) = d_0 \exp[\phi x]$$

such that $0 < \phi^2 << \lambda^2$ (which holds approximately in our empirical estimates[8]) then $P = d_0\lambda/(\lambda - \phi) \approx d_0(1 + \phi/\lambda)$. In this case, $P$ is almost a linear function of $x_{mean}$, making $x_{mean}$ a good approximation for $P$ in the linear model that follows.

*Efficient adaptation*

Let the output for the economy $F$ be a function of capital density $K$. With a discount factor $\beta \in [0,1]$, the efficient level of adaptation $e*$ is

$$(5) \qquad e^* = \arg\max \beta \cdot E_x\left[F(K_0[1 - d(x)(1-e)])\right] - I(e)$$

For simplicity, we linearize $F$ near the equilibrium values of $K$. This allows us to rewrite equation (5) as

$$(5') \qquad e^* = \arg\max \beta \cdot F(K_0[1 - P(1-e)]) - I(e)$$

in which 1-$P$(1-$e$) behaves like an expected rate of depreciation for capital[9]. Equation (5') has the simple first-order condition

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[7] Note that $P$ is in fact also dependent on the density of capital, i.e., the amount of capital per unit of land, which is related to the amount of exposure to a TC. In this model, however, an explicit treatment of capital density is not necessary as the amount of land is fixed.

[8] For example, $\lambda \approx 0.3$ and $\phi \approx 0.1$ when measuring $x$ in wind speed and using a global sample.

[9] It is worth noting that in their seminal paper on growth theory, Mankiew et al. (1992) stated "We assume that… [the rate of depreciation is] constant across countries….[T]here is neither any strong reason to expect depreciation rates to vary greatly across countries, nor are there any data that would allow us to estimate country-specific depreciation rates," when testing the Solow growth model (p. 410). Since then, this assumption seems to have persisted. The present paper is the first that we know of to seriously consider and measure differences in the rate of capital depreciation across countries.

(6) $$I'(e^*) = \beta F'(.)K_0 P$$

$F'$, $P$, $K_0$ and $\beta$ are positive constants, while $I'$ increases monotonically from zero. Thus, there always exists an $e^*$ satisfying equation (6). This equation states that the optimal level of adaptation effort $e^*$ equalizes the marginal costs of current effort with the marginal benefits from future protection, given capital and climate endowments. Increasing $P$, $K_0$ or $\beta$ only increases the term on the RHS, raising $e^*$. Decreasing the costs of protection (e.g. through technology) can reduce $I'(.)$, also raising e*.

In this paper, we focus on the prediction

(7) $$\frac{\partial e^*}{\partial P} > 0$$

which states that populations with higher initial depreciation due to cyclones will exert greater effort towards protecting themselves. The pre-adaptation rate of depreciation $P$ can increase if the probability of a storm $p(x)$ increases or the probability a unit of capital is lost to a storm $d(x)$ increases. Because $d(x)$ describes a physical relationship, we assume it is fixed across locations. However, the TC climate of a location determines the probability of storms $p(x)$, thereby determining $P$. Thus, equation (7) states that populations will adapt to intensifying TC climates by investing more in protecting themselves. The objective of this paper is to quantify this relationship by measuring how much adaptation occurs in response to changes in TC climates.

Previous work (Kahn, 2005, Toya and Skidmore, 2007, Noy, 2009) has focused on analogs to the prediction

(8) $$\frac{\partial e^*}{\partial K_0} > 0$$

which states that populations with a higher capital density will exert more effort to protect that capital from TCs (because the cost of protection is independent of $K_0$). Notably, however, none of these studies were able to control for storm intensity $x$ and thus could not control for the climate parameter $P$. If $P$ and $K_0$ were correlated, then the result in equation (7) suggests that these earlier analyses could have been biased. Because we are the first study to measure $P$, we will briefly revisit and empirically confirm equation (8) while controlling for climate.

The final prediction of equation (6), which we only note because it contrasts with common arguments, states

(9) $$\frac{\partial e^*}{\partial \beta} > 0,$$

i.e. populations that value the future less will also invest less in adaptation. During the economic analysis of anthropogenic climate change, it is often noted that voluntary mitigation of greenhouse gas emissions requires that we value future consumption. In cases where the valuation of future consumption is low, it is sometimes argued that investment in protection from climate changes (adaptation) represents a more incentive-compatible approach to global cost minimization. Unfortunately, equation (9) suggests that this notion may be optimistic, since a low valuation of future consumption represents a hazard to voluntary adaptation as well[10]. Lacking data on $\beta$, we leave empirical verification of equation (9) to future work.

*Empirical approach*

In our empirical test of equations (7) and (8), we cannot directly observe $e^*$. Therefore, we must infer $e^*$ by observing how actual damages respond to actual TC events conditional on climate and capital endowments. When adaptation effort is efficient and a TC of intensity $x$ actually strikes an economy, the capital damage $D$ is

$$(10) \qquad D = K_0 d(x)(1 - e^*)$$

which can be rewritten

$$(10') \qquad \frac{D}{F(K)} = d(x)(1 - e^*)$$

following our normalized linearization[11] $F(K) = K$. The term on the left is called "normalized damages," following Pielke and Landsea (1998) who first proposed its usage, and we explore how it responds to storm intensity $x$. If adaptive effort $e^*$ is higher, the marginal response of normalized damages to increases in $x$ will be smaller. We see this if we differentiate equation (10') first by $x$ and then by $e^*$:

$$(11) \qquad \frac{\partial^2 \frac{D}{F(K)}}{\partial x \partial e^*} = -d'(x) < 0$$

Thus, to test equations (7) and (8), we multiply them by the LHS of equation (11) to obtain the respective hypotheses

$$\text{H7:} \qquad \frac{\partial^2 \frac{D}{F(K)}}{\partial x \partial P} \approx \frac{\partial^2 \frac{D}{F(K)}}{\partial x \partial x_{mean}} < 0$$

$$\text{H8:} \qquad \frac{\partial^2 \frac{D}{F(K)}}{\partial x \partial K_0} \approx \frac{\partial^2 \frac{D}{F(K)}}{\partial x \partial F(K_0)} < 0.$$

Hypothesis H7 says that the response function of normalized damages to TC exposure ($\partial \frac{D}{F(K)} / \partial x$) is shallower when the climate endowment is more TC-prone. Hypothesis H8 says that the response function is also shallower if an economy has more capital

[10] It remains true that mitigation of greenhouse gasses requires that individuals provide a public good, a challenge that is not present for adaptation.

[11] We take advantage of the linearization here because we cannot observe capital densities and instead can only observe output levels.

(output). Hypothesis H7 is our focus, because we are interested in how economies adapt to their TC climate, however H8 should hold simultaneously. The objective of our empirical analysis is to estimate these two parameters.

## 3. Empirical analysis

Our empirical objective is to measure how much adaptation occurs in response to a particular TC climate. Our approach to this problem has three steps. First, we develop a globally comprehensive data file of every country's exposure to every TC during 1950-2008. Second, we use this new dataset to develop a general and robust specification for the response of normalized damages and normalized deaths to TC exposure. Third, we use this specification to measure how storm losses vary across climates, testing hypothesis H7 and implicitly measuring the extent of long-run adaptation.

### 3-1. Data files

Our analysis requires using data that describe economic and human losses, TC exposure, and TC climatology. Summary statistics of these data are presented in Table 1.

*Tropical Cyclone Data*

A major innovation of our analysis is the development of a comprehensive data file describing physical measures of TC incidence. Lacking such comprehensive and high-quality data, previous international studies were unable to detect any influence of storm intensity on damages or deaths (Kahn, 2005, Noy 2009), a necessary precondition to measuring whether effective adaptation to TCs is occurring. To avoid the attenuation bias that overwhelmed these previous studies, we require a dataset that is simultaneously both global in scale and sufficiently detailed that it describes economically meaningful measures of TC exposure. To achieve this, we generate measures of TC incidence by reconstructing every TC in the International Best Track Archive for Climate Stewardship (IBTrACS) database (Knapp, 2009) as a translating vortex using the Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model (see Hsiang, 2010, for a description of the model[12]). LICRICE reconstructs the wind field for all 6,712 storms by interpolating among 191,822 6-hour observations over every 0.1° × 0.1° pixel between 48°N-48°S latitude[13].

[12] Since Hsiang (2010), version 2 of LICRICE was built, substantially improving upon its original accuracy. However these improvements were focused on numerical methods and the heuristic description in Hsiang (2010) remains accurate.

[13] While there is some amount of TC activity beyond these latitude limits, it is relatively trivial. More importantly, however, the numerical scheme of LICRICE becomes unstable at high latitudes, rendering extension of the model beyond 48° cost-ineffective.

To match TC exposure with socioeconomic information, physical measures of TCs must be aggregated and spatially averaged so there is a single observation for each of 233 countries in every year[14]. We summarize annual TC exposure at a location using two different statistics: (1) the maximum TC wind speed achieved during a given year and (2) the total energy per unit area dissipated by all storms at a location over each of their respective lifetimes. For succinctness, we refer to the former statistic as "wind speed" and the latter as "energy". Neither statistic is a perfect measure of TC wind exposure, however each has its benefits.

TC *wind speed* is simply the maximum wind speed achieved at a location during the course of a calendar year. If a location experiences multiple storms, the annual maximum is the maximum of the maximum speed achieved in each storm. Pixel-specific wind speed estimates are spatially averaged[15] over each country to aggregate exposure into country-by-year observations. In all of our graphs we use *wind speed*, rather than *energy*, as our independent variable because it is easier to interpret units of "meters per second" compared to "meters-cubed per second-squared" (the units of *energy*). Also, it is important to keep in mind that reported *wind speed* values are area-averages, so locations that are hardest hit by a TC will invariably experience wind speeds greater than the values we report.

TC *energy* is more precisely described in Hsiang (2010) as a "power dissipation density index."[16] This measure is similar to "accumulated cyclone energy" (ACE), which is commonly used in the field of meteorology (Bell et al., 2000), or the "power dissipation index" (PDI) introduced by Emanuel (2005). The most important difference from these measures is that our measure is a spatial *density*, i.e. it measures the amount of energy dissipated per square-meter of land area. ACE or PDI were designed for climatological studies that were not concerned with *where* TC energy was released; only how much was released in total. However, because we are

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[14] It would be theoretically possible to match country-by-storm exposure to country-by-storm losses, rather than aggregating outcomes annually. While this approach would produce some econometric benefits, it is not computationally feasible with the current version of LICRICE. To see why, note that each of the 6,712 storms generates 960 observations (one for each 0.1° × 0.1° cell), producing a total of 6,443,520 storm-by-pixel observations that must then be matched to each of the 223,680 country-by-pixel observations.

[15] It may be possible to reduce our measurement error by using population-weights, following Jones and Olken (2010) and Hsiang et al. (2011), or capital-weights, following Nordhaus (2010), when aggregating our exposure measure. However, we fear that if populations strategically locate themselves or capital in response to TC risk, this may bias our estimated coefficients in some unknown way. Thus, we use area-weights because populations cannot manipulate this parameter, giving us confidence that our RHS variable is fully exogenous. This conservative approach may mean that our estimation is inefficient, in the sense that it does not take advantage of all available data, but this should only make our inferences more conservative.

[16] Following Hsiang (2010), the power dissipation density index (PDDI) is:

$$PDDI_{it} = \frac{\kappa}{A_i} \sum_{z \in i} \sum_{s \in t} \frac{V_s^{wind}(z)^3}{V_s^{storm}}$$

where $V_s^{storm}$ is the translational velocity of the center of a storm indexed by $s$, $V^{wind}_s(z)$ is the velocity of wind at grid cell $z$, $A_i$ is the area of country $i$, and $\kappa$ is a constant capturing drag and the density of air.

interested in social impacts that occur in a reference-frame that is not translating with each storm, we must take care to measure energy as a location-specific density. The most immediate implication of changing the reference-frame, from one that moves with a storm to one that is fixed to a location, is that the speed of a storm's motion (translation of the storm center) becomes important. Storms that pass over a location quickly will dissipate less energy at the surface when compared to storms of equal intensity that pass over a location slowly, a feature that is well captured by our *energy* measure. Throughout this paper, *energy* is presented in standardized units since its raw units ($m^3/s^2$) have little or no intuitive meaning.

In all the following tables, we present results for both *wind speed* and *energy*. Maximum wind speed is a useful concept because physical capital may fail catastrophically at a critical level of stress, as pointed out by Nordhaus (2010), and its units are intuitive. Unfortunately, maximum wind speed is unchanged if a location experiences two identical storms, compared to just one, in the same year. *Energy* is a useful independent variable in this situation, because it is natural and intuitive to sum quantities of energy released during separate events. Regrettably, the units of energy are non-intuitive and it tends to produces noisier estimates because its distribution is more highly skewed. Thus neither measure is obviously superior, motivating our presentation of both. However, the two measures are highly correlated: Figure 1 shows country-by-year observations of *wind speed* against *energy* for reference. In most of the specifications presented, models that use *wind speed* have slightly higher R-squared values, although this is not always true and the margin of improvement is very small.

As discussed in Section 2, TC risk (climatology) should be defined as the likelihood that a unit of capital is destroyed, integrated over all possible TC intensities (equation 2). Assuming reasonable functions for $p(x)$ and $d(x)$ in a linearized model, we showed that $x_{mean}$ was an approximately sufficient statistic for this integral. Therefore, we summarize the TC climatology of a country with its mean exposure over the period 1950-2008. Figure 2 depicts spatial variations of this *wind speed climatology* measure. The maps indicate that exposure to TCs is concentrated in specific geographical areas, namely, over the warm tropical oceans and the nearby coastal regions downwind (to the west) in the tropics and mid-latitudes. TC climatologies are most intense for the island countries of the Pacific Ocean and the Caribbean, while TC risk is absent for countries deep in the middle of continents and also for those very close to the equator.

*Economic data*

Data on economic losses and deaths from TCs are obtained from the Emergency Events Database (EM-DAT: OFDA/CRED, 2009). The EM-DAT data files contain information provided by national governments, international organizations, NGOs, and private companies (e.g., re-insurance companies) on a self-reporting basis. EM-DAT data of economic losses are an estimate of negative economic impacts that may include lost consumption goods, lost productive capital or cost of business interruption, depending on the protocols of the reporting institution (OFDA/CRED, 2009). However, for the sake of simplicity and the model in Section 2, our language decribes these losses *as if* they arose entirely from the loss of capital[17].

Some authors note that the reporting system for EM-DAT is prone to certain biases, possibly encouraging reporting entities to either under- or over-report losses (for example, see Skidmore and Toya, 2002). Notably, Gall et al. (2009) are able to identify systematic biases for the US data reported in EM-DAT by comparing it with other datasets of natural disasters. These endogneous reporting errors might threaten the validity of previous studies that use EM-DAT to generate independent variables for regression analysis (for example, see Noy, 2009 and Loayza et al. 2009); however, we are able to treat them as classical unobserved disturbances since we only use EM-DAT data to generate our dependant variables and restrict our independent TC variables to objective LICRICE output[18].

To match equation (10'), we normalize the raw economic damages and deaths from EM-DAT by each country's GDP and population,[19] respectively. GDP data are from the United Nations National Accounts files (United Nations, 2009), and population data are from the World Development Indicator files (World Bank, 2008).

### 3-2. A General and Global Model of Tropical Cyclone Losses

There is no established approach for estimating annualized, country-level estimates of deaths and damages from TCs using objective physical measures because no prior study had access to objective physical measures. Therefore, we begin our analysis by searching for a reasonable functional form to approximate $d(x)$ in equation (10').

*Model Specification*

To our knowledge, no country-level analysis has successfully measured the response of deaths or damages to physical measures of TC exposure. The closest related studies are Hsiang (2010), which uses the LICRICE *energy* variable to measure the GDP-growth response to TCs, and Nordhaus (2010) and Mendelsohn et al. (2010), both of which estimated storm-specific damages within only the United States. Both Nordhaus and Mendelsohn et al. estimate storm-specific losses using a log-log specification where the dependent variable is maximum wind speed (or minimum central pressure) at landfall. Both studies find astonishingly high elasticities (nine and

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[17] Mendelsohn et al. (2010) point out that capital losses to cyclones should describe the net present value of all the future output streams that would have originated from the lost capital. However, it is possible that lost capital would have provided public goods or private spillovers that are not internalized by its owner and thus would not be captured in its price.

[18] In cases where these additive errors are systematic, we hope that year fixed-effect and country fixed-effects will remove any artificial signals.

[19] The EM-DAT data contain absolute quantities of economic losses and deaths. This means that large economies with large populations tend to exhibit large losses in the dataset. This linear normalization of damages and deaths was first proposed by Pielke and Landsea (1998) and continues to be used by more recent analyses (eg. Nordhaus, 2010).

five) with respect to wind speed at landfall, results that they struggle to explain. In contrast, these extraordinary elasticities are not found in Hsiang's growth regressions when LICRICE output, which is integrated over the entire life of a storm rather than only describing landfall statistics, is employed as an independent variable. Observing this disagreement, we re-examine the basic damage model when LICRICE output is used rather than assuming that a log-log specification is appropriate.

Figure (3) compares bivariate log-linear and log-log models for normalized damages and deaths when the independent variable is *wind speed* (from LICRICE). Local linear regressions (dashed lines) suggest that when using a linear fit a log-linear model is probably more suitable. One could model the log-log relationship using a non-linear fit, perhaps by including a *wind speed*$^2$ term, however such a model might not be desirable because the logarithmic transformation distorts the independent variable at low values, causing small cyclone events to exert a large influence on regression coefficients. Thus, the preferred log-linear specification suggests that damages are an exponential function of *wind speed*, as well as *energy*, rather than being a power-function of these parameters.

*Global Estimates*

We begin by estimating the log-linear model with ordinary least squares in the general model

(12) $$\log(Z_{it}) = \alpha \cdot x_{it} + \mu_i + \theta_t + \gamma_{Temp} \cdot Temp_{it} + \gamma_{Precip} \cdot Precip_{it} + \varepsilon_{it}$$

where $Z_{it}$ is either *normalized damages* or *normalized deaths*, $x_{it}$ is one of the TC exposure measures (*wind speed* or *energy*), $\mu_i$ is a country fixed-effect, $\theta_t$ is a year fixed-effect, $Temp_{it}$ is annual mean temperature, $Precip_{it}$ is annual mean precipitation[20] and $\varepsilon_{it}$ is a disturbance term with a mean of zero. The parameter of interest is $\alpha$, the semi-elasticity of losses to TCs. Country fixed-effects are included to account for unobserved differences in average losses between countries while year fixed-effects flexibly account for unobserved changes in losses over time.

Table 2 tabulates estimates of $\alpha$ from equation (12) for both damages and deaths using both TC measures. In column 1 no controls are included, whereas country fixed-effects, year fixed-effects and weather controls are sequentially added to the model in columns 2-4. In all sixteen models we obtain estimates that are both economically and statistically significant. Moreover, across any of the four panels, the estimated value of $\alpha$ hardly varies, suggesting that to a first approximation country-effects, year-effects and weather are unimportant for unbiased estimation of $\alpha$. Nonetheless, we retain the non-parametric controls $\mu_i$ and $\theta_t$ wherever possible[21].

[20] Temperature and precipitation are spatially averaged for the same reasons that TC exposure is spatially averaged. Temperature data is from the National Center for Environmental Prediction (NCEP) reanalysis version 1 (CDAS). Precipitation data is from the CPC Merged Analysis of Precipitation (CMAP). We experimentally include these variables as controls in the model because they are correlated with storm exposure, but we find that they are unimportant.

[21] Weather controls are dropped because they are not available for all country-years and appear to be irrelevant for the estimation of $\alpha$.

Our point estimates indicate that in a globally pooled sample of countries, increasing wind speed by one meter per second[22] increases normalized damages by 10% and normalized deaths by 6%. This implies that damages (deaths) double[23] for an increase in wind speed by 6.9 (11.6) m/s. We translate these coefficients into a memorable but approximate rule of thumb: If an entire average country went from being exposed to a Saffir-Simpson Category 1 hurricane to a Category 2 hurricane, expected damages would approximately triple while expected deaths would approximately double[24].

To examine how general these estimates are, we subsample our data by continent and present these results in Table 3. Although the coefficients for Oceania and Africa are noisy and statistically insignificant due to the small number of observations in these regions, the point estimates across continents are not statistically different from one another (except for the single pair-wise comparison between North America and Asia in panel d). In the following sub-section we will explore variations in these functions attributable to climate and capital endowments; however, we feel that overall Table 3 illustrates a remarkable amount of agreement in the social responses to TCs across dramatically different regions of the world.

Taken together, Tables 2 and 3 demonstrate that a log-linear model of normalized losses to TCs, using output from LICRICE, is both statistically robust and globally general. With confidence in the fundamentals of our statistical specification, we now use it to look for evidence of adaptation to TC climates.

### 3-3. Evidence of Adaptation to Tropical Cyclone Climates

The results from equation (6) predicted that some populations would invest more effort towards costly adaptation to TCs and equation (10') illustrated how we can estimate variation in adaptation, despite our inability to directly observe adaptation effort *e*. Here, we explicitly test whether countries having more intense TC climates have lower marginal losses to cyclone exposure (H7), indirectly testing whether countries have adapted to their TC climates.

Figure 4 compares the response of deaths to wind speed in three East Asian countries, providing *prima facie* evidence that countries adapt to their TC climate and making clear the relationship that we are examining. Japan has the highest climatological wind speed (>20 m/s) and also exhibits a response function with the shallowest slope; whereas Vietnam is endowed with the lowest climatological wind speed (~12 m/s)

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[22] 1 meter per second = 2.24 miles per hour = 1.94 knots.

[23] $\log_e(2)/0.10 = 6.9$ and $\log_e(2)/0.06 = 11.6$.

[24] The +9.8 m/s increase in wind speed leads to an approximate tripling (2.7) and doubling (1.8) using the estimates from column 3 of Table 2. If the column 2 estimates of 11% and 7% are used instead, this intensification leads to an almost exact tripling (2.95) and doubling (1.99).

and exhibits the steepest response to actual TC events. The Philippines is in between these two countries in terms of both its climatology and its response. This pattern of decreasing marginal losses associated with increasing climatological wind speed is consistent with the notion that populations exposed to greater TC risk invest more effort in protection.[25]

Figure 5 uses a non-parametric approach[26] to estimate losses to actual TC wind speed conditional on either a countries' climatological or capital endowment, where income in 1970 is used as a proxy for the initial capital stock. Across all four panels, losses rise with actual wind speed across all climatologies and income levels indicating that all types of countries suffer from increased TC exposure. Furthermore, in agreement with our model of optimal adaptation, losses are largest for events in the upper-left corner of all the panels: when countries with climatologically low TC risk (capital density) are struck by intense storms, a larger fraction of capital is lost compared to countries where risk (capital density) is higher.

Using a flexible approach, Figure 5 seems to confirm hypotheses H7 and H8 in the cross-section of counties, however it is useful to put more structure on our model so that we can parameterize adaptation responses and formally test these two hypotheses simultaneously. To do this, we estimate a variant on equation (12) where we drop country fixed-effects and instead allow $\alpha$ to vary as a function of a country's TC climate and its income level in 1970. We estimate

$$\begin{aligned}\log(Z_{it}) &= [\alpha_0 + \alpha_1 \cdot mean\_x_i + \alpha_2 \cdot \ln(GCPpc1970)_i] \cdot x_{it} \\ &\quad + \omega_0 + \omega_1 \cdot mean\_x_i + \omega_2 \cdot \ln(GCPpc1970)_i + \theta_t + \varepsilon_{it}\end{aligned} \tag{13}$$

where $mean\_x_i$ is a country's climatological exposure to TC measure $x$ and ln(*GPDpc*1970) is a country's log GDP per capita in 1970. The parameter of primary interest is $\alpha_1$, which describes how changes in TC climatology alter the marginal effect of actual TC exposure $x_{it}$. We are also interested in $\alpha_2$, which explains how income influences the marginal effect of TC exposure. Hypotheses H7 and H8, respectively, predict that both of these coefficients should be negative if populations adapt optimally to their TC climate.

Table 4 presents coefficient estimates for equation (13). Columns 1-4 present the response of normalized damages while columns 5-8 tabulate the response of normalized deaths. Columns 1-2 and 5-6 contain estimates that use *wind speed* as the independent variable, while columns 3-4 and 7-8 contain estimates that use *energy*. Models in odd numbered columns only estimate interactions with *mean_x*, while even numbered columns simultaneously estimate interactions with ln(*GDPpc*1970).

[25] The steepness of the response functions for these three countries is also consistent with the other implication of the analytical model, that is, TC events with equal intensities cause less damage to a higher-income country than to a lower-income country (hypothesis H8). Indeed, Japan exhibits the highest income level among the three countries, whereas Vietnam has the lowest.

[26] The figures depict Nadaraya-Watson estimates using two-dimensional Epinechnikov kernels.

*The Effect of Climatological Cyclone Risk on Adaptive Effort*

Across all four pairs of independent and dependent variables, we estimate that TC exposure has positive marginal losses ( $\alpha_0$) and that the coefficient for the climate cross term ( $\alpha_1$) is negative. In seven out of eight models, both coefficients are highly statistically significant, with only one out of sixteen coefficients being indistinguishable from zero ( $\alpha_1$ in column 2). The main effect $\alpha_0$ for *wind speed* (*energy*) is to increase normalized damages 20% per m/s (98% per s.d.[27]) and to increase normalized deaths by 17% per m/s (73% per s.d.). These marginal effects are larger than the average effects shown in Table 2 because all countries in the pooled estimate have positive TC risk and the presence of TC risk attenuates this marginal effect through adaptation effort[28]. Examining the interaction term $\alpha_1$, we find that increasing the average *wind speed* (*energy*) exposure of a country by 1 m/s (1 s.d.) reduces marginal normalized damages by –0.7% per m/s (–27% per s.d.) and reduces normalized deaths by –0.6% per m/s (–19% per s.d.). These negative coefficients indicate that populations facing higher levels of TC risk exert more effort to protect themselves from TC events. We can infer this increase in effort because we observe that high-risk populations suffer lower marginal losses, relative to their low-risk counterparts, when both groups are struck by physically identical events.

To put these estimates into context, we display the extent of adaptation in Figure 6. Focusing on the top panel, we plot the marginal effect of actual *wind speed* on normalized damages before populations invest in any adaptive effort (20.3% per m/s). We then plot how much these marginal damages are mitigated as the climatological wind speed increases (–0.7% per m/s $\times$ *mean wind speed*). The grey area depicts marginal losses that are averted through adaptive effort, while the vertical distance between the two lines is the actual marginal loss that we observe when populations are exposed to actual TC events.

The lines in Figure 6 can be directly connected to the theory developed in Section 2. The marginal damages before adaptation are described by $d(x)$ in equation (10'), and the semi-elasticity of this function is the horizontal line in the top panel. In equation (10') the losses averted through long-run adaptation effort are $d(x)\cdot e$, and the upward sloping curve represents the semi-elasticity of this function. This function is upward sloping because adaptive effort $e$ increases with TC risk. The vertical difference between these lines is $d(x)\cdot[1-e]$, the observed normalized losses[29] on the RHS of equation (10').

The top two panels of Figure 6 suggest there is great scope to adapt to TCs, however it is important to examine where actual populations are on these curves under the current climate. To illustrate this, the bottom panel displays a histogram of countries in our dataset according to their climatological *wind speed* for the period 1950-2008. We omit all the countries with zero TC exposure (and thus zero TC risk) and only display countries with positive TC risk. A large number of countries have very low

[27] One standard deviation in *energy* is a considerably larger change than one meter per second in *wind speed*. Recall from Table 1 that one standard deviation in *wind speed* is 7.7 meters per second.
[28] The estimates in Table 2 also were derived from a pooled sample that over-sampled high risk countries relative to low risk countries.

[29] In the integrated assessment literature, an analogous value would be termed "residual damages."

(but non-zero) levels of TC risk, with an almost equal number of countries spread almost uniformly across TC risk levels up to 15 m/s. Above 15 m/s, there are very few countries, and they are exclusively from East Asia or small island states. Thus, while there is strong evidence that extensive adaptation to TCs is feasible, most populations at risk are currently in climates where they do not adapt at all or where adaptation is limited. There are very few countries in the current climate where the incentives to adapt are sufficiently strong that marginal losses are dramatically reduced (for example, $e > 0.5$).

Figure 6 can be used to give us a sense of how populations might adapt to future changes in their TC climate. In the middle panel we mark a "climate change" that increases a countries climatological wind speed by about 2 m/s, which is a large change. This raises the optimal level of adaptation $e^*$ by a small amount, reducing the actual marginal losses from storms by about a percentage point. More generally, we can use the coefficients in Table 4 to ask how much of the additional risk presented by a climatic change is mitigated by additional adaptive effort. To do this, we imagine that actual TC exposure in every year increases by 1 m/s. This necessarily implies that average exposure also increases by 1 m/s. In this thought experiment, unmitigated losses in each year would rise by $\alpha_0$, which in turn increases adaptive effort so that marginal losses in each year fall by $-\alpha_1$. For a country with a very low initial risk, the ratio $\frac{-\alpha_1}{\alpha_0}$ describes how much of the new risk posed by climate changes will be eliminated by new adaptation in the long run. According to our estimates[30] in Table 4, this ratio ranges from 0.016-0.035, indicating that if climate changes lead to a marginal increase in TC risk, about three one-hundredths (3%) of this new risk is mitigated by new long-run adaptations[31]. This relatively small value is consistent with Nordhaus' (2010) argument that if current adaptation is optimal, then by the envelope theorem (Samuelson, 1998) adaptation to climate shifts are second-order relative to the direct costs of those shifts. He argues that at the current optimum $e^*$ the marginal costs and the marginal benefits of adaptation are already equal (equation 6), so small shifts in the climate cannot generate large net gains from additional adaptation. Our estimate that most of the additional TC losses from climate changes go unmitigated suggests that $I'(.)$, the marginal cost function for adaptation, is relatively steep near the current optimum.

*The Effect of Capital Density on Adaptive Effort*

If populations optimally adapt to their TC climate according to equation (6), then, as stated in hypothesis H8, economies with a higher capital density will invest more in adaptation. This hypothesis was described, albeit less formally, by Kahn (2005), Toya and Skidmore (2007), Noy (2009) and Hsiang (2010) to explain some of their empirical findings. However, as discussed earlier, their inability to measure and control for TC-risk might have threatened the validity of their results. Here we briefly

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[30] We focus here on the estimates for *wind speed* because its units are a better approximate for marginal changes.

[31] This number is larger for countries with higher baseline risk because their baseline level of adaptation is higher. However most countries have relatively low levels of adaptive effort in the current climate, with the median country having risk levels near zero.

show that hypothesis H8 holds in the data when controlling for TC-risk, in support of these earlier findings

The even-numbered columns in Table 4 estimate the full model in equation (13) using each of the four dependant-independent variable pairs. In all four specifications, the coefficient to the interaction between ln($GDPpc$1970) and TC exposure $\alpha_2$ is negative, and it is distinguishable from zero in three out of four specifications (in the model where it is not significant, it is because the standard errors are large rather than because the coefficient is small). We find that an increase in ln($GDPpc$1970) of 0.1 (income rises 10%) leads to a decline in the semi-elasticity of normalized damages by –0.2% per m/s, this is one one-hundredth of the losses that are suffered prior to any adaptation (–20% per m/s). The effect for normalized deaths is identical, with an income gain of 10% leading to a reduction in unmitigated deaths by one one-hundredth.

*Coefficients for Risk and Capital when Not Interacted with Cyclone Exposure*

For completeness, Table 4 contains estimates for the coefficients $\omega_1$ and $\omega_2$, however we do not take these point estimates seriously. Both average TC risk and income in 1970 are correlated with many important omitted variables, such as distance to the coast and level of democracy. Thus, we control for TC risk and income in 1970 only so that they can bear the loading of these omitted variables, limiting their influence on our coefficients of interest $\alpha_1$ and $\alpha_2$. It is possible that these point estimates contain some information, but we cannot know how much. The coefficients on TC risk measures tend not to be distinguishable from zero, with signs that change across models. In contrast, the coefficients on income are reasonably consistent across models and are statistically different from zero, perhaps suggesting that they should be explored rigorously in future work.

## 4. Summary and Discussion

*Summary*

We have developed a simple analytical model of optimal adaptation to TCs in a rational and neoclassical framework. This framework allows us to infer adaptation effort using data on TC exposure and losses, enabling us to verify the model's prediction that adaptation effort increases as TC climates intensify. We are the first paper that is able to observe adaptation with this approach because we are the first to construct a global dataset of TC exposure that is based on physical parameters, allowing comparisons across countries.

We document a large amount of variation in adaptive effort across countries, indicating there is tremendous scope for adaptation to TCs. Moreover, we are able to estimate statistically precise estimates for the adaptive response to changes in TC climates. However, while we find strong evidence that adaptation is occurring, we can confidently reject the scenario where marginal changes in climate are accompanied by substantial changes in adaptive effort.

*Adaptation in the Current Climate*

It is sometimes suggested that natural disasters occur because of mismanagement, political actions or irrational behavior. While our results do not refute these claims, they reject the notion that we would no longer observe disaster losses if we eliminated irrational behavior, politics or mismanagement. In an economy that is rationally and optimally managed, there will always be positive losses to disasters so long as there are sufficiently convex costs to protection. It will never be rational to mitigate all disaster risk and so some losses will persist. With regards to the TC events analyzed in this study, we find no evidence that the management of these risks was irrational.

*Adaptation in the Future Climate*

We find strong evidence that if TC climates intensify, *ceteris paribus*, it will induce populations to increase their investment in adaptation. However, the estimated magnitude of the response is both small and precise, so we can confidently reject the hypothesis that climate changes will themselves lead to large investments in adaptation. Our results make it clear that adaptation to TCs is technologically feasible, since some countries already exhibit extensive adaptation. However, major adaptive investments will not be cost-effective for most populations if changes to future TC climates are relatively marginal.

The small adaptive response that we measure (~3%) is consistent with Nordhaus' (2010) application of the Envelope Theorem to climate adaptation, however it is strikingly smaller than some related estimates in the integrated assessment literature. For example, the assumptions of the AD-DICE model generate projections of new adaptive investments that reduce marginal losses by ~30% (de Bruin et al, 2009). Importantly, the AD-DICE model accounts for a variety of adaptive investments that mitigate many types of climatic changes while our estimates are only applicable to changes in the TC climate, so it is expected that their estimates will not equal ours. However, the fact that our estimates differ by a full order of magnitude motivates us to question why our estimates are so dissimilar. Our theory suggests that adaptive responses to marginal climate changes will be small when the cost function for adaptation $I(.)$ is very convex, i.e. $I'(.)$ is steep (recall equation 6). Thus, our results suggest that in the present equilibrium, the marginal cost of adaptation already increases sufficiently fast that it prevents additional investments. In contrast, large adaptive efforts seem to emerge from integrated assessment models when they assume that the first several units of effort come at low or zero marginal cost. We think that in the current equilibrium, it is certainly plausible that the marginal cost of adapting to non-TC changes is lower than the marginal cost of adapting to TCs; although, it seems equally plausible that in the absence of solid empirical estimates, modeling groups have underestimated the convexity of adaptation costs. Hopefully, future empirical work on adaptation to non-TC changes will tell us which of these two scenarios dominates.

*Adaptation and Wealth*

Our results underscore previous findings that the marginal damage of disasters decline with the income level (Kahn, 2005, Toya and Skidmore, 2007, Noy 2009, Hsiang, 2010), by demonstrating that the relationship holds even when disaster risk is accounted for. In contrast, we find no evidence to support the arguments of Kellenberg and Mobarak (2007) or Schumacher and Strobl (2008) that the damage-income relationship should be an inverted U-shape with the highest relative damages in the middle-income countries[32]. Our theory provides a clear logic for why marginal damages decline monotonically with income: income is correlated with capital density and high capital densities increase the benefits of adaptive investments. Unlike previous theories, ours is simple and does not require a model of credit constraints or for preferences to change with income[33]. Furthermore, it is unified with the theory that explains why populations adapt to more intense TC climates.

[32] An inverted U-shape would be visible in our non-parametric plots in Figure 5.

[33] In a closely related empirical literature, Jones and Olken (2010) and Hsiang (2010) find that the influence of surface temperature variations on GDP growth is largest for low-income countries. Similarly, Hsiang et al. (2011) find that ENSO variations influence conflict most strongly in low-income countries. A formal model explaining these interactions has not been proposed, however it is possible that low capital densities may also play a role in these situations.

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**Table 1.** Summary statistics of the data

| Variable | Units | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Annual economic losses | thousand US$ | 575 | 968478 | 7310460 | 5 | 1.58E+08 |
| Annual deaths | lives | 772 | 1179.4 | 13072 | 1 | 300000 |
| Wind speed | meters per second | 13688 | 3.39 | 7.70 | 0 | 78.34 |
| Energy | standard deviations | 13688 | 0.23 | 1.00 | 0 | 23.46 |
| Climatological wind speed 1950-2008 | meters per second | 233† | 3.39 | 5.69 | 0 | 27.73 |
| Climatological energy 1950-2008 | standard deviations | 233† | 0.23 | 0.54 | 0 | 4.32 |

† Signifies the number of unique observations (countries)

**Table 2.** Global tropical cyclone economic losses and deaths

| Models: | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | | | |
| Country Fixed-Effects | NO | YES | YES | YES |
| Year Fixed-Effects | NO | NO | YES | YES |
| Temp. & Precip. Controls | NO | NO | NO | YES |
| | Panel (a) | | | |
| | Dependent variable: log(damage/GDP) | | | |
| Wind speed (m/s) | 0.108*** | 0.106*** | 0.101*** | 0.109*** |
| | [0.012] | [0.015] | [0.013] | [0.017] |
| | | | | |
| Observations | 420 | 420 | 420 | 359 |
| R-squared | 0.170 | 0.537 | 0.630 | 0.641 |
| | Panel (b) | | | |
| | Dependent variable: log(killed/population) | | | |
| Wind speed (m/s) | 0.085*** | 0.070*** | 0.058*** | 0.054*** |
| | [0.006] | [0.010] | [0.007] | [0.009] |
| | | | | |
| Observations | 667 | 667 | 667 | 468 |
| R-squared | 0.181 | 0.561 | 0.656 | 0.700 |
| | Panel (c) | | | |
| | Dependent variable: log(damage/GDP) | | | |
| Energy (s.d.) | 0.548*** | 0.404*** | 0.425*** | 0.507*** |
| | [0.064] | [0.074] | [0.067] | [0.069] |
| | | | | |
| Observations | 420 | 420 | 420 | 359 |
| R-squared | 0.153 | 0.519 | 0.620 | 0.638 |
| | Panel (d) | | | |
| | Dependent variable: log(killed/population) | | | |
| Energy (s.d.) | 0.349*** | 0.278*** | 0.243*** | 0.286*** |
| | [0.036] | [0.042] | [0.040] | [0.048] |
| | | | | |
| Observations | 667 | 667 | 667 | 468 |
| R-squared | 0.116 | 0.556 | 0.654 | 0.699 |

Standard errors in brackets (clustered by year), *** p<0.01

**Table 3.** Tropical cyclone economic losses and deaths by continent

| Sample: | North America | Oceania | Asia | Africa |
|---|---|---|---|---|
| | | Panel (a) | | |
| | | Dependent variable: log(damage/GDP) | | |
| Wind speed (m/s) | 0.086** | 0.091 | 0.129*** | 0.375 |
| | [0.035] | [0.101] | [0.042] | [0.174] |
| Observations | 161 | 49 | 173 | 33 |
| R-squared | 0.683 | 0.974 | 0.548 | 0.956 |
| | | Panel (b) | | |
| | | Dependent variable: log(killed/population) | | |
| Wind speed (m/s) | 0.053*** | 0.045 | 0.074*** | -0.028 |
| | [0.015] | [0.034] | [0.018] | [0.054] |
| Observations | 204 | 68 | 335 | 54 |
| R-squared | 0.783 | 0.878 | 0.547 | 0.854 |
| | | Panel (c) | | |
| | | Dependent variable: log(damage/GDP) | | |
| Energy (s.d.) | 0.410*** | 0.913 | 0.426** | 0.933* |
| | [0.141] | [0.587] | [0.183] | [0.383] |
| Observations | 161 | 49 | 173 | 33 |
| R-squared | 0.682 | 0.979 | 0.515 | 0.953 |
| | | Panel (d) | | |
| | | Dependent variable: log(killed/population) | | |
| Energy (s.d.) | 0.355*** | 0.125 | 0.167*** | -0.045 |
| | [0.087] | [0.192] | [0.052] | [0.205] |
| Observations | 204 | 68 | 335 | 54 |
| R-squared | 0.793 | 0.869 | 0.534 | 0.850 |

White standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1
All models include country fixed-effects and year fixed-effects.

**Table 4.** Evidence of long-run adaptation to tropical cyclone climates

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Dependent variable: log(damage/GDP) | | | | Dependent variable: log(killed/population) | | | |
| Wind speed ($ms^{-1}$) | 0.203*** | 0.185*** | | | 0.169*** | 0.156*** | | |
| | [0.021] | [0.021] | | | [0.012] | [0.013] | | |
| Wind speed * climatological wind speed | -0.007*** | -0.003 | | | -0.006*** | -0.005*** | | |
| | [0.002] | [0.002] | | | [0.001] | [0.001] | | |
| Energy (s.d.) | | | 0.983*** | 1.002*** | | | 0.732*** | 0.786*** |
| | | | [0.094] | [0.093] | | | [0.066] | [0.072] |
| Energy * climatological energy | | | -0.269*** | -0.255*** | | | -0.188*** | -0.187*** |
| | | | [0.066] | [0.063] | | | [0.024] | [0.024] |
| Wind speed * logGDPpc1970 | | -0.020** | | | | -0.017*** | | |
| | | [0.009] | | | | [0.006] | | |
| Energy * logGDPpc1970 | | | | -0.068 | | | | -0.081** |
| | | | | [0.065] | | | | [0.039] |
| Climatological wind speed | -0.065* | -0.096*** | | | 0.001 | 0.005 | | |
| | [0.034] | [0.035] | | | [0.019] | [0.019] | | |
| Climatological energy | | | -0.189 | -0.143 | | | 0.047 | 0.149 |
| | | | [0.221] | [0.220] | | | [0.106] | [0.103] |
| log(GDP per capita 1970) | | -0.283*** | | -0.411*** | | -0.217*** | | -0.347*** |
| | | [0.093] | | [0.082] | | [0.065] | | [0.057] |
| Constant | -8.588*** | -6.648*** | -7.934*** | -5.242*** | -16.165*** | -14.861*** | -15.112*** | -12.993*** |
| | [0.750] | [0.988] | [0.772] | [0.942] | [0.441] | [0.632] | [0.413] | [0.568] |
| Observations | 420 | 420 | 420 | 420 | 667 | 660 | 667 | 660 |
| R-squared | 0.379 | 0.422 | 0.364 | 0.408 | 0.355 | 0.399 | 0.278 | 0.329 |

Climatological variables are demeaned. White standard errors in brackets. All models include year fixed-effects. *** p<0.01, ** p<0.05, * p<0.1

**Figure 1.** Country-by-year observations of *wind speed* and the standardized *energy* measure: power dissipation density index.

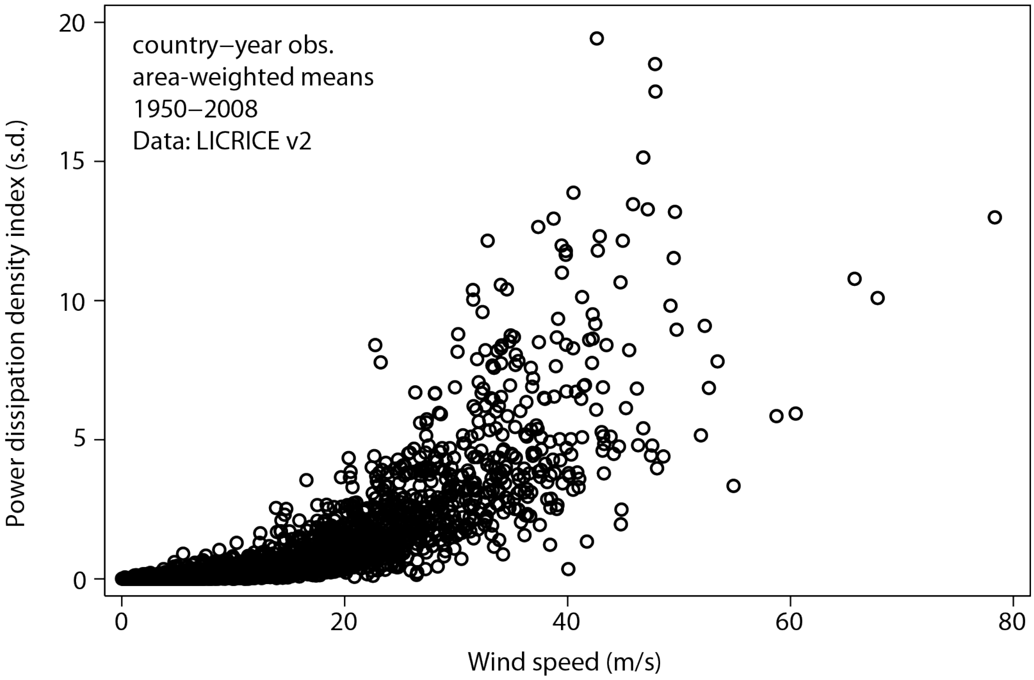

**Figure 2.** Climatology (mean) of annual maximum wind speed (m/s) achieved by tropical cyclones at each location during 1950-2008.

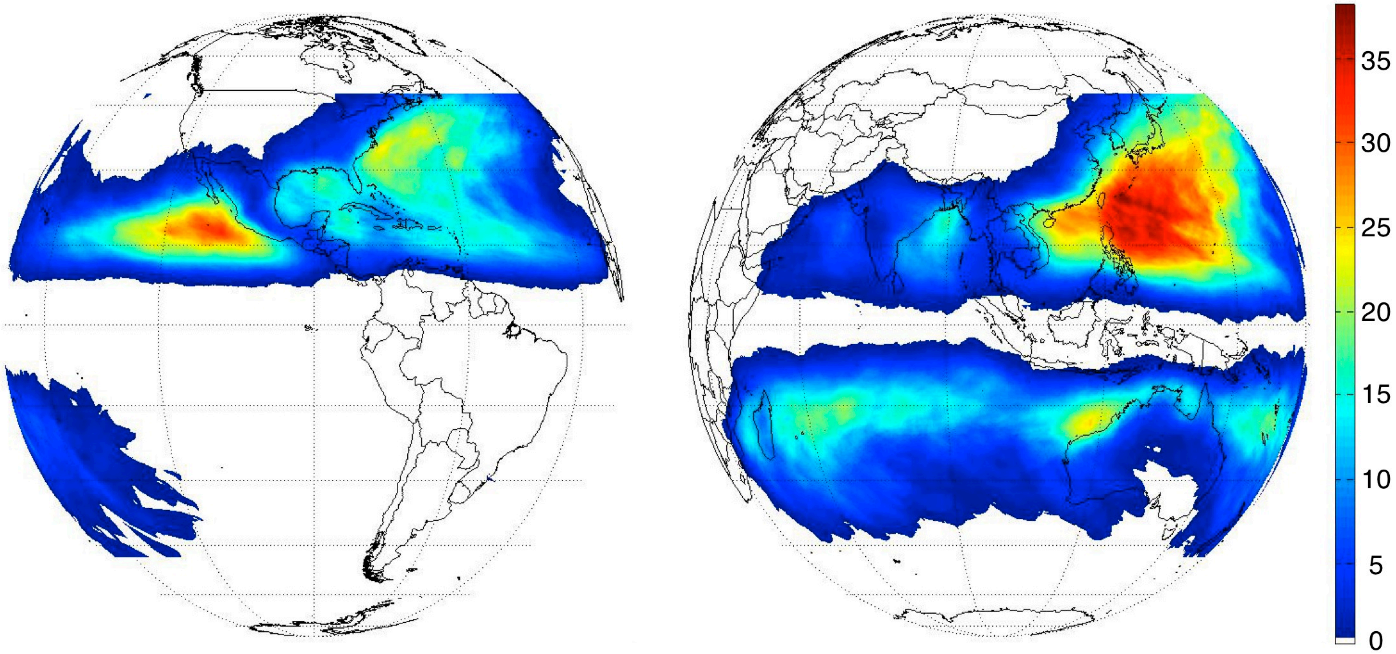

**Figure 3.** A comparison of log-linear models and log-log models for normalized damages and normalized deaths. Dashed lines are locally-weighted fits.

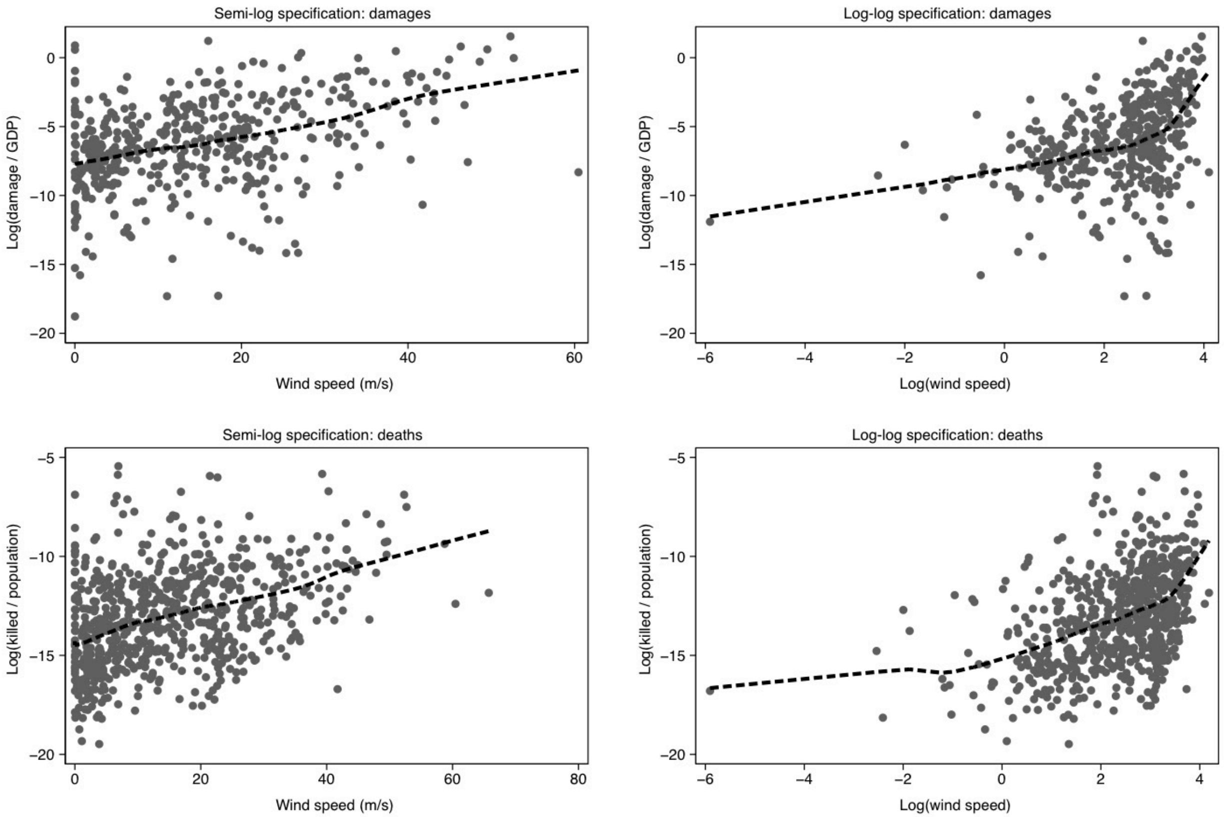

**Figure 4.** *Prima facie* evidence of adaptation to cyclone climates: OLS fit of normalized deaths to actual *wind speed* for three East-Asian countries. The vertical line marks the climatological (mean) *wind speed* for each country during 1950-2008.

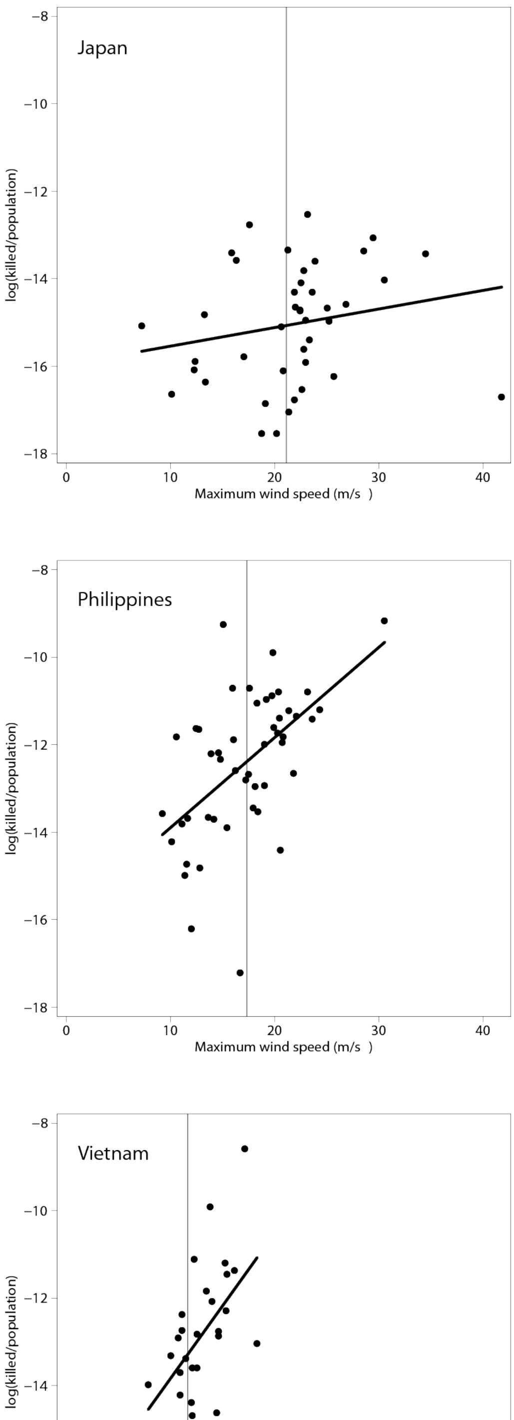

**Figure 5.** Non-parametric estimates of economic damage (top) and deaths (bottom) conditional on actual wind speed and either the climatological wind speed (left) or income in 1970 (right).

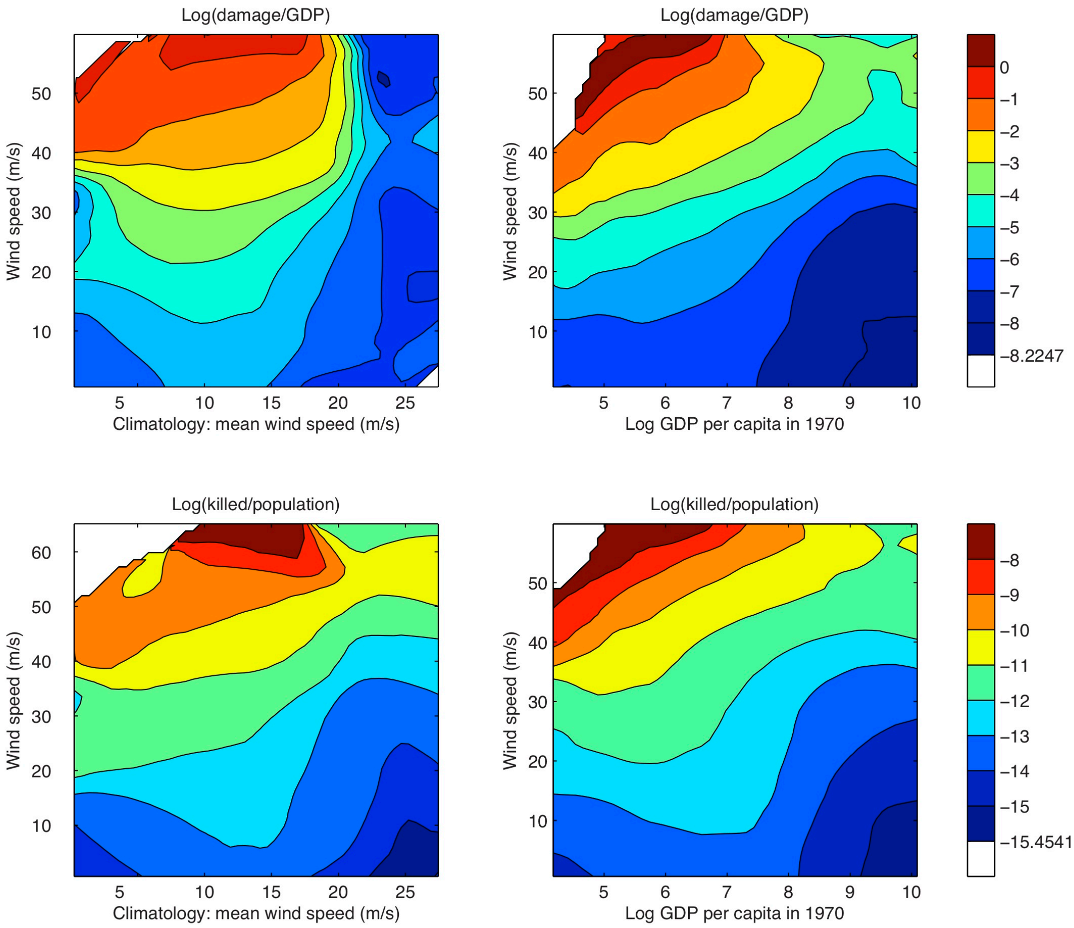

**Figure 6.** Top: Empirical estimate of marginal damages before adaptation and marginal damages averted with effort as a function of tropical cyclone climate. Actual marginal loss is the space between the two lines. Middle: same, but for deaths. Arrows illustrate the response to changes in the climate. Bottom: The distribution of tropical cyclone climates for the period 1950-2008 (only non-zero values are shown).