The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones*

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JEL codes: O11, O44, Q51, Q54, R11, H87

Abstract

Does the environment have a causal effect on economic development? Using meteorological data, we reconstruct every country's exposure to the universe of tropical cyclones during 1950-2008. We exploit random within-country year-to-year variation in cyclone strikes to identify the causal effect of environmental disasters on long-run growth. We compare each country's growth rate to itself in the years immediately before and after exposure, accounting for the distribution of cyclones in preceding years. The data reject hypotheses that disasters stimulate growth or that short-run losses disappear following migrations or transfers of wealth. Instead, we find robust evidence that national incomes decline, relative to their pre-disaster trend, and do not recover within twenty years. Both rich and poor countries exhibit this response, with losses magnified in countries with less historical cyclone experience. Income losses arise from a small but persistent suppression of annual growth rates spread across the fifteen years following disaster, generating large and significant cumulative effects: a 90th percentile event reduces per capita incomes by 7.4% two decades later, effectively undoing 3.7 years of average development. The gradual nature of these losses render them inconspicuous to a casual observer, however simulations indicate that they have dramatic influence over the long-run development of countries that are endowed with regular or continuous exposure to disaster. Linking these results to projections of future cyclone activity, we estimate that under conservative discounting assumptions the present discounted cost of "business as usual" climate change is roughly $9.7 trillion larger than previously thought.

*We thank Jesse Anttila-Hughes, Scott Barrett, Chris Blattman, Marshall Burke, Christopher Costello, Melissa Dell, Anthony Fisher, Joshua Graff Zivin, Michael Greenstone, Michael Hanemann, Hilary Hoynes, Meha Jain, Benjamin Jones, Gordon McCord, Kyle Meng, Edward Miguel, Daiju Narita, Matthew Neidell, Suresh Naidu, Serena Ng, Benjamin Olken, Michael Oppenheimer, Billy Pizer, Valerie Ramey, Ricardo Reis, Jeffrey Sachs, Wolfram Schlenker, Glenn Sheriff, Thomas Sterner, James Stock, Jan von der Goltz, Gernot Wagner, Reed Walker, and seminar participants at AEA, BREAD, Chicago, Columbia, Cornell, EDF, EPA, IBM Research, IZA, LBL, NBER, NEUDC, Oxford, Oklahoma, PacDev, Princeton, UC Berkeley, UC San Diego, USF, Lausanne, and Zurich for discussions and suggestions. This work was funded in part by a grant from the Center for International Business Education and Research at Columbia University, a doctoral fellowship at Columbia University, and a Postdoctoral Fellowship in Science, Technology and Environmental Policy at Princeton University. Emails: `shsiang@berkeley.edu` and `amirjina@uchicago.edu`

1 Introduction

The influence of environmental conditions on global patterns of economic development is the subject of continuing debate, primarily because identifying these causal effects is challenging. We examine how a specific type of environmental disaster, tropical cyclones, affect countries' growth in the long-run. We construct a novel data set of all countries' exposure to all cyclones on the planet using ground-, ship-, aerial-, and satellite-based meteorological observations combined with information on cyclone physics. We exploit natural random variation in the formation, path, and intensity of each storm as a source of exogenous within-country variation in disaster exposure, allowing us to identify cyclones' long-run impact on economic growth. Applying a difference-in-differences approach, we compare each country's growth rate to itself in the years immediately before and after exposure while accounting for the distribution of lagged effects imposed by cyclones strikes in preceding years. We obtain estimates that are both economically large and statistically precise: each additional meter per second[1] of annual nationally-averaged wind exposure lowers per capita economic output 0.37% twenty years later. When we explore the generalizability of this result, we find that it is "globally valid" in the sense that it holds around the world, appearing in each region independently and for countries of different income and geographic size.

The structure and impact of short-run macroeconomic disasters has been carefully studied (e.g. Barro (2006); Jones and Olken (2008); Gabaix (2012)) and recent empirical work has begun to identifying the long-run growth effects of specific shocks, such as currency crises, banking crises, political crises and civil wars (Cerra and Saxena (2008)), financial crises (Reinhart and Rogoff (2009)), tax increases (Romer and Romer (2010)), changes in temperature (Dell, Jones and Olken (2012)), and democratization (Acemoglu, Naidu, Restrepo, Robinson (2014)). By assembling the first objective and comprehensive history of cyclone exposure, we build on these earlier results to provide the first global estimates of the effect of large-scale environmental disaster on long-run growth. The economic response to environmental disaster shares many features with the response to these previously studied shocks, in particular all of these shocks have persistent effects on income. In Table 1 we compare the magnitude and duration of these effects on income, including cyclone impacts from this study. The national income loss associated with a one standard deviation cyclone event is comparable in magnitude to loss associated with a tax increase equal to 1% of GDP, a currency crisis, or a political crises in which executive constraints are weakened. The income loss associated with a 90th-percentile cyclone event is comparable to losses from a banking crisis. The top percentile of cyclone events have effects that are larger in magnitude and endure longer than any previously studied shocks except democratization. These results suggest that in addition to human-caused political and financial crises, large-scale natural environmental disasters play a important role in shaping patterns of global economic activity.

A key feature of the macroeconomic response to cyclones is that incomes do not recover in the long-run, defined here as the twenty years after a storm. This fact has profound implications. Unlike relatively rare financial crises, political crises, and civil wars, cyclones occur regularly and repeatedly, often striking the same population as prior events because the location of storms are determined by geophysical constraints. Because incomes do not recover after a cyclone, repeatedly exposing the same population to frequent storms results in an accumulation of income losses over time, effectively lowering

[1] 1 m/s = 3.6 km per hour ≈ 2.24 miles per hour.

Table 1: Effects of cyclones and other shocks to income per capita

Event Type	**Effect on Income**	**Observed After**	**In-Sample Probability**
Temperature increase (+1°C)*[1]	−1.0%	10 yrs	6.4%
Civil war[2]	−3.0%	10 yrs	6.3%
Tax increase (+1% GDP)**[3]	−3.1%	4 yrs	†16.8%
1 standard deviation cyclone	**−3.6%**	**20 yrs**	**14.4%**
Currency crisis[2]	−4.0%	10 yrs	34.7%
Weakening executive constraints [2]	−4.0%	10 yrs	3.7%
90th percentile cyclone	**−7.4%**	**20 yrs**	**5.8%**
Banking crisis[2]	−7.5%	10 yrs	15.7%
Financial crisis[4]	−9.0%	2 yrs	<0.1%
99th percentile cyclone	**−14.9%**	**20 yrs**	**0.6%**
Democratization[5]	+21.2%	30 yrs	1.4%

*Poor countries only. **USA only. †Number of quarters with any tax change.

[1]Dell, Jones & Olken (AEJ: Macro, 2012), [2]Cerra & Saxena (AER, 2008), [3]Romer & Romer (AER, 2010), [4]Reinhart & Rogoff (AER, 2009), [5] Acemoglu, Naidu, Restrepo, Robinson (2014)

that population's average growth rate relative to a cyclone-free counterfactual. Mathematically, the effect of increasing the average exposure to cyclones is very similar to increasing the rate of capital depreciation in standard growth models. Quantitatively, the in-sample probability of cyclones is most similar to that of banking crises (Table 1), which also slow growth when they occur repeatedly in the same country.

This result informs two important literatures. First, the role of geography in economic growth has been widely debated, with some authors suggesting that geographic condition may matter because they determine the "initial conditions" of an economy by affecting its institutions (Acemoglu, Johnson and Robinson (2002), Rodrik, Subramanian, and Trebbi (2004)) while other authors suggest that geographic conditions determine the "boundary conditions" of an economy throughout its development, perhaps by affecting the health of a population (Gallup, Sachs and Mellinger (1999); Kremer and Miguel (2004)) or the costs of trade (Frankel and Romer (1999)). Our results do not reject any of these theories, but they do provide empirical evidence that repeated exposure to cyclones is a specific boundary condition to development that, alongside institutional and capital factors, may be quantitatively important in certain contexts.

Second, the economic impact and optimal management of global climate change is heavily researched with strong theoretical foundations (Nordhaus (1996); Stern (2008); Weitzman (2009); Tol (2009); Heal (2009)) but less satisfying empirical grounding (Pindyck (2013)). Prior work has focused on temperature's effect on agriculture (e.g. Schlenker and Roberts (2009)), health (e.g. Deschênes, Greenstone, and Guryan (2009)), labor (e.g. Graff Zivin and Neidell (2014)), energy (e.g. Deschênes and Greenstone (2011)), social conflict (e.g. Hsiang, Burke, and Miguel (2015)), and growth generally (e.g. Dell, Jones and Olken (2012)). Yet, the growth impact of tropical cyclones has not been considered in previous assessments of climate change. It is expected that the frequency and intensity of cyclones will change in response to climate change (Knutson et al. (2010); Camargo and Hsiang (2014)), which our results indicate may have important economic consequences.

To identify the growth effect of tropical cyclones, we exploit random, within-country, year-to-year variation in the formation, path, and intensity of cyclones that is driven by stochastic ocean and atmospheric conditions. We apply the difference-in-differences approach developed by Deschênes and Greenstone (2007) whereby we identify the effect of storms using the residual variations in both cyclone exposure and growth that remain after country fixed effects, country-specific trends, and year fixed effects have absorbed average cross-sectional correlations and trends in both variables.

By including our physical measures of cyclone exposure in a flexible and robust model of growth, we are able to recover the within-country long-run effect of cyclones with precision. We find that GDP growth rates are depressed for the fifteen years that follow a cyclone strike, causing the trajectory of long-run income to diverge significantly from its pre-disaster trend. Within the twenty years following a cyclone there is no rebound in growth, so affected national incomes remain permanently lower than their disaster-free counterfactual. Our conclusion that no recovery occurs is robust, passing numerous specification and data checks. Furthermore, this result is strikingly general since we obtain similar estimates for marginal effects independently in each major cyclone region, in response to both large and small cyclone events, in countries of high and low income, and in countries of all different sizes. Our interpretation that these effects are causal is strengthened by a series of randomization procedures where we demonstrate that assigning the exact timing of specific cyclone events to correct countries is essential for obtaining our result—it is extremely unlikely that these findings could be a spurious artifact of global cross-sectional correlations or trends in growth. Furthermore, the long-run response of alternative macroeconomic measures corroborate this central finding. Interestingly, we find evidence that the effects of cyclones are largest in countries with less historical cyclone experience and smaller in more experienced countries. We interpret this finding as evidence that frequently exposed populations adapt to their local cyclone-climate by undertaking costly investments that partially insulate their economies from cyclones (Hsiang and Narita (2012)).

The effect of cyclones on growth is both large and persistent, causing it to exert substantial influence over global patterns of economic development. A one standard deviation in a year's cyclone exposure lowers GDP by 3.6 percentage points twenty years later, setting an average country back by almost two years of growth. For countries that are infrequently exposed to cyclones, this effect has only minor long-run implications as an average country's GDP is likely to grow by 50 percentage points during that period. However, tropical cyclone climates are a geographic feature of countries that are determined by oceanic and atmospheric patterns, so some countries are endowed with substantially higher levels of exposure than others. Because the effects of cyclone strikes do not fade with time, those countries that are repeatedly exposed to cyclones suffer from an income penalty that grows with each event. Thus, a cyclone-prone climate lowers a country's long-term growth rate substantially; however, because the onset of cyclone-induced losses is gradual, there is no obvious feature in its GDP series that a casual observer would be likely to notice.

To develop a sense of how important cyclones might be for determining global patterns of long-run growth, we simulate "counterfactual" GDP series where the effect of each country's cyclone history is artificially removed. While this approach generates only a coarse partial-equilibrium estimate for a cyclone-climate's total long-run effect, our simulations indicate that regular disaster exposure plays a major role in determining national income growth in regions where these storms are frequent since the cyclone-climate of many countries cost them several percentage points in their average annual growth rate. Within heavily exposed regions, we find that these simulated losses to cyclones explain roughly a quarter of the cross-country variation in long-run growth. For example, our results predict that the cyclone climates of China and the Philippines (neighbors separated by only 380 miles) generate a 6.2 percentage point difference in their average annual growth rates, when the observed difference in actual growth is 5.6 percentage points. Aggregating these simulation results globally, we estimate that the 4,174 cyclone-by-country events that occurred between 1950-2008 had the total effect of slowing the annual growth rate of World GDP by roughly 1.27% during the period 1970-2008. All of these simulation results should be interpreted with caution, as it is of course impossible to directly test if these estimated effects would manifest should all cyclones disappear from the planet—but they nonetheless force us to carefully consider the potential centrality of environmental disasters in determining both the distribution and quantity of global wealth.

We conclude by evaluating how these results alter our understanding of the social cost of anthropogenic climate change. We first develop a theoretical framework for computing the present discounted value of growth trajectories that are permanently altered by a changing cyclone climate. We then apply our estimates to this framework, combining them with future projections from the scientific literature, to compute the cost of future changes in the global tropical cyclone climate. We find that accounting for the long-run growth effects of a changing cyclone climate substantially alters the global cost of climate change under "business as usual." For example, we estimate that the present discounted value[2] (PDV) of losses rise by 6% of current GDP for the United States, 17% of GDP for Mexico, and 83% of GDP for the Philippines. Globally, accounting for this novel pathway raises the PDV of future losses by roughly $9.7 trillion (13.8% of current World GDP). For comparison, we note that Nordhaus (2008) estimates that the total PDV of optimal global climate policy is $5 trillion (in comparison to "no regulation", using a similar discount rate) which costs $2 trillion to implement, for a net gain of $3 trillion – with $17 trillion in residual damages.

The remainder of the paper is as follows. In Section 2 we provide background on tropical cyclones and the economic impact of natural disasters. In Section 3, we describe our construction of a global data file describing cyclone exposure for each $1^\circ \times 1^\circ$ pixel of the planet and how these data are collapsed to match macro-economic data. In Section 4 we explain and evaluate our econometric model. In Section 5 we present our main results for growth, numerous robustness checks, tests for spatial spillovers, and compare effect sizes to prior studies. We also show results for non-growth outcomes and prove evidence of adaptation. We then consider the implications of these result through simulations of cyclone-free growth (for comparison to recent history) and calculations for the expected cost of climate change incurred by altering the global cyclone distribution. In Section 6 we conclude with a discussion of policy implications.

[2] We use a 5% discount rate.

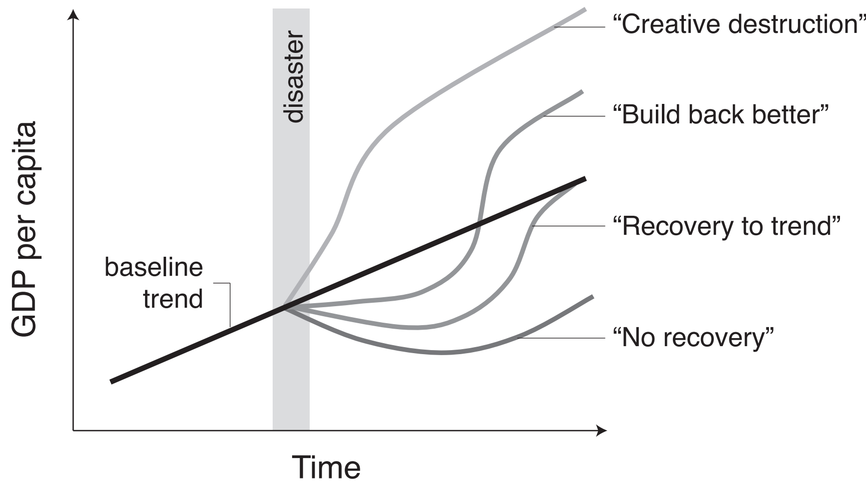

Figure 1: Four hypotheses, proposed in the literature, that describe the long-term evolution of GDPpc following a natural disaster.

2 Background

Economics of natural disasters

The notion that environmental disasters might have permanent long-run effects on income is not obvious, in part because it is frequently suggested that these events elicit economic responses fundamentally different from human-caused macroeconomic disasters (e.g. banking crises). In the absence of clear empirical evidence, prior literature has converged on four competing hypotheses that describe how economic output might respond to environmental catastrophes in the long-run, however no study has credibly falsified any of the four and the actual behavior of economies is widely disputed (Field et al. (2012)). Figure 1 schematically illustrates these four hypotheses:

1. The **"creative destruction" hypothesis** argues that disasters may temporarily stimulate economies to grow faster because demand for goods and services increase as populations replace lost capital, because inflowing international aid and attention following disaster may promote growth, or because environmental disruption stimulates innovation (Skidmore & Toya (2002)). This notion is partially motivated by the observation that construction industries often exhibit short-lived (1-2 year) increases in output after catastrophes (Belasen and Polachek (2008); Hsiang (2010); Deryugina (2011)), but it is unknown if this transient sector-specific response has enduring impact on the broader economy.

2. The **"build back better" hypothesis** argues that growth may suffer initially, since lives may be lost and productive capital destroyed, however the gradual replacement of lost assets with modern units has a positive net effect on long-run growth since the capital that is destroyed in a disaster may be older and outdated (Cuaresma, Hlouskova and Obersteiner (2008); Hallegatte and Dumas (2009)). This hypothesis might be true if firms do not upgrade their capital efficiently

in the absence of disasters and if the productivity benefits of post-disaster capital upgrading exceed the productivity losses imposed by the disaster in the long run.

3. The **"recovery to trend" hypothesis** argues that growth should suffer for a finite period, but that it should eventually rebound to abnormally high levels, causing income levels to converge back to their pre-disaster trend. It is argued that this rebound should occur because the marginal product of capital will rise when capital and labor become relatively scarce after a disaster (due to destruction and mortality), causing individuals and wealth to migrate into devastated locations until output recovers to the regional trend (Yang (2008); Strobl (2011)). The underlying logic of this hypothesis has mixed empirical support: disasters do tend to trigger transfers of wealth into the affected region (Strömberg (2007); Yang (2008); Deryugina (2011)), however population inflows occur roughly as often as outflow or no migration (Smith et al. (2006); Vigdor (2008); Belasen and Polachek (2009); Hornbeck (2012); Strobl (2011); Boustan, Kahn and Rhode (2012); Bohra-Mishra, Oppenheimer, and Hsiang (2014)). The net effect of these wealth and population reallocations on long-run growth is unknown.

4. Finally, the **"no recovery" hypothesis** argues that disasters slow growth by either destroying productive capital directly or by destroying durable consumption goods (e.g. homes) that are replaced using funds that would otherwise be allocated to productive investments—but no rebound occurs because the various recovery mechanisms above fail to outweigh the direct negative effect of losing capital[3] (Field et al. (2012)). The latter effect may be particularly important if, in the wake of disaster, consumption falls so that the marginal utility of consumption rises enough that post-catastrophe consumption becomes preferable relative to investment (Anttila-Hughes and Hsiang (2011)). According to this hypothesis, post-disaster output may continue to grow in the long run, however it remains permanently lower than its pre-disaster trajectory.

Recent reviews of the literature argue that the long-run effects of disasters remain a critical open question because recent attempts have not convincingly demonstrated whether any of the four hypotheses above can be rejected or hold generally (Cavallo and Noy (2011); Kellenberg and Mobarak (2011); Field et al. (2012)). This failure to eliminate hypotheses is theoretically unsatisfying, however we resolve this indeterminacy by using better data. The quality of prior estimates are affected by the endogenous nature of their independent variables: self-reported disaster counts and losses that are usually from the Emergency Events Database (EM-DAT). The quality and completeness of these self-reported measures are known to depend heavily on the economic and political conditions in a country (Kahn (2005), Strömberg (2007), Kellenberg and Mobarak (2008), Noy (2009), Hsiang and Narita (2012)), factors which also affect growth and thus might confound these results.

We overcome the challenges of omitted variables bias and endogenous disaster reporting by developing a novel data file describing year-to-year variation in each country's physical exposure to disaster. To do this, we focus on tropical cyclones, the class of natural disaster that includes hurricanes, ty-

[3] In addition to the impact of capital losses, it is also thought that disasters may generate enduring economic impacts by permanently altering the preferences of affected individuals (e.g. Cameron and Shah (2013)), by motivating populations to irreversibly disinvest in durable human or physical capital (e.g. Maccini and Yang (2009)) or by triggering political actions that have lasting economic consequences (e.g. Healy and Malhotra (2009)).

phoons, cyclones and tropical storms[4], and reconstruct every storm observed on the planet during 1950-2008. Unlike the self-reported statistics contained in EM-DAT, our objective measures of wind speed exposure and energy dissipation are fully exogenous, constructed using physical parameters and meteorological observations, so they are unlikely to be influenced by economic behavior or political actions within each country[5].

Tropical cyclones

Constructing a physical index of disaster exposure is essential to obtaining reliable inferences for their causal effect. However, because building a physical model to produce these indices is difficult, we focus on only a single type of disaster: tropical cyclones. We estimate that roughly 35% of the global population is seriously affected by tropical cyclones, making them one of the most broadly relevant forms of disaster, in addition to being one of the most costly (Bevere, Rogers and Grollimund (2011)).

Tropical cyclones are large, violent and fast-moving storms that form over the oceans and cause physical damage and loss of life via intense winds, heavy rainfall, and ocean surges. We focus on tropical cyclones both because they are common and because variation in their timing, strength and location allow us to identify their effects using quasi-experimental techniques (Holland (1986), Freedman (1991), Angrist and Pischke (2008)). Tropical cyclones are considered "rapid onset" events[6], usually arriving, affecting and passing a given location within one or two days. They are unambiguously recognizable by meteorologists and are well defined in space, with an intense core roughly 100-200 kilometers across. Tropical cyclones' formation, over warm oceans, and trajectory, which may extend thousands of kilometers, are stochastic and difficult to predict more than a few days in advance. Thus, cyclone exposure at a specific location varies exogenously in its timing, intensity and duration. This randomness is essential to our analysis, since our ability to identify the causal effect of cyclones relies on the unpredictable year-to-year variation in the intensity of each country's cyclone exposure (Deschênes and Greenstone (2007)).

3 Data

Our central innovation is our construction of a novel data file describing the physical exposure of all countries to all known cyclones during 1950-2008, which we link to standard macroeconomic datasets. Because macroeconomic data are available at the country-by-year level but we initially compute cyclone

[4]Tropical cyclones are known as "tropical storms" or "hurricanes" in the Atlantic Ocean, "typhoons" in the Pacific Ocean, and "cyclones" in the Indian Ocean. Here, we refer to them as "tropical cyclones" or simply "cyclones."

[5] Our approach is identical to the desirable method outlined (but not implemented) by Noy (2009), who used EM-DAT data as an independent variable and assumed that it was not determined endogenously:

> "Without the exogeneity assumption, the only way to infer causality from our specifications would entail finding an appropriate instrument for the initial disaster impact (i.e., an index of disaster magnitude that is completely uncorrelated with any economic indicator). Regrettably, we did not find such an instrument.... The exogeneity issue can potentially be fully overcome by producing an index of disaster intensity that depends only on the physical characteristics of the disaster (e.g., area affected, wave height, or storm circumference). 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." - p. 224

[6]In contrast to "slow onset" hazards, such as drought.

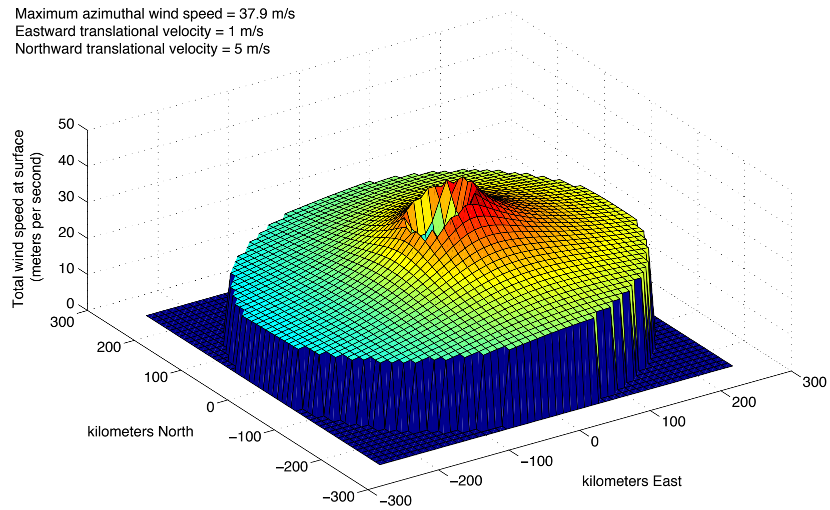

Figure 2: An example of the wind model used in the LICRICE model to reconstruct surface-level exposure to tropical cyclone winds. This particular example is a Category 1 storm traveling north-northeast.

data at a $0.1^{\circ} \times 0.1^{\circ}$ global grid, a secondary contribution is developing a formal framework for aggregating spatially granular environmental exposure data to coarser country-by-year units that can be matched to macroeconomic data.

Summary statistics for both geophysical and economic data, aggregated to the country-by-year level, are presented in Appendix Table A.1.

Tropical cyclone data

We expand on the approach of Hsiang (2010) and Hsiang and Narita (2012) to measure each location's history of cyclone exposure. We combine a database of ground, ship, aerial, and satellite-based observations with estimates for the distribution of winds within each cyclone at each moment in time to reconstruct what individuals on the ground would have experienced as each cyclone passed over them. We then use the micro-economic findings of Anttila-Hughes and Hsiang (2011) to provide insight into how we may collapse this spatially explicit data over countries of various sizes into scale-invariant measures that are appropriate for econometric analysis of economic growth, another scale-invariant measure.

Reconstructing a global history of tropical cyclone exposure

We generate measures of tropical cyclone incidence by reconstructing the wind field for every cyclone in the International Best Track Archive for Climate Stewardship (IBTrACS) database (Knapp et al. (2009)), the most complete global database of tropical cyclone observations[7]. IBTrACS merges

[7] These data are publicly available through the National Climate Data Center at `http://www.ncdc.noaa.gov/ibtracs/index.php` where they are described in detail.

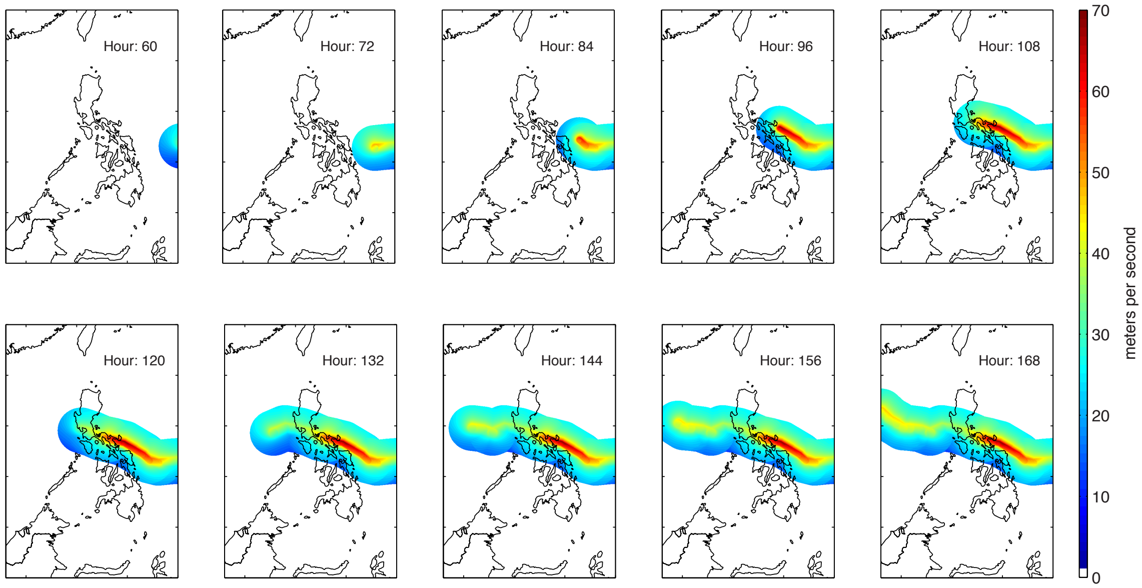

Figure 3: An example LICRICE reconstruction of location-specific tropical cyclone maximum wind speed exposure throughout the evolution of Super Typhoon Joan as it made landfall over the Philippines in October of 1970.

tropical cyclone data collected from weather monitoring agencies and scientists around the world, who in turn have collected information on the intensity and position of tropical cyclones from ground, ship, aerial, and satellite based observations. For this analysis, we use IBTrACS records for 6,712 storms observed during 1950–2008. The completeness of this record is considered strongest since the late 1970's when satellite surveillance provided reliable monitoring of storms because changing patterns of human activity on the surface have raised concerns that earlier portions of the record are incomplete. For example, the opening of the Panama Canal in 1915 and World War II both substantially altered the spatial distribution of trans-Atlantic boat traffic, which in turn changed the likelihood that mid-ocean cyclones would be encountered and reported by ships (Vecchi and Knutson (2008)). However, we do not think these changes substantially bias the portions of the record that we utilize, since we are primarily concerned with economic activity over land and land-based observations of these storms are very likely more reliable prior to the satellite era.

IBTrACS provides only limited information regarding the state of each storm, which we transform into economically meaningful measures of exposure using an improved version of the Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model first applied in Hsiang (2010) for the more limited Caribbean Basin context. IBTrACS reports the location of a cyclone's center, its minimum central surface air pressure, and its maximum sustained surface winds every six hours. Taken alone, this sequence of point-wise observations allows researchers to plot the trajectory of a storm's center and it's core intensity on a map, but it is difficult to infer the exposure of national economies to these events using only this single line. For example, the recorded trajectory of Hurricane Allen in 1980 completely missed the national boundaries of Haiti (i.e. Allen never made "landfall" in Haiti) but it would be a mistake to conclude that Haiti was not exposed to the storm:

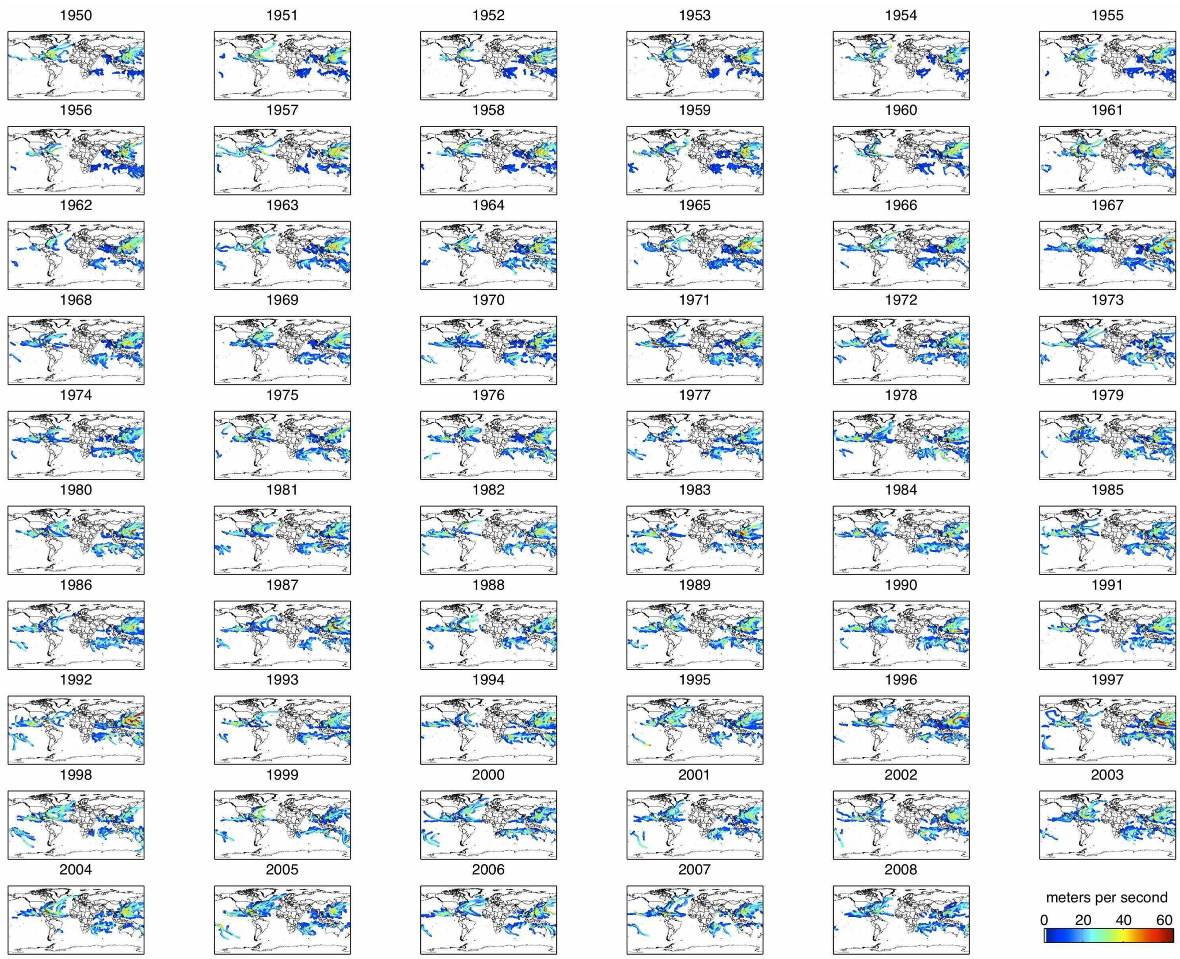

Figure 4: Global tropical cyclone exposure displayed as maximum wind speed for each pixel, for each year in the dataset.

Hurricane Allen passed along the southern coast of Haiti, side-swiping Port-au-Prince, causing $400 million (1980 USD) in damage, destroying 60% of the nation's coffee crop and leaving 835,000 people homeless (Longshore (2009)). Thus, to accurately capture the exposure of economies to cyclones, we reconstruct the winds that individuals and assets on the surface would have been exposed to rather than simply tracking each storm's center. LICRICE does this by estimating the instantaneous wind field within the storm at each moment in time based on interpolations of the 6-hourly observations recorded in IBTrACS (see Figure 2 for an example). The structure of the wind field within each storm is based on (1) a statistical prediction for the size of the storm's inner core (known as the "eye") where the statistical model is fitted to detailed observations from aircraft reconnaissance missions that fly through a storm's center; (2) a structural model of the surface winds within a cyclone vortex that is scaled to the size estimate in (1) and the intensity measures from IBTrACS; and (3) the speed that the storm is translating over the surface. Using these reconstructed estimates for the wind field at each moment in time, LICRICE then integrates the exposure that pixels on the surface would have experienced during the life of the storm (see Figure 3 for an example).

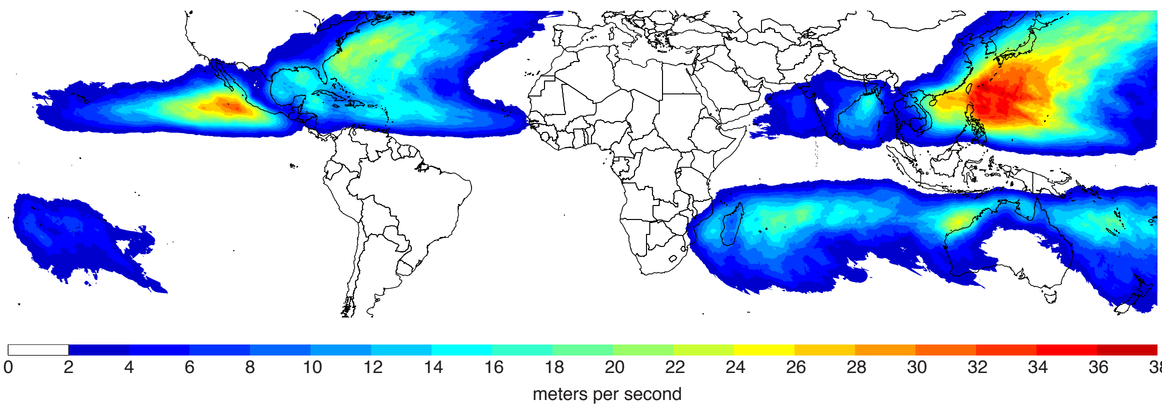

Figure 5: Global tropical cyclone exposure climatology derived from LICRICE. Colors denote the average (across years) maximum wind speed for all tropical cyclone events during 1950-2008. See Figure 4 for year-by-year data.

We reconstruct wind exposure indices at each $0.1° \times 0.1°$ pixel between 48°N–48°S latitude for all 6,712 storms in the IBTrACS database during 1950–2008. This involves interpolating among the 191,822 points that represent storm-specific observations. Figure 4 displays this new data set of wind exposure for all points on Earth for every year in the sample.

To provide a useful point-wise summary statistic of this new data, we average pixel-level exposure across all 59 years of data for each pixel. This recovers the expected experience at each pixel, which we term the "cyclone-climate" of that pixel and display in Figure 5. Cyclone exposure is not uniformly distributed around the planet, but instead it is concentrated in coastal countries in the tropics and middle latitudes. Countries very near the equator, such as Singapore, are not exposed to cyclones because the storms curve away from the equator as they conserve angular moment. Also, countries on the eastern coast of continents (eg. Madagascar) are generally more exposed than countries on western coasts (eg. Nigeria) because tropical cyclones are driven towards land by the westward blowing winds that dominate atmospheric circulations over regions where these storms form.

In principle, it is possible to develop numerous measures of wind exposure. Here we utilize two wind indices, based on climate physics, that summarize cumulative cyclone wind exposure in different ways. Each index has its own strengths and weaknesses.

The first measure is a *power dissipation density index* (hereafter "energy"), first developed in Hsiang (2010), which describes the total quantity of energy that a storm dissipates at the surface as it passes over a location[8]. Storms with more intense winds dissipate more energy, as do storms that move more slowly over a location. The power dissipation density index is an intuitive measure for aggregating exposure across storm events or across pixels within a country because energy is a conserved physical quantity, making it a sensible value to sum across events. However, the units are the relatively unintuitive *meters-cubed per seconds-squared* (m^3/s^2), so we standardize its units for expositional and notational convenience.

The second index of cyclone exposure is the *maximum wind speed* (hereafter "wind speed") expe-

[8]This measure is related to "accumulated cyclone energy" (ACE) and the "power dissipation index" (PDI) which are commonly used in the field of meteorology (Emanuel (2005)).

rienced over the course of all storms in a given year, which was first introduced in Hsiang and Narita (2012). Measuring incidence with maximal wind exposure is appealing because most rigid materials used to construct durable capital fail catastrophically at a critical level of stress, so only the maximum wind speed is essential for predicting whether capital will be heavily degraded[9]. Wind speed has the additional benefit that it is measured in the physically intuitive units of meters per second (m/s), so we leave wind speed unstandardized. Notably, unlike energy, a pixel's measure of wind speed is unchanged if a second weak storm strikes that pixel after a stronger event has already passed.

Wind speed and energy are correlated with one another, but we focus our attention on results that use wind speed as an independent variable because its units are intuitive, it produces more conservative estimates in this study, and it produced more robust estimates in Hsiang and Narita (2012), probably because its distribution is less skewed than energy. For related reasons but in different contexts, Hsiang and Narita (2012) and Anttila-Hughes and Hsiang (2011) also focus on wind speed, a fact that proves useful when we compare our results to those of these other studies. Nonethelsss, we also present results using energy as an independent variable to check the robustness of our findings.

We do not explicitly model other dimensions of tropical cyclones that are known to be economically meaningful, such as excess rainfall, storm surges, and landslides. We do not characterize countries' exposure to these other processes because they are more heavily influenced by idiosyncratic geographic features, making them computationally difficult to model, however the impact of these measures will be captured by our estimates to the extent that they are correlated with these wind field indices. For physical reasons, all three factors will be correlated with overall wind exposure. Thus our wind indices can be considered proxy measures for all dimensions of cyclone exposure.

Matching cyclone data to economic units of observation

The data file of reconstructed storm exposure can be resolved with high spatial and temporal resolution, since each $0.1° \times 0.1°$ pixel of the Earth's surface takes different values every hour. Yet the unit of observation for macroeconomic data that we match with cyclone exposure is the country-by-year. Linking these two data sets requires that we collapse the cyclone exposure data in an economically sensible way. Economic growth is a scale-free measure that does not depend on the size of an economy. Ideally, we may construct an appropriate measure of cyclone exposure at the country-year level that is similarly scale-free and does not depend on the physical or economic size of a country, so that we recover a scale-invariant relationship between economic growth and cyclone exposure. Such a relationship would describe the average pixel-level relationship between pixel-level growth and pixel-level exposure[10].

Prior micro-econometric work by Anttila-Hughes and Hsiang (2011) indicates that the probability of destruction of assets, loss of total income, and increase in infant mortality change approximately linearly with local wind exposure. Because of this, we can collapse pixel-level wind exposure to the

[9]This idea was first discussed in the economics literature by Nordhaus (2010).

[10]Using scale-free variables to link geophysical measurements of cyclones to economic measurements has been successfully replicated at the national level in regional (Hsiang (2010)) and global data sets (Hsiang and Narita (2012)) and at the level of both provinces and larger administrative regions using Filipino household data (Anttila-Hughes and Hsiang (2011)). As one might expect when using scale-free variables, in all of these cases the estimated effect-sizes were approximately invariant in the geographic size of the observational units.

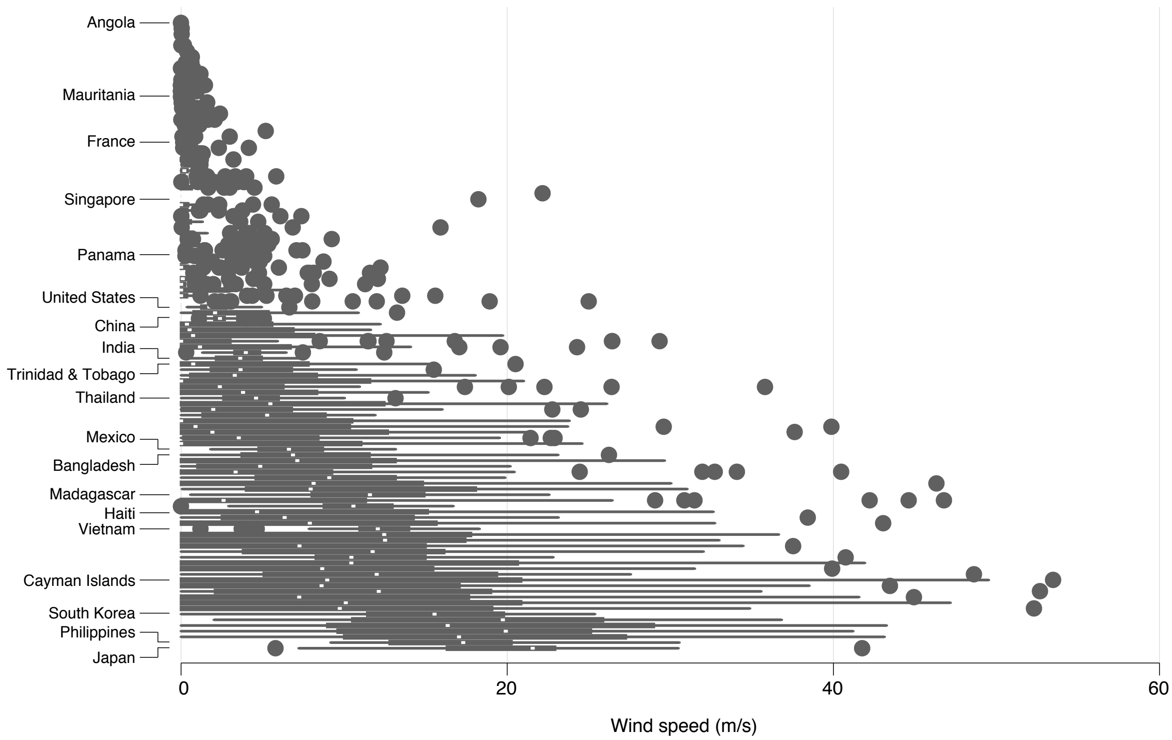

Figure 6: Boxplot of within-country distributions of country-by-year wind speeds during 1950-2008 for exposed countries. Boxes are interquartile ranges, white stripe is the median, circles are outliers. Countries are ordered according to their mean exposure across years. Countries with no positive exposure observations are not shown.

country-by-year unit using a spatially-weighted average over all pixels in a country[11]. For pixels indexed by p each of area a_p exposed to wind speeds (or energy) S_p, contained in country i which has n pixels in total, this is simply

$$\bar{S}_i = \frac{\sum_{p \in i} S_p a_p}{\sum_{p \in i} a_p} \tag{1}$$

This measure can be thought of intuitively in one of two ways: it is the expected exposure of a unit of land that is selected at random from a country or it is the exposure all units of land would have if wind exposure could be "spread out" evenly across all locations in a country. Because many pixels in a country may experience low wind exposure in a year and these values are averaged along with high exposure pixels, spatially averaged country-by-year wind speed measures will tend to be substantially lower than the maximum wind speeds reported at the center of intense storms. Figure 6 displays the distribution of country-by-year average wind speed exposure across years for all countries that ever have a non-zero value in the sample (hereafter "exposed countries"). Notably, there is substantial year-to-year variation in exposure within most countries and there is substantial overlap in exposure levels across countries. Japan and the Philippines experience the highest average exposure while India and Trindad & Tobago have median levels of average exposure (among exposed countries).

Constructing the scale-free measure $\bar{S}_i$ requires that the weighted sum of all pixel-level exposures is

[11]For the United States, Alaska is omitted from the average.

divided by the area of a country. This normalization is analogous to normalizing GDP by population to recover per capita GDP or normalizing new income by previous income to recover income growth in percentage terms. As with all normalizations, a larger denominator will result in a smaller measure of $\bar{S}_i$ if the numerator is held fixed. Thus a physically identical cyclone event that affects exactly one pixel will result in a larger value for $\bar{S}$ in a small country relative to a large country. This is the desired effect of using a scale-free measure, since *ceteris paribus* the single pixel affected by the storm will be more economically important in percentage terms in the smaller country because it is a larger fraction of the entire country. This approach follows the spirit of Nordhaus (2006) and aims to recover the average effect of cyclone exposure on an average pixel—it is agnostic about how land in a pixel is used[12]. One may think of this approach as trying to capture cyclone activity as one dimension of a pixel's endowment. We are essentially asking whether cyclone activity affects growth similar to how one might ask whether good soils or freezing temperatures affects growth in a pixel.

Two important questions invariably arise when cyclone exposure is collapsed using Equation 1. First, does area-weighting somehow bias response functions in favor of small countries, since their denominator is small? Our approach scales exposure to the pixel level, but it is possible that pixels within a small country will have a fundamentally different response from pixels within a large country, so one might be concerned that our results over-represent the unique response of small country pixels. This issue, however, is a question about heterogenous responses to cyclones and not a question of scaling, so it is best addressed by stratifying samples according to country size—an exercise we conduct in our results section (we find that countries exhibit remarkably similar responses at the pixel level across all sizes, except for the very smallest and largest countries). Second, will our estimates be biased because some cyclones strike heavily populated or economically critical locations while other cyclones strike empty regions? This is not a concern, so long as there is not correlation between the overall intensity of a storm (as measured by the average across pixels) and the likelihood that the most intense regions within that storm strike the most economically active (or vulnerable) pixels within a country. The condition for unbiased estimation restricts the spatial correlation of exposure and economic activity *within* a storm to be unrelated to the intensity *across* storms.[13]. So long as relatively more intense storms do not differentially strike centers of economic activity within a country,

[12] It may be possible to reduce our measurement error by using population-weights, following Dell, Jones and Olken (2012) and Hsiang, Meng and Cane (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 cyclone risk, this may bias our estimated coefficients in some unknown way since some populations may be more or less likely to relocate based on other factors that are unrelated to cyclones but might also affect growth. Thus, we use area-weights because populations cannot manipulate this parameter, giving us confidence that our independent 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.

[13] Suppose pixels have heterogenous pre-storm capital K_p (capital could be physical, human, social, political, etc.) which has a long run production $f(K_p)$. Damage to this capital from a storm suffered at p is $D(S_p, K_p)$, a function of storm intensity S_p experienced at pixel p. Anttila-Hughes and Hsiang (2011) find $D(S_p, K_p) = \alpha K_p S_p$, where α is a constant describing the marginal fraction of capital that is destroyed by each additional unit of S_p. Thus, $\alpha S_p \in [0, 1]$ for observed values of S_p. We assume a similar linear form holds generally.

Long-run output lost to a storm is the difference between output with baseline capital when no storm occurs (our simple counterfactual here, but a trend could be accounted for) and output with storm-damaged capital, both summed over all pixels in country i:

$$lost\_income_i = \sum_{p \in i} f(K_p) - \sum_{p \in i} f(K_p - \underbrace{\alpha K_p S_p}_{D(S_p, K_p)}).$$

If changes to the total capital stock from a single storm are modest relative to the curvature of $f(.)$, by Taylor's theorem it is unnecessary to account for the spatial distribution of economic activity in our measure of storm exposure in order to obtain an unbiased estimate for the effect of storms on growth.

Economic data

We obtain gross domestic product (GDP) data for 1970-2008 from the Penn World Tables[14] (PWT) (Summers and Heston (1991)) as well as the World Development Indicators (WDI) file (World Bank

we can linearize $f(K_p - \alpha K_p S_p) \approx f(K_p) - f'(K_p)\alpha K_p S_p$ at each pixel. Letting $g(K_p) = f'(K_p)\alpha K_p$, we write

$$\begin{aligned} lost\_income_i &\approx \sum_{p\in i} f(K_p) - \sum_{p\in i} \big(f(K_p) - f'(K_p)\alpha K_p S_p\big) \\ &= \sum_{p\in i} g(K_p) S_p \end{aligned}$$

Thus losses are roughly the inner product of storm intensity in each pixel and the marginal effect of storm intensity on production in each pixel, where the latter depends on both the capital density at p and the shape of the production function. Because we do not have observations of $g(K_p)$ for each pixel, we must find some way to estimate aggregate lost growth as a function of wind exposure. As in Equation 1 we denote area averages with a bar such that $\bar{x}_i = \sum_{p\in i}(x_p a_p)/\sum_{p\in i} a_p \approx \sum_p x_p/n_i$. The approximation holds if pixel areas do not vary substantially within a country, which is a reasonable approximation for almost all countries since pixel area is proportional to cosine of latitude and few countries exposed to tropical cyclones span large ranges of latitudes at high latitudes (where the derivative of cosine is large). Because there are many pixels in each country, we rewrite the sum of pixel impacts, i.e. the total lost income, in terms the average over pixels:

$$\begin{aligned} lost\_income_i &\approx n_i\ \overline{(g(K_p)S_p)}_i \\ &= n_i\ \overline{g(K_p)}_i\ \bar{S}_i + n_i \mathrm{Cov}_p(g(K_p), S_p) \end{aligned}$$

where the second term is the covariance across pixels between $g(K_p)$ and storm intensity for a specific cyclone event. Because the size of these terms scale with the size of a country n_i, we normalize by the initial size of the economy $n_i\ \overline{f(K_p)}_i$ so lost income is in terms of lost growth, a scale-invariant economic measure

$$lost\_growth_i = \frac{lost\_income_i}{initial\_income_i} \approx \underbrace{\left(\frac{\overline{g(K_p)}_i}{\overline{f(K_p)}_i}\right)}_{\hat{\beta}} \bar{S}_i + \underbrace{\frac{\mathrm{Cov}_p(g(K_p), S_p)}{\overline{f(K_p)}_i}}_{\varepsilon} \qquad (\aleph)$$

where the coefficient of interest, labeled $\hat{\beta}$, does not scale with the size of the country n_i. The form of Equation $\aleph$ is useful because it links a national summary statistic describing area-averaged cyclone exposure $\bar{S}_p$ to a national summary statistic describing economic growth. The factor denoted $\hat{\beta}$ is the coefficient that we will attempt to measure empirically—it is the average marginal effect of cyclone exposure on long-run output in percentage terms. The form of Equation $\aleph$ is what motivates us to use the spatial average of cyclone exposure across pixels to aggregate pixel-level cyclone exposure to the country-year level to match the units of observation in macro-economic data.

The term denoted ε is a residual that is likely mean zero—it is the covariance across pixels of cyclone exposure in a single storm and the marginal effect of cyclone exposure across pixels, normalized by total output of i. Importantly, it is a country-by-storm specific residual. The intuition behind this term is that sometimes a cyclone will cause unexpectedly large damages because the most intense part of the storm will pass directly over a location that has either a high capital density or a large sensitivity to cyclones (e.g. Hurricane Katrina), this will cause covariance between S_p and $g(K_p)$ to be positive and the lost growth from this event to be abnormally large relative to what we expect based on the average intensity of exposure $\bar{S}_p$. In other cases, the most intense part of a storm may pass over an uninhabited region, in which case this covariance will be negative and the lost growth will be abnormally low relative to expectation. On average across years, we assume ε is approximately zero because cyclone exposure within each storm is unlikely to be systematically correlated with economic activity on the ground.

Importantly, holding other factors constant, we will obtain an unbiased estimate of $\hat{\beta}$ if we estimate the expected value of Equation $\aleph$ using observed values of $\bar{S}_i$ so long as ε is not correlated with $\bar{S}_i$. Thus ordinary least squares will be unbiased if

$$\mathrm{Cov}_t\left(\frac{\mathrm{Cov}_p(g(K_p), S_p)}{\overline{f(K_p)}}, \bar{S}_i\right) = 0$$

where the outer covariance is across years (i.e. different storms). The intuition behind this condition is that Equation $\aleph$ is unbiased if there is no correlation between the average intensity of a storm ($\bar{S}_i$) and the likelihood that the most intense regions within that storm strike the most economically active (or vulnerable) pixels within a country ($\mathrm{Cov}_p(g(K_p), S_p)$).

[14] We use version 7.0 of the PWT (from 2011), however our results also hold if we use version 6.2 and 6.3.

(2008)). GDP is inflation adjusted and measured in *per capita* units. For robustness, we separately examine and compare results using both PWT and WDI which, in combination with our two cyclone measures, provides us with four pairs of independent and dependent variables that we evaluate separately. In robustness checks, we also utilize other macroeconomic measures from the WDI file, such as international aid.

Additional climate data

Because recent evidence suggests that temperature and precipitation both influence economic growth (Miguel, Satyanath and Sergenti (2004); Barrios, Bertinelli and Strobl (2010); Hsiang (2010); Dell, Jones and Olken (2012)) and these variables may be correlated with patterns of tropical cyclone exposure over time (Auffhammer, Hsiang, Schlenker and Sobel (2013)), we construct spatially averaged measures of annual mean temperature and precipitation using data files from the Center for Climatic Research at the University of Delaware (Legates and Willmot (1990a), Legates and Willmot (1990b)). However, because the University of Delaware (UDEL) data relies on spatial interpolation of weather station observations, it does not provide coverage for many island countries around the world. To overcome this issue, we also utilize "reanalysis" output from the Climate Data Assimilation System produced by the National Center for Environmental Prediction (NCEP) and the National Center for Atmospheric research (Kalnay et al. (1996)). Reanalysis techniques use a physical model (similar to a weather model) to assimilate data sources, allowing all missing data points to be estimated based on observed data and known physical relationships (see Auffhammer, Hsiang, Schlenker and Sobel (2013) for a complete discussion), enabling us to retain our entire sample of interest while also accounting for historical temperature variations.

4 Empirical approach

To estimate the causal effect of cyclones on long run growth we adopt a differences-in-differences approach, modeling first differences of the logarithm of GDP (economic growth) as an impulse-response function that is linear in contemporaneous and historical area-averaged tropical cyclone exposure $\bar{S}$ out to a maximum lag length k. Our approach follows the general framework for identifying the effect of random weather events laid out in Deschênes and Greenstone (2007). We account for unobservable differences in average growth rates between countries using a country fixed effect γ, which might arise, for example, because of countries' different geographies (Gallup, Sachs and Mellinger (1999)), cultures (Sala-i-Martin (1997)) or institutions (Acemoglu, Johnson and Robinson (2002)). We flexibly account for common nonlinear trends and year-specific common shocks using a year fixed effect δ, and we account for country-specific trends in growth rates θ, which may account for country-specific changes in economic policies as well as long-run conditional convergence (Barro and Sala-i-Martin (2003)). Because growth is the first derivative of income levels, including both country fixed effects and country-specific trends in a growth regression allows the trajectory of income levels in each country to exhibit an independent intercept, an independent slope and an independent curvature. In extensions of our main model, we also control for various time-varying controls X, such as trade openness (Sachs, Warner, Aslund and Fischer (1995)) or rainfall (Miguel, Satyanath and Sergenti (2004)). Indexing countries by i and years by t, this approach leads us to the flexible and parsimonious model:

$$\ln(GDP_{i,t}) - \ln(GDP_{i,t-1}) = \sum_{L=0}^{k} \left[\beta_L \times \bar{S}_{i,t-L}\right] + \gamma_i + \delta_t + \theta_i \times t + \eta \times X_{i,t} + \epsilon_{i,t} \tag{2}$$

where the parameters of interest are the coefficients β. We estimate Equation 2 using ordinary least squares (OLS) and follow the approach in Hsiang (2010) by assuming that the disturbance ϵ may be heteroscedastic and serially correlated within a country for up to 10 years (Newey and West (1987)) and spatially correlated across contemporaneous countries up to a distance of 1000 km[15] (Conley (1999)). The timing, location and intensity of cyclone exposure is unpredictable and stochastic across years, conditional on each country's average climate and trends in climate, whose effects are absorbed by country fixed effects, year effects and county specific trends. This allows us to assume that $\bar{S}$ is exogenous and uncorrelated with other unobserved factors ϵ that influence growth, permitting the causal effect of cyclones β to be identified. We note that it is unlikely that social, political or economic events within a country systematically influence our measurement of cyclone exposure because the LICRICE reconstruction of $\bar{S}$ primarily relies on satellite or other scientific observations.

Equation 2 does well at capturing a variety of behaviors for the slow moving changes in income that have been observed since 1970, as demonstrated in the top row of Figure 7 where predicted values from Equation 2 are integrated to estimate log income for four countries with varied economic trajectories. Idiosyncratic and temporary disturbances in growth are not captured well with this model, however these high-frequency variations are not the focus of this analysis since we are interested in long-run growth; and the overall performance of the model is strong despite this shortcoming. Predicted income and observed income have an ins-sample overall correlation of 0.99[16].

We estimate Equation 2 in first differences of $\ln(GDP)$ because year-to-year GDP growth is approximately trend-stationary. However, for a tropical cyclone that occurs in year t, we are interested in long-run GDP growth out to the period $t+j$, which is the sum of year-to-year growth effects for the years t to $t+j$ inclusive. Thus, after we estimate Equation 2, we construct the cumulative effect of a cyclone j years after exposure via the summation

$$\Omega_j = \sum_{L=0}^{j} \beta_L. \tag{3}$$

For brevity and clarity, we only present the long-run growth effects Ω_j and omit estimates of β_L, however it is straightforward to difference our estimates for Ω to recover the OLS coefficients β.

Previous studies have estimated variations on Equation 2 with fewer lags and focusing only on the years during and just following disaster exposure, often measured as a binary variable. However, previous studies could not or did not try to identify whether the long-run growth effect Ω was measurable or economically important. Thus, in addition to our novel data, another innovation in our analysis is to examine a model that spans two full decades ($k = 20$), the longest lag length for which our estimates

[15] 1000 km was chosen because it is roughly twice the diameter of a storm and it also roughly describes the approximate average distance inland that storms may travel after landfall.

[16] This value refers to the correlation between the full set of model predicted values and observations, not the R^2 value of the model.

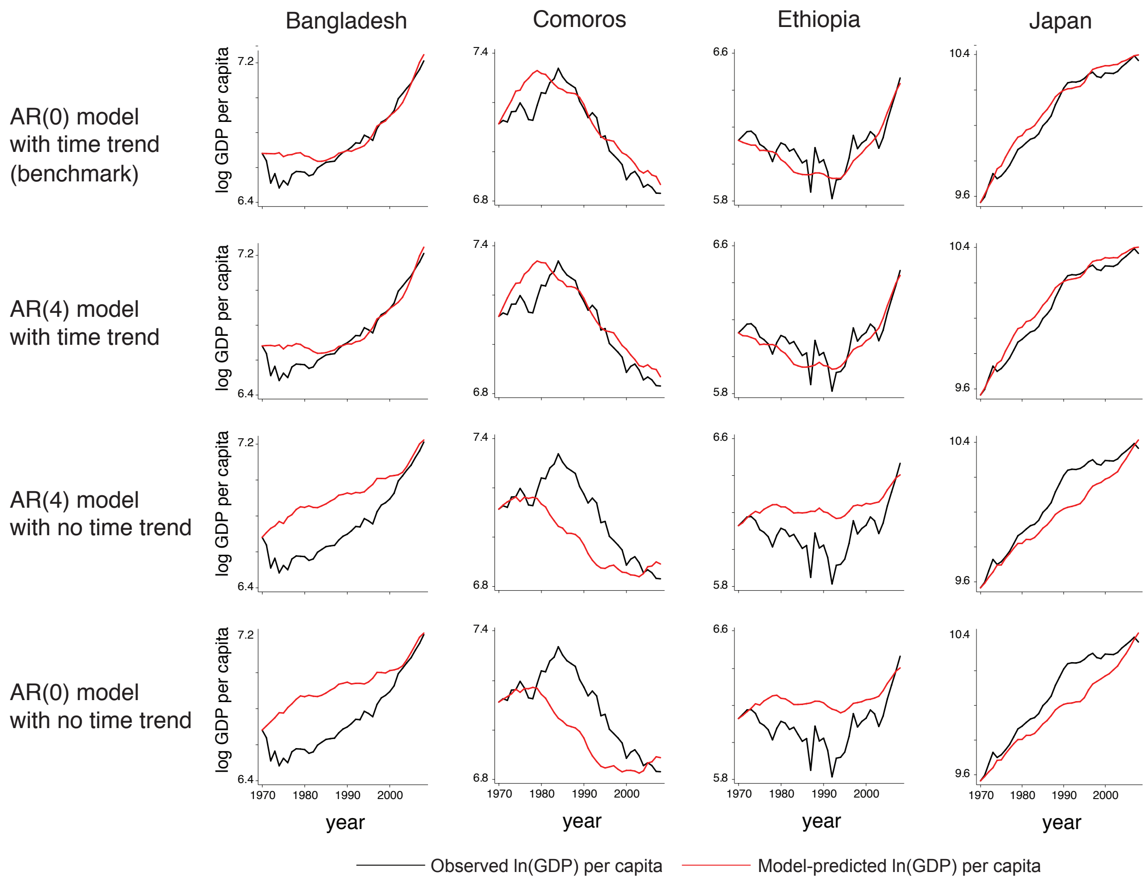

Figure 7: Model predictions compared to observed income trajectories for example countries. Model specifications differ by row, varying whether zero or four auto-regressive terms are included as regressors and whether country specific trends in growth θ_i are included. Top row is the benchmark model.

seem reliable (our panel is 39 years long) and for which we do not have to drop any observations (our cyclone data reconstruction begins in 1950). In our results section we experiment with alternative lag lengths and observe no appreciable change in our results.

Our main specification (Equation 2) is a distributed lag model, where the lags of interest describe current and historical cyclone exposure. This simple approach has been successfully employed by other studies of growth where the regressors of interest are temporary events that are plausibly exogenous (Miguel, Satyanath and Sergenti (2004); Romer and Romer (2010); Barrios, Bertinelli and Strobl (2010); Dell, Jones and Olken (2012)) since it is unbiased (Greene, (2003)). Yet growth in the short run tends to be auto-regressive, leading many researchers to estimate auto-regressive distributed lag models in these settings (Cerra and Saxena (2008); Romer and Romer (2010); Hsiang (2010)). We employ this latter approach in a robustness check to our main result where we follow Cerra and Saxena (2008) and Romer and Romer (2010) by introducing up to four years of lagged growth as regressors in Equation 2.

One feature of our specification that is not always present in regressions of this form is the country-specific linear trend in growth θ_i[17]. This term describes how each country's growth rate may drift over time relative to global trends in growth. Because growth is the first derivative of income, allowing a trend in growth rates is equivalent to allowing countries' income trajectories to have a non-zero second derivative, i.e. each 40-year income trajectory may be curved differently. Inspection of Figure 7 suggests that this component of the model is likely important, since different countries have income trajectories that are convex and concave, as well as some with almost zero-curvature[18]. Inclusion of four years of auto-regressive terms in the model does not correct for this issue, as we demonstrate in Figure 7 where we show comparisons of model predictions with and without θ_i and auto-regressive terms. Auto-regressive terms help the model capture high-frequency but small amplitude business cycles while inclusion of θ_i is often important for accurately modeling long-rung income growth. Nonetheless, for completeness we also estimate a version of Equation 2 that omits θ_i as a robustness check.

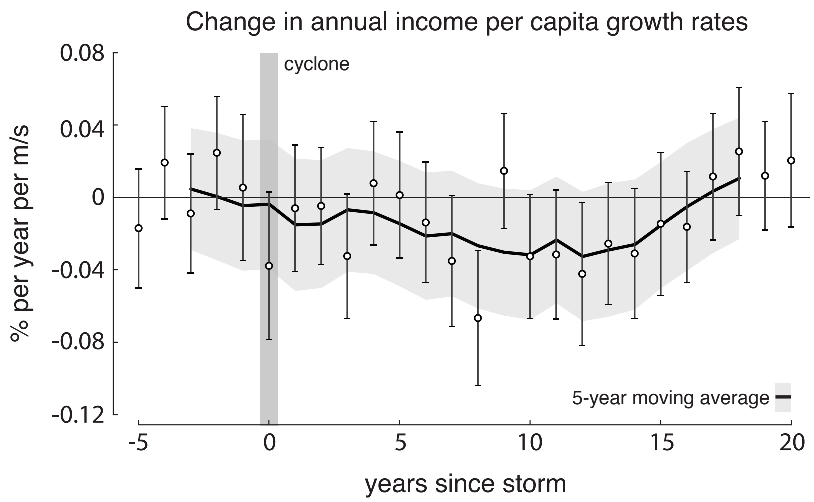

Figure 8: Point estimates (circles) and 95% confidence intervals (whiskers) for β_L, the marginal effect of a cyclone L years prior on annual growth rates. 5-year moving average indicates small but persistently negative effects for 15 years following a cyclone.

5 Results

We first establish that tropical cyclones have a large and robust negative effect on long-run GDP per capita that is broadly consistent in size with related results from the literature. We then demonstrate that other macroeconomic variables exhibit similar behavior and we provide evidence that populations adapt to their geographically determined cyclone-climate. We next use simple simulations to understand the extent to which these effects might influence global patterns of economic development and compare our results, quantitatively, to related findings in the literature. Finally, we conclude by computing how these results influence estimates for the social cost of climate change.

[17]See Hsiang, Burke and Miguel (2015) for a discussion.

[18]Failing to include country-specific values for θ_i in our model is equivalent to assuming that the income trajectories of all countries are curved equally, a hypothesis that we easily reject with a joint F-test for the restriction $\theta_i = 0 \; \forall \; i$ (Hsiang and Meng (2014)).

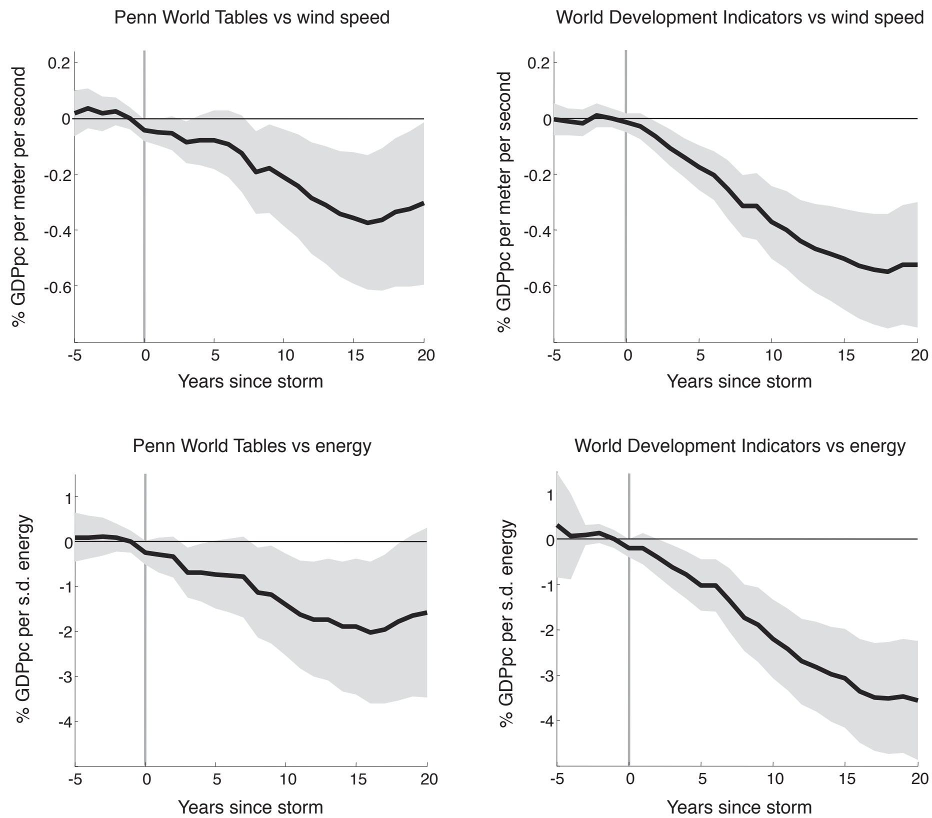

Figure 9: The marginal cumulative effect of tropical cyclone exposure on long-run GDPpc growth Ω_j. A zero-effect would indicate that a country follows its baseline trajectory after it was exposed to a cyclone. Each panel uses a different pairing of dependent variable data source and a different measure of cyclone exposure. 95% confidence intervals (robust to spatial and serial correlation) are shaded. Appendix Table A.2 reports exact estimates.

Main result: the long-run effect of disaster on GDP growth

Figure 8 displays our estimates for the coefficients β_L, the marginal lagged effect of a cyclone on annual growth rates. The year a cyclone strikes (year 0), countries experience a sharp and marginally significant decline in annual growth. The following 15 years exhibit systematically suppressed growth rates, which is clearly seen by the 5-year moving average. These individual annual growth effects are each modest and are not generally statistically significant individually. However, their summation produces estimates for the cumulative effect Ω_j that are both economically and statistically significant.

The first panel of Figure 9 presents our main finding: the long-run effect of tropical cyclones on GDP (Ω_j) relative to a country's pre-disaster baseline trend[19]. The plot depicts $\Omega_{t\in[-5,20]}$ after Equation 2 is estimated. Following a cyclone event, GDP declines steadily for roughly fifteen years relative to a counterfactual trajectory that would have been observed had the event never occurred. Fifteen years after a strike, GDP is 0.38 percentage points lower for every additional 1 m/s of wind

[19]As discussed above, the "baseline trend" is depicted as a straight line, however we allow the baseline trend in our models to have intercepts, slopes and curvatures that vary by country as well as common year-specific shocks.

speed exposure and exhibits no sign of recovery after twenty years.

The magnitude of the observed effect is large. Within the set of countries (58%) that are ever hit by cyclones, a one standard deviation increase in wind speed is equal to 9.4 m/s of wind exposure, generating a loss of $9.4 \times 0.38 = 3.57$ percentage points two decades later. A "one-in-ten" country-year event[20] reduces long-run GDP by 7.4% and a "one-in-one-hundred" country-year event depresses it 14.9%. The largest event in our sample (78.3 m/s) is estimated to have reduced long-run GDP by 29.8%. Appendix Figure A.1 displays the distribution of country-by-year cyclone observations and the long-run GDP loss associated with 5, 10, 20 and 40 m/s events.

The structure of this result allows us to decisively reject the hypotheses that per capita national incomes benefit from tropical cyclone incidence ("creative destruction") ($p < 1 \times 10^{-4}$) or recover to their pre-disaster trajectory ("build back better" or "recovery to trend") within twenty years ($p <$ 0.001). Following a cyclone disaster, the *instantaneous growth rate of GDP* stabilizes near the pre-disaster growth rate after 15 years, however income levels remain permanently lower than the pre-disaster trend line. The "no recovery" hypothesis (Figure 1) describes the true behavior of GDP following a cyclone disaster.

Robustness of the main result

We check the robustness of this result by using alternative data sets, alternative specifications, randomization tests, subsampling of our data, and spatial lag models.

Data selection We replicate our main finding using the WDI, our alternative measure of GDP, and energy, our alternative measure of cyclone exposure. The remaining panels of Figure 9 presents these alternative estimates. Under all four pair-wise combinations of the data, we obtain essentially the same result, although estimates using WDI as the dependent variable tend to have smaller standard errors. We present exact parameter estimates for several lags in Appendix Table A.2[21] using all four pairs of data, noting that if the effect sizes are standardized, wind speed produces estimates that are 33% larger than those using energy, although they are not statistically different from one another and both are statistically different from zero. We also note that the estimated effect one year after exposure is 30–50% smaller if the WDI data file is used instead of the PWT data file, however the point estimates converge in the following year.

Trends In order to produce reliable inferences, it is essential that we account for basic cross-sectional patterns and trends using country and year fixed effects. However, we continue to obtain our main result if we omit country-specific trends θ_i or if we introduce region-by-year fixed effects, as shown in columns 1 and 3 of Appendix Table A.3. Allowing countries to exhibit independent trends in growth causes the long-run growth effects to be slightly larger than if country-level trends are omitted, however we easily reject the hypothesis that country-specific trends in growth are common across countries. Further, we find additional evidence that a model omitting country-specific trends is misspecified when we conduct a test of forward lags (leads) and find that forward lags are statistically significant (they should not be). Thus, for the remainder of the paper we rely on the model with both common year

[20] The 90th percentile in wind speed is 19.5 m/s and the 99th percentile 39.2 m/s.
[21] Table A.2 presents values from models without forward lags.

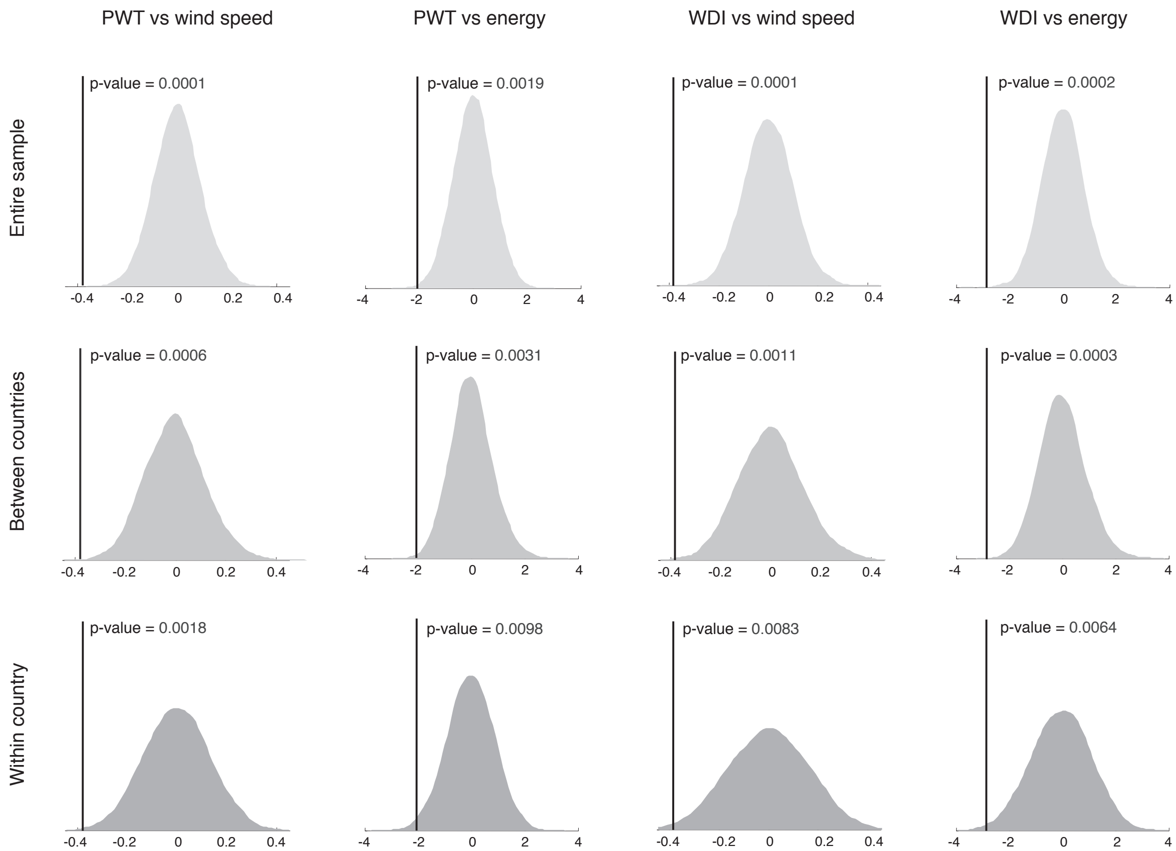

Figure 10: Distribution of point estimates for 15-year lag determined by re-estimating Equations 2-3 on randomized placebo datasets. Each distribution corresponds to the different dependent-independent variable pairing (columns) for one of three different randomization schemes (rows). Each distribution is constructed by repeating the randomization and estimation procedure 10,000 times. Coefficients from the estimate using real data are shown as vertical lines with exact p-values. In all 12 cases, exact p-values <0.01.

effects and country-specific trends (column 2 of Appendix Table A.3) since it is the most parsimonious model that passes this forward lag test. Notably, all estimates of Ω are significantly different from zero when the statistically irrelevant forward lags are dropped, explaining why the tabulated standard error estimates appear different from those presented in Figure 9.

Randomization tests To check whether our model is mis-specified, a fact that might generate spurious or biased findings, we randomize our sample to generate false data that we then use to re-estimate the model in Equation 2. As an ancillary benefit, these placebo tests also allow us to check whether the asymptotic confidence intervals we use for inference are properly sized. Holding observations of GDP fixed, we randomize observations of cyclone exposure (either wind speed or energy) without replacement 10,000 times, each time re-estimating Equations 2-3. We conduct this randomization in three different ways[22]:

[22] A Stata function to implement these three randomization procedures in a generalized panel context is available at `http://blogs.cuit.columbia.edu/asj2122/code/randomization-code`.

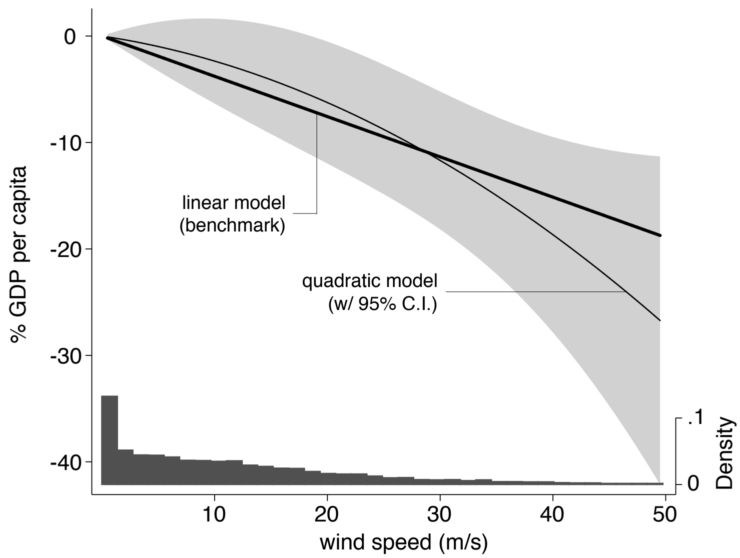

Figure 11: 15-year cumulative effect of cyclone exposure estimated with nonlinear and linear specifications.

1. Entire sample – Randomly re-assign each cyclone observation.

2. Between countries – Randomly re-assign each country's complete history of cyclone exposure to another country while preserving the ordering of years. This preserves the time structure within the data, thereby testing whether global or regional trends might generate spurious correlations.

3. Within country – Randomly re-order each country's time-series of cyclone exposure while keeping it assigned to the original country. This alters only the time structure of the data, thereby testing whether time invariant cross-sectional patterns across countries might generate spurious correlations.

Figure 10 displays the the distribution of point estimates for the fifteenth year ($\Omega_{t=15}$) under each of these randomization schemes using each of the four pair-wise combinations of data – the figure depicts the result of 120,000 randomizations in total. Under all three procedures and all four sets of data, the distribution of point estimates are properly centered at zero, indicating that the model in Equation 2 is unlikely to produce biased results. Furthermore, the point estimate we obtained when we used the true data is plotted as a vertical line, accompanied by an exact p-value that we compute by using the outcomes from these randomizations. In each of the twelve cases, these p-values remain below 0.01 – suggesting that our result is extraordinarily unlikely to occur by chance.

Testing for non-linearity Work by Nordhaus (2010) and Mendelsohn, Emanuel, Chonobayashi and Bakkensen (2012) indicated that direct damages from cyclones in the United States are a highly nonlinear power function of maximum wind speed at landfall, reporting "super elasticities" of 9 and 5, respectively. Hsiang and Narita (2012) use output from LICRICE at the country-by-year level to examine whether this super-elastic relationship holds generally, but instead obtain an elasticity of unity. This suggests that once the over-land trajectory of storms is accounted for, the relation is at most an exponential function. Hsiang (2014) reconciles this difference by demonstrating that the previously reported super elasticities were an artifact of assuming a power-function relationship when wind speeds are so high that their logarithm is essentially a linear function, and that parameter estimates similar to Hsiang and Narita (2012) are obtained with Nordhaus' original data if a power function is not assumed *ex ante*. Yet, when Antilla-Hughes and Hsiang (2011) use LICRICE to examine capital and income losses at the household level, they find that both are linear in wind speed. As it remains unexplained why aggregate damage estimates should be nonlinear when local loss is linear[23], it is important that we examine whether our linear model of long-run growth is justified, especially since the assumption of local linear loss was used to inform the area-averaging used to collapse pixel-level cyclone data. To test the linearity of the long-run growth effect, we estimate a model that allows the cumulative effect of cyclone exposure to be quadratic in wind speed for each lag. Figure 11 displays the effect of cyclone exposure fifteen years after a storm using both linear and quadratic models. Estimated effects using the nonlinear model are not statistically different from the linear model, which approximates the expected nonlinear response well.

Lag length We examine whether the maximum lag length k we select alters our result by estimating the model using 10 and 15 lags instead of 20. The results are shown in Appendix Figure A.2A. Estimates using only 10 lags do not diverge from zero for the first five years and then are negative but smaller in magnitude. Estimates using 15 lags are essentially identical. In general, there is greater risk of including too few lags in a distributed lag model rather than too many, since unnecessary distant lags will simply appear as noise and will not bias a model but too few lags may generate bias if omitted lags important and are correlated with included lags (Greene, 2003). We thus consider the longer lag models more reliable, but note that negative—albeit smaller—effects are observable using only ten lags.

Auto-regressive controls We examine whether accounting for auto-regressive behavior in growth affects our results by including 1-4 auto-regressive controls in the model, following Cerra and Saxena (2008) and Romer and Romer (2010). Results for AR(1)-AR(4) models are shown in Appendix Figure A.2B, plotting only the direct effects captured in β and not the indirect effects through the auto-regressive process. Auto-regressive models recover results that are indistinguishable from our benchmark model, which is AR(0).

Climatological controls We examine whether time-varying climatic conditions affect our results. We are particularly concerned about climatological confounders (Auffhammer, Hsiang, Schlenker and Sobel (2013)), since the intensity and distribution of tropical cyclones are influenced by global climatic patterns that also may affect economic outcomes[24]. In column 2 of Table 2 we account for country-level exposure to changes in temperature, a variable that affects annual growth rates (Dell, Jones

[23]Perhaps it is because estimates of direct damages contain systematic biases, since they require on-the-ground tabulation of losses which are subject to observational errors.

[24]For example, the El Niño-Southern Oscillation inhibits storm formation in some regions while promoting it in others (Tartaglione, Carissa, Smith and O'Brian (2003); Camargo and Sobel (2005); Hoyos, Agudelo, Webster and Curry (2006)) while it also influences economic outcomes around the world by altering global rainfall and temperature patterns (Brunner (2002); Hsiang, Meng and Cane (2011)).

Table 2: Controlling for climatic variables

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Growth (%) from PWT				
Sample restrictions			Missing small islands†		
	Pooled exposed and unexposed countries				Exposed only‡
Marginal cumulative effect of 1 additional m/s wind speed					
5 years	-0.0895**	-0.0882**	-0.0166	0.00482	-0.0152
	(0.0427)	(0.0436)	(0.0511)	(0.0519)	(0.0526)
10 years	-0.223***	-0.220***	-0.163*	-0.127	-0.182**
	(0.0711)	(0.0730)	(0.0918)	(0.0895)	(0.0898)
15 years	-0.378***	-0.370***	-0.265**	-0.207*	-0.302**
	(0.0938)	(0.0964)	(0.125)	(0.123)	(0.122)
20 years	-0.374***	-0.363***	-0.236	-0.181	-0.299**
	(0.113)	(0.117)	(0.147)	(0.145)	(0.142)
Temp. (NCEP data)		Y			
Temp. (UDEL data)			Y	Y	Y
Precip. (UDEL data)				Y	Y
Observations	6415	6376	5737	5737	3232
Adjusted R^2	0.144	0.142	0.137	0.136	0.157

All models contain country fixed effects, year fixed effects, and country-specific linear trends. Temperature and precipitation are spatially averaged over each country-year in the sample and are each allowed to influence growth linearly. NCEP reanalysis temperature data is fully global in coverage. UDEL temperature and precipitation data come from a gridded reconstruction based on interpolated station data. Standard errors in parentheses are robust to spatial (1000km) and serial (10-year) correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ †Because UDEL data is interpolated, data for many small islands that are strongly affected by cyclones are missing, causing them to be dropped from the sample. ‡Dropping countries that are never exposed to tropical cyclones in the sample.

and Olken (2012)), using NCEP reanalysis data that allows us to retain all countries in the original sample. Our point estimates are unchanged relative to our benchmark model in column 1. In column 3 we control for temperature using UDEL data, a different data source, and we find that our point estimates are roughly 30% smaller and less significant, although this change is not itself statistically significant. The change in point estimates and standard errors is primarily due to our dropping 600+ country-year observations for small islands that are missing from the UDEL data[25], but we opt to use the UDEL data because it allows us to also account for precipitation[26]. Accounting for both temperature and precipitation in column 4 appears to to reduce the magnitude and significance of cyclones further, however this change in estimates is mostly driven by countries that are never exposed to tropical cyclones. When we remove countries that are never exposed to cyclones (e.g. Bolivia) but

[25]The UDEL data is interpolated from land-based weather stations, so many islands that do not have their own weather stations are dropped from the reconstruction.

[26]Rainfall data from NCEP is less reliable because it is driven by a model simulation.

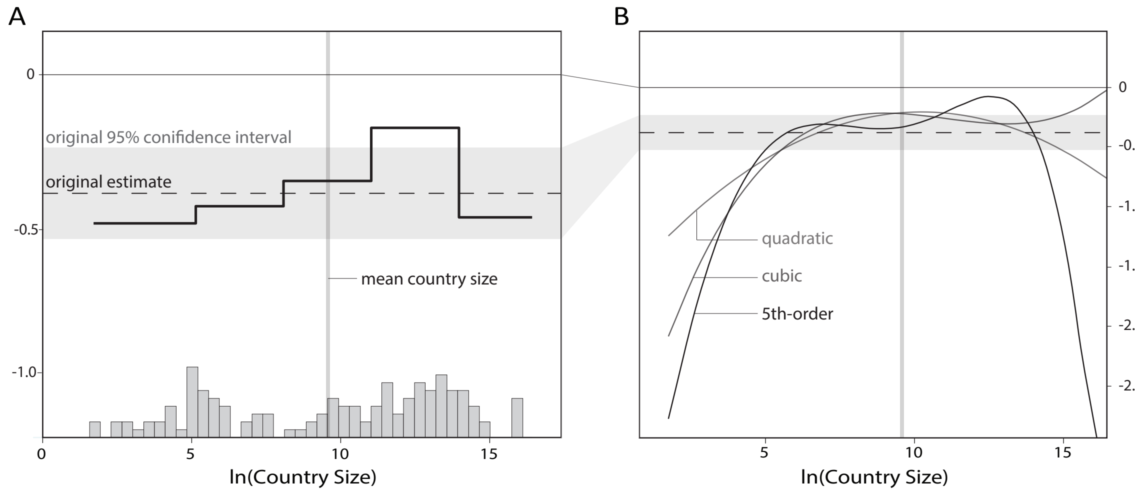

Figure 12: Non-linear interactions with country size. A) Effect of the 15-year lag term on growth estimated as an interaction with log country size in 5 discrete bins. Original estimate and 95% confidence interval are shaded. B) 15-year lag term on growth with country size interacted as quadratic, cubic, and 5th-order polynomials. Original estimate and 95% confidence interval are shaded.

continue to account for temperature and precipitation using the UDEL data, shown in column 5, we obtain estimates that are similar in both magnitude and significance to our baseline result using the full sample.

Endogenous controls We examine whether the inclusion of some time-varying control variables that a population determines endogenously, but are traditionally included in growth regressions[27], affect our result. Including these endogenous controls is likely to be a case of "bad control" (Angrist and Pischke (2008)), since unobservables may influence these controls as well as how populations respond to cyclones[28]. Thus, we only present these results as a robustness check and do not think that they should be interpreted causally. In Appendix Table A.4 we account for lagged income[29], population growth and trade openness, both for the full sample and the restricted sample of exposed countries (column 6). We find that our estimates are similar to our baseline result using the full sample.

Country size As discussed above, we measure cyclone exposure using scale-free intensive variables, a fact that should make the physical size of countries irrelevant. We explicitly check this assumption by reestimating our model including flexible interactions for log of country size with cyclone exposure for every year. We plot the 15-year cumulative effect of 1 m/s wind speed exposure for five equally sized bins of log country size in Figure 12 as well as this cumulative effect as quadratic, cubic, and quintic polynomials of log country size. Overlaying the pooled estimate, we see that the long run

[27]For examples, see Sachs, Warner, Aslund and Fischer (1995), Barro (1998), Sala-i-Martin (1997) and Barrios, Bertinelli and Strobl (2010).

[28]See Hsiang, Burke and Miguel (2015) for a discussion of this issue.

[29]Careful readers may notice that the coefficient on lagged income is larger in magnitude than traditional estimates for convergence rates (Barro and Sala-i-Martin (2003)). This is because we flexibly allow for countries to have trending growth rates, which is not the standard approach in traditional models. In Appendix Table A.5, we demonstrate that if we remove these country-specific trends from the model then we obtain more familiar estimates for convergence rates.

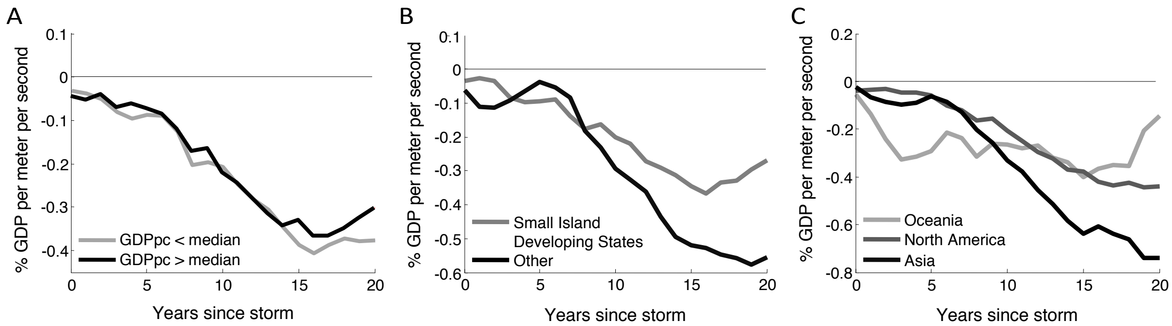

Figure 13: The estimated effect of cyclones on GDPpc for subsamples stratified by A) income in 1970, B) Small Island Developing State (SIDS) status, and C) region.

effect for most county sizes falls within the confidence interval of the pooled estimate and is always negative. There is some indication that cumulative effects shrink in magnitude slightly as countries become larger, but this pattern is not significant and reverses for the highest country size bin. There are more extreme negative effects for the very smallest countries and the very largest countries in the quintic polynomial model, but the most extreme effects do not show up in the binned model as they are driven by outlier cases. The marginal effects estimated at any location in the size distribution are not significantly different from the pooled estimate. This is a weak test because the sample is thin (these point-wise effects are also not statistically different form zero), but the structure of the point estimates indicate that the pooled sample estimate is a good approximation for the behavior of the sample in general and that our scale-free collapse of cyclone exposure is a reasonable approach for comparing countries of different sizes[30].

Subsamples of the data In Figure 13 we check whether specific subgroups of countries are driving our result and find that our estimates are globally generalizable. In the first panel we stratifying the sample according to whether they are above and below the median income in 1970, however we find that the two groups respond almost identically. In the second panel we isolate Small Island Developing States (SIDS) and find that their response is similar to that of other countries. Finally, we examine Asia, North America and Oceania separately and find, consistent with Hsiang and Narita (2012), that the response to cyclones in these three geographic regions are similar.

Spatial lag models We examine whether cross-country spillovers within a region drive our result. It might not be the case that cyclones are bad for growth but instead being nearby a cyclone is *good* for long-run growth, e.g. additional moderate rainfall might be beneficial (Barrios, Bertinelli and Strobl (2010)) or tourists may change their behavior if a cyclone strikes a potential destination[31] (Hsiang (2010)). We account for these spatial spillovers using a spatial lag model (Cressie and Wikle (2011)) where i's growth is affected by i's cyclone exposure plus all temporal lags in the average exposure of neighbors j whose centroids fall within concentric annuli (around i's centroid) with 400km widths[32] out

[30] We thank Benjamin Jones for this suggestion.
[31] We thank Wolfram Schlenker for this suggestion.
[32] This distance was chosen based on the average size of a single storm, which is on the order of 200km.

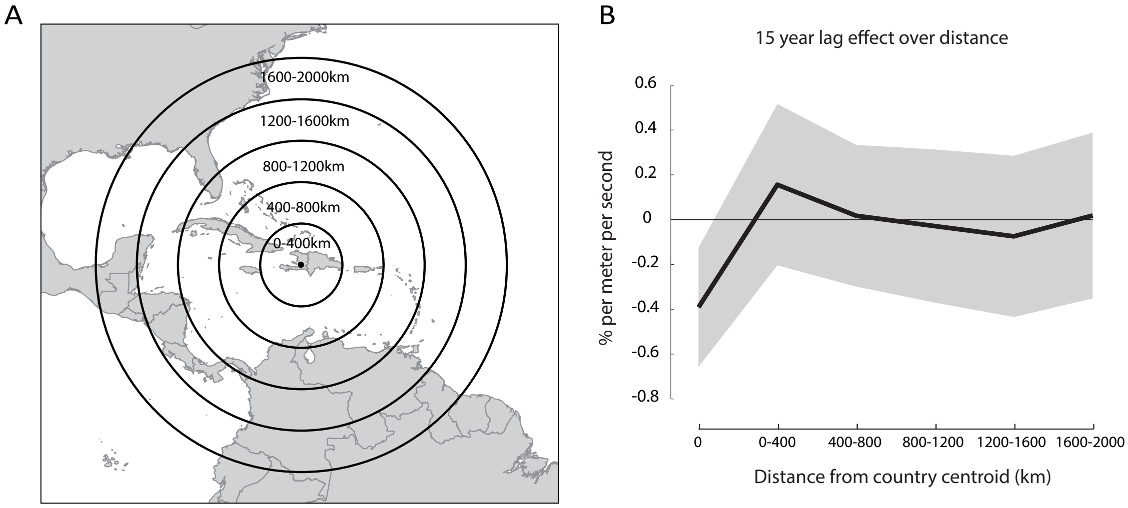

Figure 14: Spatial lag model illustrating the potential spillover effects of tropical cyclones. A) Example of the annuli used to construct spatial lags used in the model. B) Estimates of the 15-year lag term for the growth effect of tropical cyclone exposure for all spatial lags, i.e. the effect on i's growth when j at a distance d_{ij} is exposed to cyclones. d_{ij} is binned using annuli as in (A) and plotted on the horizontal axis. 95% confidence intervals are shaded.

to a maximum distance of 2000km. Figure 14A displays an example of these annuli around Haiti. This spatio-temporal distributed lag model is extremely flexible and has 120 lags estimated simultaneously: 20 temporal lags for each of 5 annuli plus each country's own set of 20 lags (the zero radius annulus). Coefficients describing how cyclone exposure 15 years prior at various distances affect a country's growth are plotted in Figure 14B, where the effect at "0 km" is the effect on i of i's own cyclone exposure. We find that there is essentially no effect of cyclones at distances greater than 400 km and there is suggestive but insignificant evidence of a modest positive spillover among immediate neighbors. Importantly, the estimated effect of a country's own exposure remains essentially unchanged from the baseline model.

Comparison with other studies: Are these effects reasonable?

No prior study has estimated the effect of large scale environmental catastrophes on long run growth, so it is inherently difficult to determine whether the effect sizes we estimate are reasonable. Given the absence of any quantitative priors for these values, a natural reaction to these results is to dismiss them as implausibly large — if cyclones have such large effects on long run growth one might assume that we would already know of such effects. Here we evaluate whether the size of cyclone effects on growth seem reasonable given the limited number of comparable studies. In a later section we discuss why this effect has not been previously characterized.

Subnational exposure and household micro-data Anttila-Hughes and Hsiang (2011) use province-level cyclone exposure and household micro-data from the Philippines to estimate the effect of wind

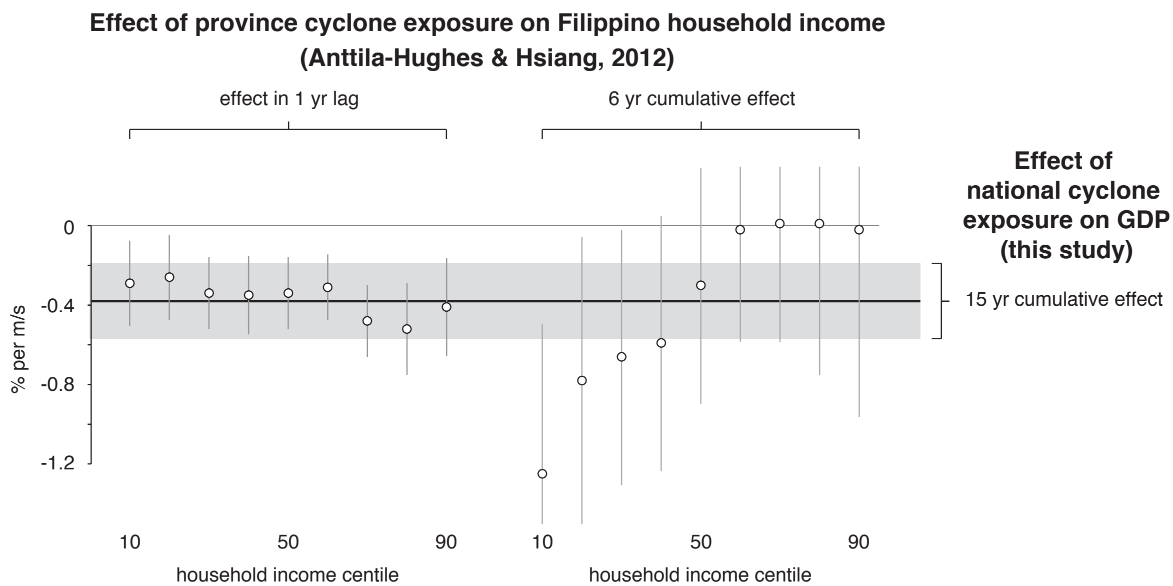

Figure 15: Comparison of long-run GDP loss with cumulative household income loss in the Philippines 1 and 6 years after cyclone exposure, from Anttila-Hughes and Hsiang (2011). Estimates are computed separately for deciles of the income distribution, whiskers are 95% confidence intervals.

speed on household income. Analogous to the method we apply in this study, they measure cyclone exposure with area-average maximum wind speed from LICRICE and exploit within-province changes in exposure over time, allowing us to make direct quantitative comparisons. Figure 15 overlays the cumulative effect on household income estimated by Anttila-Hughes and Hsiang one and six years after cyclone exposure, for each decile of the income distribution. In household data, the marginal effects of wind speed the year following exposure are tightly clustered around the long-run -0.38% per m/s loss we estimate. After six years, average effects remain centered around our long-run estimate, although the wealthiest 40% of households recover completely while poorer households exhibit fractional income losses larger than our long-run estimate. Notably, effects in Anttila-Hughes and Hsiang are not estimated for the two decades we study here because their panel is shorter. Without a theory relating short and long-run income losses after disaster, we refrain from speculating whether the short-run losses identified Anttila-Hughes and Hsiang represent the exact same income losses that we observe in this study. However, the *magnitude* of average losses in the subnational micro-data are similar, suggesting that the national long-run estimates we present here are not unreasonably sized.

Subnational exposure and firm micro-data Basker and Miranda (2014) use firm-level micro-data in Mississippi to estimate the effect Hurricane Katrina on firm survival, using FEMA assessments of physical damage based on satellite imagery at the sub-county level. These estimate do not permit a direct quantitative comparison, but are qualitatively useful. Basker and Miranda find that firm survival in extensively damaged areas was lowered by 30% relative to undamaged locations and that this difference in survival rates persists for five years, through the end of their sample. Consistent with our finding that wealthy countries are affected similarly to poor countries, Basker and Miranda find

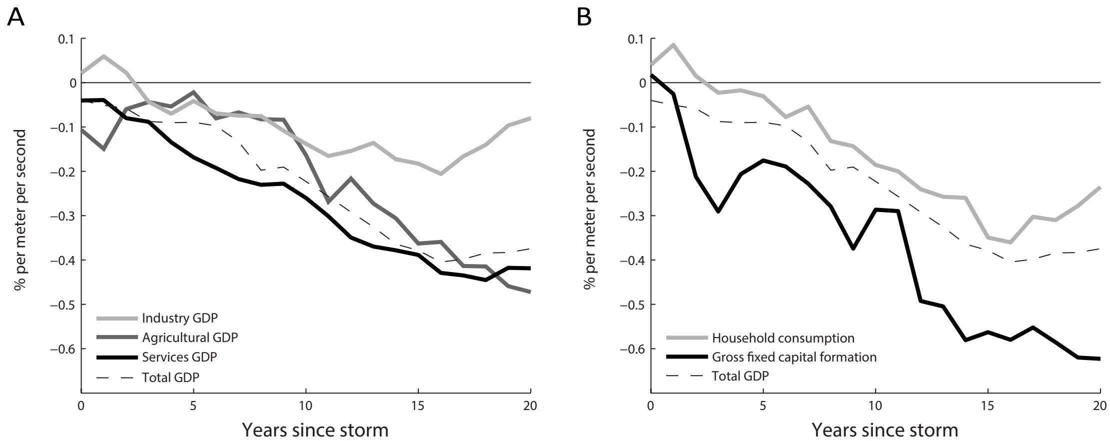

Figure 16: A) The estimated effect of cyclones on different components of GDP and B) on consumption and capital formation. Dashed line is the effect on total GDP for comparison.

effects in the United States that are both quantitatively large and persistent.

National exposure and self-reported damages Hsiang and Narita (2012) examine how self-reported damage, such as lost physical infrastructure, in the Emergency Events Database (EM-DAT) respond to wind speed from LICRICE. Globally, linearization of their result suggests damage increases roughly 0.33% of GDP per m/s on average, which is similar in magnitude to our estimate of 0.38% of GDP per m/s in long-run GDP losses (Appendix Figure A.4). The self-reported EM-DAT data are known to contain systematic biases, some of which are accounted for by Hsiang and Narita, so this result is interpreted cautiously. Nonetheless, similarity in the size of direct damages and long-run growth effects again suggest that our estimates are not unreasonably sized.

Other long-run macroeconomic impacts of environmental disaster

Having demonstrated that the long-run GDP response to cyclones is economically large, robust and generalizable, we check whether other macroeconomic variables exhibit similar behavior. To do this, we estimate analogs to Equations 2-3 replacing GDP with other microeconomic variables. We plot the long-run effects Ω in the panels of Figure 16. Overall, the behavior of these alternative macroeconomic measures broadly corroborate our main finding that cyclones adversely affect long-run income growth.

Sources of income In Figure 16A, we decompose GDP into income from agriculture, industry and services to examine how each responds to tropical cyclone exposure. All three types of income decline gradually, exhibiting long-run effects that are not statistically different from the long-run effect of total GDP (dashed line). Long-run declines in agriculture and services are similar to total GDP, however the long-run losses in industry are roughly half the size (in percentage points) of total GDP losses. Industry might suffers less because it requires a high spatial-density of capital, and thus firms face a stronger incentive to invest in capital protection (Hsiang and Narita (2012)), but we lack the data to test this hypothesis.

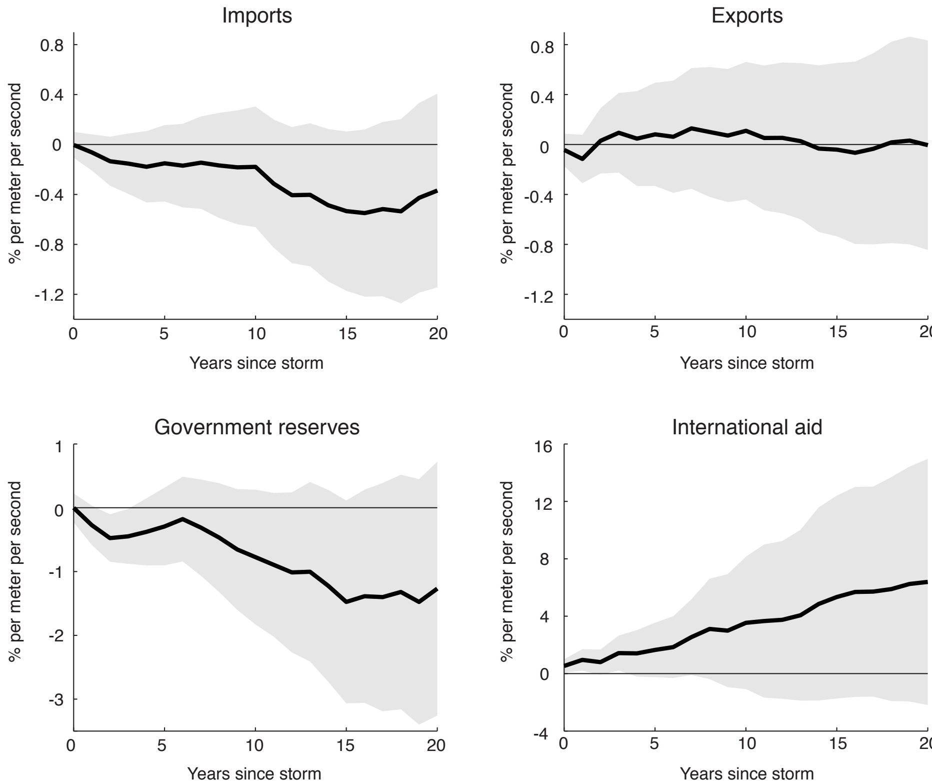

Figure 17: The estimated effect of cyclones on long-run growth of imports, exports, government reserves and international aid. 95% confidence intervals are shaded.

Consumption and Investment If populations insure themselves, they may smooth their consumption to insulate themselves from transient income losses[33] (Udry (1994); Townsend (1995); Kunreuther and Michel-Kerjan (2009)). However, long-run income losses to cyclones are persistent and exhibit no recovery, so insurance and savings mechanisms aimed at long-run income will be unsustainable, giving populations no choice but to lower their consumption to match their long-run income. In Figure 16B, we observe this pattern: the magnitude and dynamics of the consumption response closely matches that of the income response. Figure 16 also shows that long-run gross capital formation (investment) declines in the wake of cyclones, again matching the response of income.

Trade Cyclone incidence and the resulting long-run loss of GDP does not generate an obvious prediction for trade patterns – for example, a disaster might increase imports of capital used in rebuilding efforts, but the observed decline in GDP might also reduce the demand for costly imported goods. The latter probably explains the true response better, since as we show in Figure 17, long-run imports fall at roughly the same rate as income. In contrast, we find no long-run effect on exports. Such an asymmetric trade response is consistent with demand-driven models of trade, since cyclone events

[33]It is worth noting that recent evidence from the Philippines indicates that households struggle to smooth consumption across the transient component of cyclones-induced income losses (Anttila-Hughes and Hsiang (2011)). Anttila-Hughes and Hsiang hypothesize that this is due to the spatially-coherent nature of these income shocks, which makes them more difficult to insure than spatially-uncorrelated, idiosyncratic events (Townsend (1995)).

should have no effect on distant economies that consume exported goods[34].

Government reserves Government reserves decline in the long-run (Figure 17); however, the magnitude of this decline is much larger than the long-run income loss: for each addition 1 m/s in cyclone exposure, government reserves decline by more than 1% in the long run. The long run effect on reserves is only marginally significant, but a differentially rapid depletion of government reserves is unsurprising since governments provide disaster relief and absorb many uninsured losses, generally without expanding their revenue (Kunreuther and Michel-Kerjan (2009), Deryugina (2011)).

International Aid A substantial literature has examined the size, structure and political economy of domestic and international relief aid immediately following disasters (Garrett and Sobel (2003), Achen and Bartels (2004), Eisensee and Stromberg (2007), Stromberg (2007), Yang (2008), Healy and Malhotra (2009), Deryugina (2011)). However, to the best of our knowledge, no study has examined whether disasters generate long-run impacts on international non-relief aid payments. If international donors redistribute wealth based on international differences in income, then a gradual reduction of income should have the secondary impact of gradually increasing international transfers to the affected country. In Figure 17, we display that this intuition is consistent with the data, further supporting our main results: in the decades following a cyclone, international non-relief transfers gradually but permanently rise relative to their counterfactual trajectory[35]. Understanding this phenomenon will be pursued in future work.

Evidence of adaptation to disaster-prone environments

As illustrated in Figure 5, the risk of tropical cyclone exposure varies dramatically. Theory predicts that in countries where the cyclone climate is intense, populations will find it beneficial to invest in protective measures (Hsiang and Narita (2012)). Thus, to further support our main result that cyclones reduce long-run growth, we examine whether our estimated long-run GDP response exhibits patterns of adaptation that are consistent with economic theory.

Optimal Adaptation in Theory Assume that countries can exert costly adaptive effort e to reduce their long-run losses in the event that a cyclone strikes[36]. If the cost function for e is convex, then populations will exert adaptive effort until the marginal cost of additional effort equals its expected marginal benefit. The benefit of this adaptive effort is determined by a country's cyclone climate, because effort only provides benefits when a cyclone actually strikes, so countries that experience more intense or more frequent cyclones should have greater returns to adaptation. Thus, we expect that countries endowed with more intense cyclone climates will invest more in costly adaptation, reducing their marginal long-run losses when a cyclone strikes. Denoting a country's optimal level of adaptive

[34]It is worth noting that an economically small, temporary and statistically insignificant decline in exports does occur just following a cyclone strike. Perhaps this occurs because export infrastructure is damaged or because domestic production of exports temporarily declines, similar to the temperature-related findings of Jones and Olken (2010).

[35]Deryugina (2011) described an analogous phenomena for non-disaster domestic transfers to counties within in the United States, where unemployment payments increase for ten years after a cyclone strikes. Here we document the appearance of a similar phenomena that lasts two decades in the "international social safety net."

[36]For example, governments could build seawalls or invest in early-warning systems.

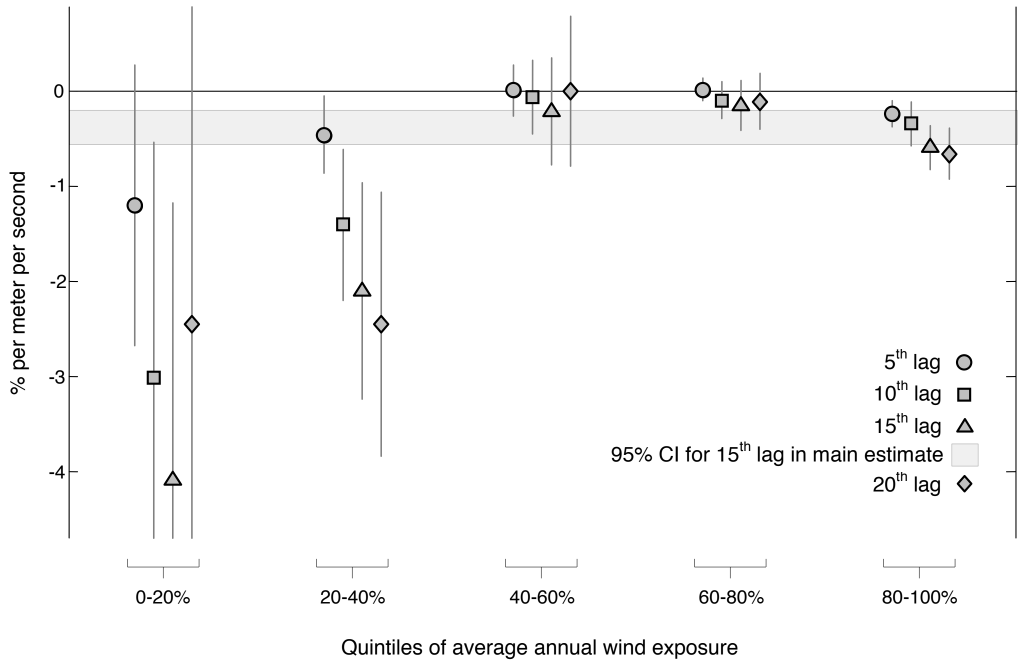

Figure 18: The cumulative GDPpc response to TC exposure, stratified by countries' cyclone climate (defined as average exposure over all years). For each quintile, four lagged effects are shown (5-, 10-, 15-, and 20-year effects). Vertical lines represent the 95% confidence intervals. The grey horizontal bar shows the confidence interval of the 15th-lag in our main (pooled) estimate.

effort e^* and income Y, the above logic predicts

$$\frac{\partial e^*}{\partial \bar{\bar{S}}} > 0 \tag{4}$$

where $\bar{\bar{S}}$ is expected storm exposure, a summary statistic for a location's typhoon-climate[37]. Unfortunately, we cannot directly observe whether this is true because we do not observe e^*. However, increasing effort reduces marginal long-run losses ($-\partial Y/\partial S$) to a fixed level of actual cyclone exposure $\bar{S}$

$$\frac{\partial}{\partial e} \cdot \left(-\frac{\partial Y(e)}{\partial \bar{S}} \right) < 0. \tag{5}$$

This enables us to infer that adaptation is occurring if we see that marginal losses decline as climates intensify. Assuming populations optimize and noting that $\Omega = \partial Y/\partial \bar{S}$, we can multiply Equations 4 and 5 to obtain

$$\frac{\partial}{\partial \bar{\bar{S}}} \cdot \frac{\partial Y(e^*)}{\partial \bar{S}} = \frac{\partial \Omega(e^*)}{\partial \bar{\bar{S}}} > 0 \tag{6}$$

[37]Hsiang and Narita (2012) demonstrated that average exposure was an approximately sufficient statistic for the incentive to adapt in the context of direct aggregate damages.

a result that we can investigate empirically. For a more complete treatment of optimal adaptation to tropical cyclone climates, as well as additional empirical evidence, we refer readers to Hsiang and Narita (2012).

Cross-Sectional Evidence of Adaptation We test Equation 6 by examining whether cyclone-induced losses vary with the climatological endowment of different countries. To do this, we stratify our sample of countries into quintiles according to their average level of cyclone exposure $\bar{S}$. We then estimate Equation 2-3 for each quintile separately and display the marginal long-run growth effect of disaster $(\partial\Omega(e^*)/\partial\bar{S})$ in Figure 18. Consistent with Equation 6, the marginal effect of cyclone exposure becomes more positive (declining in magnitude) as the average risk of exposure increases. The effect of disaster on the quintile with lowest risk (0–20%) is the most negative, while the effect on the second quintile (20–40%) is less negative and the effect on the three quintiles with highest risk (40–100%) is closest to zero. These three quintiles with high cyclone risk all exhibit responses that are statistically indistinguishable from the average effect presented throughout this study (grey stripe) and the magnitude of the "naive" response among poorly adapted populations (in the first quintile) is roughly eight times larger. Taken together, these findings support the hypothesis that populations adapt to cyclones, bolstering our main thesis that cyclones adversely affect growth since there would be no incentive for populations to adapt if cyclones were benign.

It is important to note three important features of this adaptive response. Firstly, unadapted countries, though having larger marginal income losses due to tropical cyclone exposure, experience far fewer storms. This implies that total losses over the sample period are likely smaller in these countries than in frequently exposed countries. Secondly, even though heavily exposed populations appear to adapt extensively compared to "naive" populations, these heavily exposed populations continue to suffer losses that are both economically large and statistically indistinguishable from the average response presented in Figure 9. This implies that the average effect presented in Figure 9 describes the effect of cyclones on highly adapted and regularly exposed populations[38], so it is a good approximation for the average economic impact of most cyclones observed on the planet. Finally, no countries undertake "complete adaptation" by driving their marginal damages to zero despite the fact that populations currently exposed to cyclones have been similarly exposed for centuries. If one assumes that populations are well-informed, this would indicate that the net benefit of additional adaptation effort is zero, or very low, given each country's current equilibrium level of adaptive effort $e^{\star}$, suggesting the cost function in e is likely convex (Hsiang and Narita (2012)).

The effect of cyclone-prone climates on long-run economic development

Up to this point, we have identified the long-run growth effect of cyclones using a within-country estimate that relies only on each country's year-to-year variation in cyclone exposure. The country fixed effects of our model absorb all cross-sectional differences in cyclone climates and growth, preventing these average differences from influencing our estimates. However, as discussed in the last section and

[38]The average effect presented throughout the study is dominated by the response of high risk countries because those countries experience more cyclone effects during the period of observation.

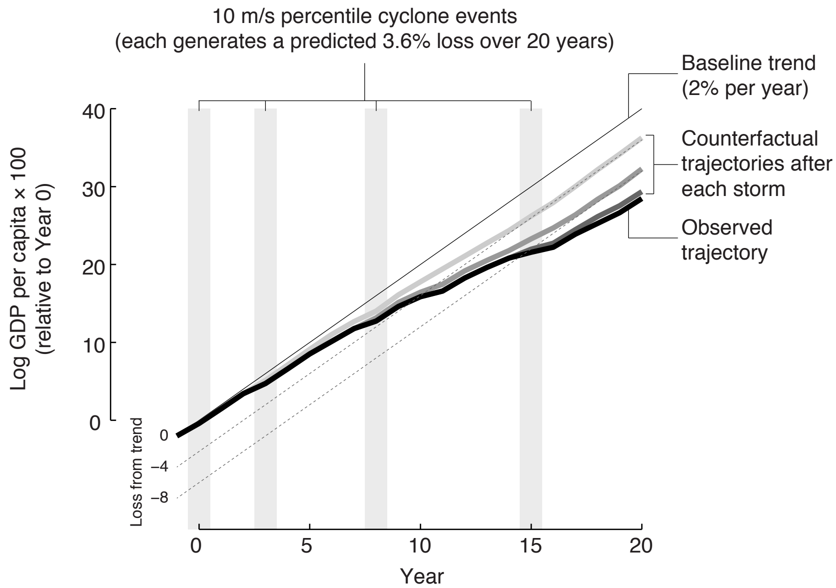

Figure 19: An example GDPpc trajectory in the presence of repeated cyclone exposure. We set exposure to 10 m/s in years 0, 3, 8, and 15. The penalty to income increases with each event, leading to a substantial divergence from the pre-disaster trend in income growth. The counterfactual trajectories that the country would have followed, had exposure stopped after each of the first three storms, are grey. The observed trajectory (black) appears as an almost-smooth line with an average growth rate that is depressed relative to the pre-disaster baseline.

illustrated in Figures 5 and 6, there are strong cross-sectional differences countries' average cyclone exposure: some countries are regularly struck by strong cyclones while other countries are rarely hit. How do the long-run growth effects that we estimate above interact with these cross-sectional patterns in countries' geographic endowments to influence their long-run economic development?

If a country is repeatedly hit by cyclones, that country will continuously accumulate growth penalties that can substantially alter that country's income trajectory. Figure 19 illustrates this process by demonstrating how the effect of sequential storms add up for a single country. Each storm has a long-run effect that permanently alters a country's growth trajectory, and any storms that follow further lower that country's long-run growth. Had the "build back better" or "recovery to trend" hypotheses been true, then the effect of sequential storms would be smaller or would vanish, since later storms would either replace or offset the effects of earlier storms. However, because national incomes exhibit "no recovery," the effect of sequential storms simply add to one another, creating an income penalty (relative to the trend) that grows monotonically with time.

Two aspects of this process make it particularly insidious for detection by analysts, possibly explaining why this effect has not be characterized in earlier studies. First, the long-run growth response of an individual storm onsets very gradually (recall Figure 9), so detecting the cumulative effect of cyclones by visually examining GDP time-series should be nearly impossible. Consider Figure 19: four large storms (> 1 s.d.) strike over the course of two decades, however the observed trajectory of GDP appears smooth and almost perfectly linear. There is no "trend-break" of otherwise abrupt movement in GDP that would attract the attention of an analyst, a problem that would only be compounded if realistic noise were added to this figure. Second, the cross-sectional variation in average cyclone exposure is correlated with many other confounding static variables, such as latitude or distance to coasts, so it is unlikely that any cross-sectional regression of average growth rates could alone reliably identify the long-run growth effect of a country's stationary cyclone climate. Together, these two facts make it very difficult to detect the effect of cyclone climates on long-run development using analytical methods other than the deconvolution that we employed here. Nonetheless, given the strength of the results above, we see little choice but to conclude that for those countries which are regularly or perpetually exposed to cyclone disasters, a new permanent reduction in long-run national income is quietly suffered each time a storm strikes, accumulating on top of similar historical penalties and causing these countries to grow slower than they otherwise would.

Simulating alternative development trajectories The tropical cyclone climate of each country is stationary, preventing us from directly identifying the effect of a *cyclone climate* on average growth rates in the presence of other omitted geographic variables – however we can use our inter-temporally-identified estimate for the effect of an *individual cyclone* to estimate the cumulative influence of each countries' climate (repeated exposure to individual cyclones) on its average rate of growth. To estimate the partial effect of each cyclone climate on long-run development, we use our parameter estimates to compute how each country's income trajectory (starting in 1970) would have looked had its cyclone exposure been fixed at zero since 1950. This approach is simplistic, since it assumes that nothing else in a country changes when all cyclones are removed, but it is a useful benchmark since it provides us with a sense of scale for the overall effect of each countries' cyclone climate. To remove the effect of all cyclones from historical growth, we preserve the coefficients from our baseline model (Equation 2) but eliminate the tropical cyclone terms. Letting $\mathbf{S_{i,t}}$ be the vector of cyclone exposure for years t to $t-k$, we rewrite Equation 2

$$\Delta \ln(GDP)_{i,t} = f(\mathbf{\bar{S}_{i,t}}) + g_{i,t} + \epsilon_{i,t}, \tag{7}$$

to make clear that our model is additively separable in the cyclone-related terms contained in $f(.)$ and "everything else" contained in $g_{i,t}$: country fixed effects, year fixed effects and country-specific trends. Using our parameter estimates, we predict "actual" historical growth for each country by using all the terms of Equation 7. We then construct a "cyclone-free" growth history for each country by setting $\bar{S}_{it} = 0$ for all observations[39] while keeping g unchanged and predicting annual growth again. Using observed incomes in 1970 as initial conditions, we can integrate both "actual" and "cyclone-free" income trajectories using these two alternative growth histories. For each country, the difference between these two trajectories represents our estimate for the partial effect of that country's tropical cyclone climate.

Cyclone climates and global economic development

Figure 20 displays the simulated "actual" income trajectory using the full model (red) and the "cyclone-free" model (blue), overlaid with the observed trajectory of income (black) for twelve example countries

[39]Effectively dropping $f(.)$ from the model.

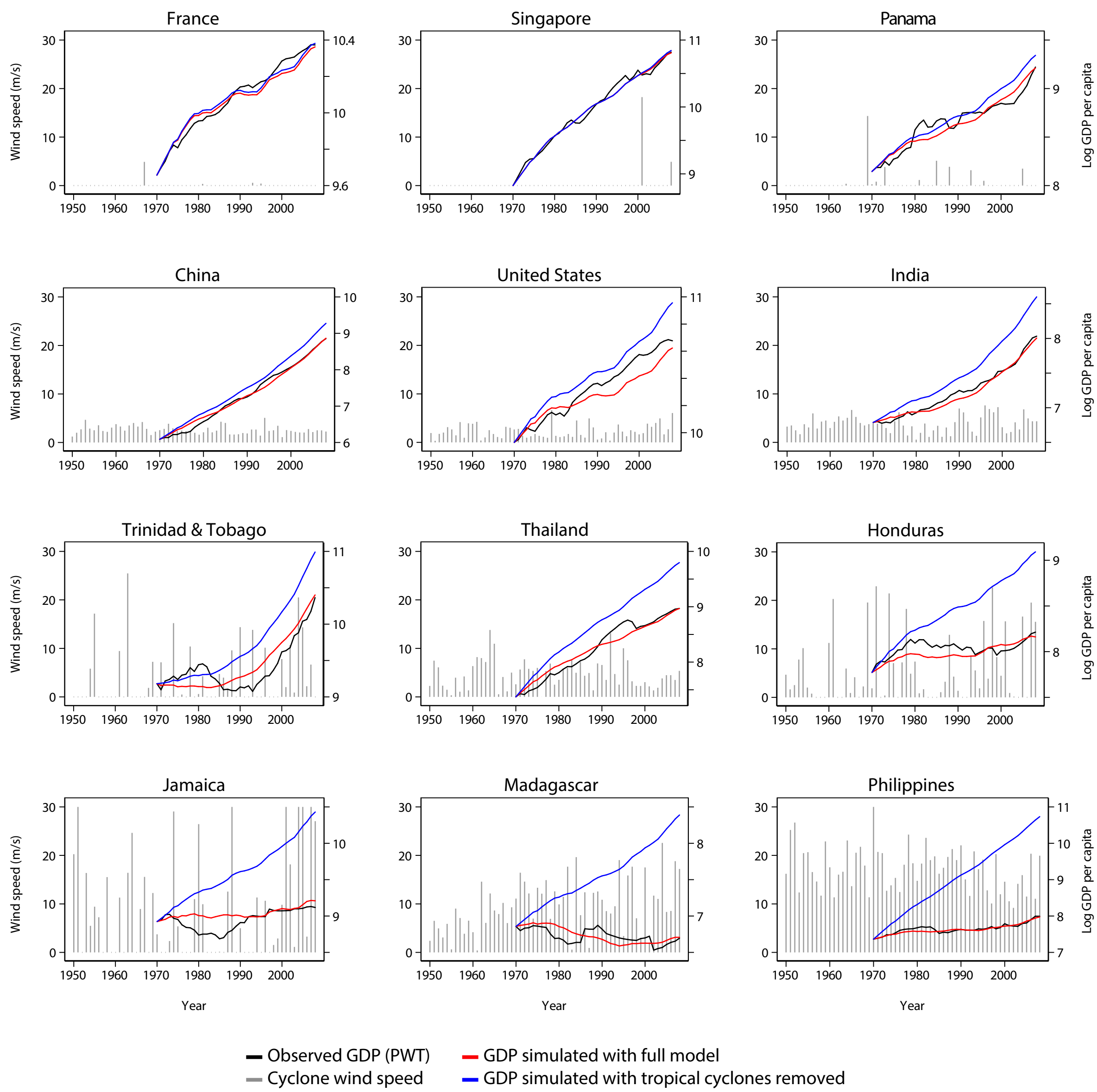

Figure 20: Simulations of log GDPpc growth with (red) and without (blue) tropical cyclone exposure. Observed log GDPpc is black and cyclone exposure in each year are vertical grey lines. Countries are presented in ascending order based on their average tropical cyclone exposure, from low (France, top left) to high (Philippines, bottom right). The difference between the slopes of the red and blue simulations gives an estimate of the partial-equilibrium growth effect of observed tropical cyclone exposure in comparison to a counterfactual "no storm" world (which is never observed). India and Trinidad & Tobago represent the median tropical cyclone climates within the sample of countries that are ever exposed.

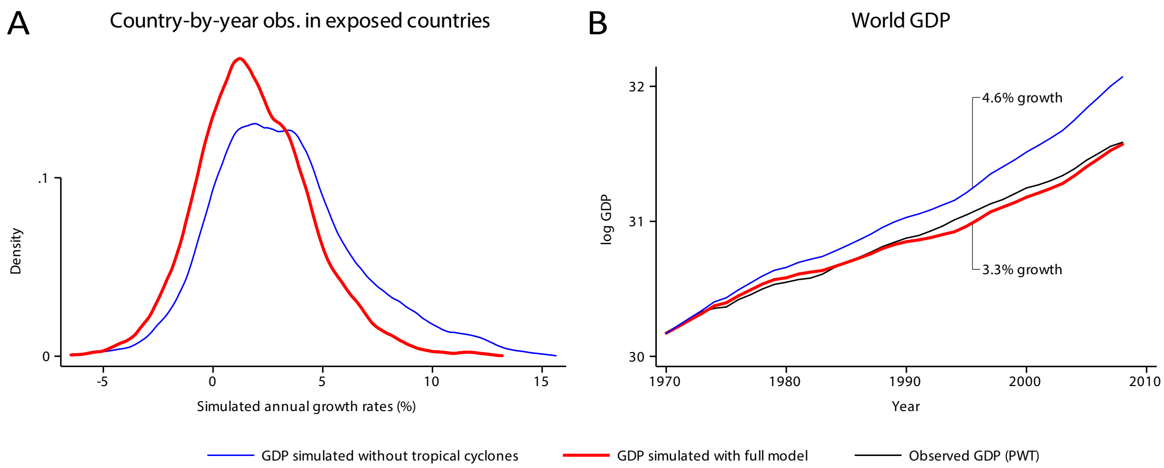

Figure 21: A) The global distribution of predicted annual growth rates for exposed countries using the complete growth model (red) and the model where historical cyclone exposure is removed (blue) during 1970-2008. B) the observed trajectory of World GDP (black, 3.5% growth) and simulated trajectories with and without tropical cyclones included in the model. Japan, Taiwan and Hong-Kong are not included in these plots (see text).

that face a variety of cyclone climates[40] (cyclone events are grey). In countries endowed with very weak cyclone climates (eg. France and Singapore), removing storms has almost no effect on the model's prediction for long-run income: both the full and truncated model essentially predict identical trajectories that both mirror the true trajectory. However, as cyclone climates become progressively more intense, the long-term trajectories for income begin to diverge. The "cyclone-free" model invariably predicts higher incomes because cyclones negatively influence growth, but the magnitude of this divergence depends strongly on the cyclone climate. For countries endowed with median cyclone climates, India and Trinidad & Tobago, models with and without cyclone effects forecast income levels that differ by roughly fifty log-points (65%) after an integration period of thirty-nine years (1970-2008). In countries endowed with stronger cyclone climates, such as as Thailand or Honduras, removing cyclones from the model increases final incomes by about one-hundred log-points (172%) during the same integration period. In some countries that exhibit almost no actual growth, such as Jamaica, or negative growth, such as Madagascar, the removal of cyclones from our model generates forecasts for moderate rates of positive growth. Finally, in countries endowed with extremely intense cyclone climates, such as the Philippines, our simulations suggests that growth is slowed dramatically: the cyclone-free model exceeds the full model by 300 log-points (2,000%) after the thirty-nine year integration period. This effect of removing Filipino cyclones is one of the most extreme cases, equivalent to raising the average annual growth rate in the Philippines by roughly 7.3 percentage points, and would cause growth in the Philippines to match that of its near neighbor China. For all countries in the simulation, we list the estimated effect of their cyclone climate on their average growth rate in Appendix Table A.6.

We summarize the total effect of cyclones on global economic growth in Figure 21. Panel A plots the distribution of annual country-by-year growth rates with and without cyclones included in the model.

[40]Equation 7 predicts the long term evolution of income well (when all terms are retained), regardless of the cyclone climate in each country.

When cyclones are removed, the distribution of growth rates shifts upwards, with the mean increasing from 2.01% per year to 3.80% per year. Importantly, we remove Japan, Taiwan and Hong-Kong from this exercise since their growth rates become so high (> 13%) that it seems unlikely that they could plausibly sustain such high growth rates, since factors unrelated to cyclones are likely to limit output growth in other ways. Collecting results across the remaining 107 countries for which GDP data in 1970 exists (63 of which are ever exposed to cyclones), we compute the trajectory of World GDP during 1970-2008, using both the full and cyclone-free simulations. The results are displayed in Figure 21B. Using the full model, World GDP grows at 3.28% annually, near the 3.55% growth rate that was actually observed. When cyclones are removed from the simulation, World GDP grows 4.56% per year. Differencing the trajectories of the two simulations suggests that World GDP has been growing 1.27% slower (95% confidence interval = [1.08, 1.47]) than it would in a "counterfactual" world with no cyclones.

Cyclone climate as an explanatory variable in cross-country comparisons of growth

There are large differences in the tropical cyclone climates that countries are endowed with, and our simulations suggest that cyclones can have a large impact on average growth rates in countries that are repeatedly exposed to them. Thus, we can ask how much of the cross-country variation in average growth is explained by cross-country variation in cyclone climates. To explore this question, we compute the average annual growth rate in simulations with and without cyclones – the difference between these two numbers is growth that is "missing," which we attribute to each country's cyclone climate[41]. In Appendix Figure A.3 we examine three regions where cyclones are prevalent, adding each country's "missing" growth to its historically observed growth, allowing us to visualize how the distribution of growth rates might change if cyclones had not affected these countries. If cyclones explained all of the cross-country differences in growth rates within each region, then we would expect all countries within a region to have the same growth rate once we accounted for the cyclone growth penalty. We do not observe this, indicating that cyclones are only one of many factors that probably influence growth – however, we do observe that the distribution of growth rates within each region flattens out somewhat once the cyclone growth penalty is accounted for. For examples, we point out that in the absence of cyclones our estimates suggest that average growth rates in Jamaica and Trinidad & Tobago would be substantially nearer to one another (4.0:4.7 rather than 0.8:3.1), similar to Guatemala and Panama (3.3:3.2 rather than 1.1:2.9) and the Philippines and China (8.9:8.4 rather than 1.7:7.3).

In the right column of Appendix Figure A.3, we formalize this comparison by plotting the cross-sectional regression of each country's observed average growth against our estimate for each country's cyclone-induced growth penalty. Within each region, countries with a larger (more negative) growth penalty tend to grow more slowly. In Appendix Table A.7 we present coefficients for this regression, including region fixed effects to account for the large differences in average growth rates between regions[42]. In this simple cross-sectional model, average growth tends to fall 0.38% per year for each

[41] The annual average growth rate in the full simulation is equal to the observed annual average growth rate. This is because the sample average is equal to the average prediction in OLS.

[42] Because we estimate a cumulative growth effect of cyclones that is linear in exposure, these results are equal to a rescaling of results presented in Hsiang and Jina (2015).

1% increase in the simulated cyclone-induced growth penalty (column 1). In this limited sample of cyclone-exposed countries, the within-region R-squared is 0.28, indicating that the cyclone climates of countries predicts a substantial amount of the observed cross-country variation in their average growth rates. It is likely that this estimate suffers from some attenuation bias – since we measure cyclone exposure imperfectly – and probably omitted variables bias as well – since there are important covariates that are correlated with cyclone climate which we do not attempt to account for here. Nonetheless, we think it is notable that the positive correlation between our calculated growth penalty and actual growth reduction appears independently within different regions with a relatively stable magnitude[43] (columns 2-6).

These simulations help us understand the extent to which repeated disaster exposure might influence economic development in countries endowed with different cyclone climates, however they should be interpreted cautiously. Even though we account for adaptation to average cyclone exposure, in terms of expected losses, we cannot account for the numerous and interacting general equilibrium adjustments that might accompany a large change in the global distribution of cyclones. For example, if all cyclones were removed from the Earth, patterns of global trade would surely adjust – an effect that we do not capture here. In addition, there are likely unobservable factors that limit growth, so it seems probable that some countries (e.g. Hong Kong, South Korea) would be unable to achieve the growth rates that our cyclone-free models suggest. However, it is also worth noting that in some cases, these estimates may underestimate the effect of cyclones since there may be secondary impacts – such as a civil war that might not have occurred without disaster-induced economic contraction (Hsiang, Burke and Miguel (2015)) – that further reduce long-run growth. We feel that all these caveats are substantive enough that the exact values retrieved from the "cyclone-free" simulations should not be interpreted too literally. However, we think that the general distribution and magnitude of these quantities indicate that tropical cyclones, and perhaps disasters more generally, are a feature of the planet that exert a strong influence over global patterns of economic development.

Projecting the cyclone-related cost of anthropogenic climate change

There is concern that anthropogenic climate change may cause the frequency and distribution of tropical cyclones to change, thereby raising (or lowering) cyclone-induced costs borne by coastal populations (Emanuel (2005), Stern (2006), Nordhaus (2010), Mendelsohn et al. (2012), Hsiang & Narita (2012)). Forecasting the response of cyclones to future climatic conditions has proven difficult and it remains a field of active research – however, there is some consensus on general patterns (Knutson et al. (2010)). Globally, there are likely to be fewer total storms that achieve tropical cyclone status but the storms that do occur are likely to stronger on average. There is likely to be a reduction in the absolute number of relatively weaker storms, little change in the absolute number of strong storms, and an increase in the absolute number of very strong storms[44]. However, these statistics are global statistics and stronger patterns are expected at the basin level in some cases. For example, there is relatively

[43] Because the sample sizes are small and the variation in the independent variable is limited for samples that do no include East Asia, the standard errors for these estimates tend to be large.

[44] We refer interested readers to Knutson, Landsea and Emanuel (2010) and Knutson et al. (2010) for reviews of this active literature.

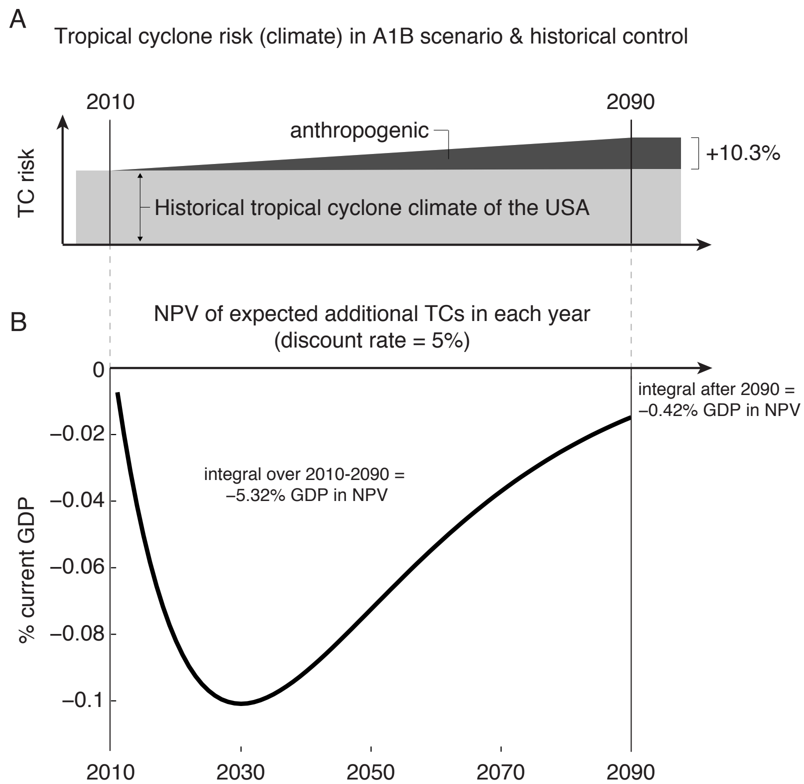

Figure 22: Example calculation of NPV of changes to the tropical cyclone climate of the United States under "Business as usual" (as tabulated in Table 3). (A) The tropical cyclone climate of the United States linearly intensifies to the projected intensity between 2010 and 2090 (the midpoint of the 2080-2100 averaging period of Emanuel et al). After 2090, the climate of the United States remains unchanged at it's new intensity. (B) The NPV (discount rate = 5%) of income losses that are expected to be incurred by the intensified climate (as it will be experienced in each year) is computed for each year and integrated to $t = \infty$. Most of the expected loss in NPV will be caused by cyclone events before 2040.

broad consensus across models that total energy dissipation over the West Pacific will increase and that it will decrease over the Southern Hemisphere. Here we use basin-level forecasts to estimate the Present Discounted Value (PDV) of anthropogenic changes to the global tropical cyclone climate under a "business as usual" scenario (A1B).

Valuing an altered income trajectory caused by an altered cyclone climate

Let expected cyclone exposure in the absence of anthropogenic forcing be S_0 in every period and the expected exposure under climate change be

$$S(t) = S_0 + \Delta(t) \tag{8}$$

where $\Delta(t)$ is the total effect of all historical climate changes on S at the moment t. Before T_1, human activity has no effect so $\Delta(t) = 0$ for $t < T_1$. At some point T_2 in the future, the climate stabilizes so we set $\Delta(t) = \bar{\Delta}$ for $t > T_2$. Between T_1 and T_2, the cyclone climate exhibits transient behavior. Panel A of Figure 22 displays an example case we consider, interpolating $\Delta(t)$ as a linear function between mean climate change estimates in Emanuel et al (2008).

We are interested in the PDV of $\Delta(t)$, the component of the cyclone climate that current policy might affect. To compute this PDV, there are three steps to the discounting procedure. First, the economic losses that results from a cyclone at time t, which are experienced in periods $t + j$, are discounted back to time t. Let the marginal NPV of an additional 1 m/s of cyclone exposure discounted to the moment of exposure be κ. Second, the expected additional exposure caused by climate change at each time t must be multiplied by its marginal cost discounted to t to obtain the schedule of expected costs of future storms, all discounted to the moment each storm is expected to strike. Finally, this schedule of future costs ($\Delta(t) \times \kappa$) must all be discounted back to the present. Panel B of Figure 22 displays the schedule of costs, in PDV with a 5% discount rate, using actual mean climate forecasts for the United States – most of the loss in PDV arises from the intensification of the cyclone climate that occurs during 2020-2050 because the distant future is still heavily discounted, even though climate changes increase monotonically.

Details of this discounting calculation and some generic examples are detailed in the Appendix.

Application to a "Business as usual" scenario We combine our empirical estimates of Ω_j with basin-specific estimates of $\Delta(t)$ from Emanuel et al (2008) (shown in Appendix Figure A.5 for reference). Emanuel et al do not model transient cyclone climates because it is computationally expensive – instead they model the cyclone climates during 2080-2100 under the A1B scenario as if it were a steady-state climate[45]. Thus, we set $T_1 = 2010$ and $T_2 = 2090$, because it is the midpoint of the averaging period in Emanuel et al. Emanuel et al report $\bar{\Delta}$ for each basin in aggregate, averaged over seven climate models. For simplicity, we follow Emanuel (2011) and assume that $\Delta(t)$ increases linearly from zero in 2010 to $\bar{\Delta}$ in 2090, analogous to the third generic scenario described above, and that the climate of each country intensifies in proportion to the basin-level aggregate. Figure 22 depicts how estimates from Emanuel et al (2008) are converted to a cyclone climate trajectory for the United States, which is then valued at each moment in time.

The lower panels of Table 3 present the PDV of the A1B scenario for several major countries in each basin, as a percentage of each country's current GDP. Because the timing of these climatological changes are assumed to be identical across basins, the difference between countries arises from differences in the sign and magnitude of climatic change across basins as well as the differing baseline climatologies of each country[46] (far right column). Anthropogenic climate change is expected to cause moderate intensification of North Atlantic cyclone activity[47] (+10.3%), which has a sizable negative NPV for many countries (we again focus on the 5% discount rate). Caribbean islands lose the largest fraction of income, with losses that generally exceed 20% of current GDP in NPV, while mainland North America loses somewhat less, with losses in the vicinity of 5-15% of current GDP. The United

[45] Emanuel et al also model the cyclone climate during the twentieth century as if it were a steady state and report the difference, which is analogous to $\bar{\Delta}$. This procedure is useful because it removes any constant bias exhibited by individual models.

[46] These estimates are a linear rescaling of the third generic scenario (Eq. A.4) where $\bar{\Delta}$ is set to the fractional intensification of basin-level activity times each country's baseline climatology.

[47] "Cyclone activity" here is total power dissipation.

Table 3: PDV of changes to the global tropical cyclone climate under "business as usual" (A1B)

	PDV as percentage of current GDP					**Current climate**
Discount rate:	1.0%	3.0%	5.0%	7.0%	10.0%	(m/s)
North Atlantic: linear increase up to +10.3% in 2090						
Bahamas	-3048	-160	-32.2	-10.4	-3.0	12.4
Belize	-2029	-106	-21.5	-6.9	-2.0	8.3
Costa Rica	-304	-16	-3.2	-1.0	-0.3	1.2
Cuba	-2673	-140	-28.3	-9.1	-2.6	10.9
Dominican Rep.	-2738	-144	-29.0	-9.3	-2.7	11.2
Guatemala	-1304	-68	-13.8	-4.5	-1.3	5.3
Honduras	-1455	-76	-15.4	-5.0	-1.4	5.9
Haiti	-2625	-138	-27.8	-9.0	-2.6	10.7
Jamaica	-2420	-127	-25.6	-8.3	-2.4	9.9
Mexico	-1629	-85	-17.2	-5.6	-1.6	6.6
Nicaragua	-1081	-57	-11.4	-3.7	-1.1	4.4
Trinidad & Tobago	-950	-50	-10.0	-3.2	-0.9	3.9
United States	-560	-29	-5.9	-1.9	-0.5	2.3
West Pacific: linear increase up to +19.1% in 2090						
China	-1194	-63	-12.6	-4.1	-1.2	2.6
Japan	-9600	-504	-101.5	-32.8	-9.4	21.1
Korea	-6937	-364	-73.4	-23.7	-6.8	15.2
Laos	-4492	-236	-47.5	-15.3	-4.4	9.9
Malaysia	-235	-12	-2.5	-0.8	-0.2	0.5
Philippines	-7878	-413	-83.3	-26.9	-7.7	17.3
Thailand	-2176	-114	-23.0	-7.4	-2.1	4.8
Vietnam	-5291	-278	-56.0	-18.1	-5.2	11.6
Oceania: linear decrease down to -13.8% in 2090						
Australia	1238	65	13.1	4.2	1.2	3.8
Indonesia	71	4	0.7	0.2	0.1	0.2
New Zealand	904	47	9.6	3.1	0.9	2.7
Papua New Guinea	194	10	2.0	0.7	0.2	0.6
North Indian: linear decrease down to -5.8% in 2090						
Bangladesh	1054	55	11.1	3.6	1.0	7.6
India	533	28	5.6	1.8	0.5	3.9
Sri Lanka	499	26	5.3	1.7	0.5	3.6

Estimates for climatic intensification are the relative changes in basin-wide power dissipation between simulations of the twentieth-century and the period 2080-2100 under the A1B emissions scenario averaged across seven climate models (Emanuel et al. (2008)). Also see discussion in (Knutson et al. (2010)). Projections assume that country-level exposure increases in proportion to basin-level activity and basin-level activity strengthens or weakens linearly between 2010 and 2090 (the midpoint of the 2080-2100 averaging period). Models agree strongly on the sign of West Pacific (7/7) and Oceania (6/7) projections. Models disagree more regarding North Atlantic (4/7) and North Indian (4/7) projections (see Appendix Figure A.5). Estimates using the 5% discount rate are converted to 2010 US$ in Table 4. †See Figure 22 for a graphical explanation of this calculation.

States, is expected to lose the NPV-equivalent of 5.9% of current GDP. The West Pacific faces the most extreme intensification of cyclone activity[48] (+19.1%) causing large losses for many countries in East Asia. The NPV of expected losses exceed 40% of GDP for many countries, such as Vietnam and South Korea, and rises above 80% of current GDP in the cases of the Philippines and Japan. China is expected to lose the equivalent of 12.6% of its current GDP. Oceania and the North Indian Ocean are anticipated to have *reduced* tropical cyclone exposure under anthropogenic climate change (−5.8% and −13.8% respectively), causing their expected income streams to rise in the future. Because these climatological changes are small to moderate in magnitude and the initial cyclone climatology of these countries is somewhat weaker, these gains from climate change tend to be smaller (in percentage terms) than the losses described above. Australia and Bangladesh benefit the most in percentage terms, with gains valued at 13.1% and 11.1% of current GDP (resp.). India is expected to gain the NPV-equivalent of 5.6% of its current GDP.

6 Summary and discusion

A growing literature has examined the short-run economic impact of natural disasters and environmental insults more generally, however it has been widely debated whether extreme events have any permanent long-run impact on economic outcomes. Here, we have constructed a novel global dataset of exogenous natural disasters and are the first to demonstrate that permanent losses to national income are large, frequent and generalizable to populations around the globe, regardless of their income level, geography or the scale of the disaster. Permanent changes in consumption, investment, trade and international aid all reflect the observed changes in national income, corroborating this result. Furthermore, our result is supported by global patterns of income losses, which match theoretical predictions for the structure of climate-based adaptations, and two prior studies that produce similarly sized estimates using different data. Collectively, these findings lead us to reject the "creative destruction," the "build back better," and the "recovery to trend" hypotheses for post-disaster impacts – leading us to embrace the "no recovery" hypothesis as the best description of the data.

The estimated impact of cyclones on long-run growth emerges gradually, rendering it virtually undetectable to a casual observer, but it persists for more than a decade, generating strikingly large cumulative losses that have dramatic implications for economic development. Within the 58% of countries that are affected by cyclones, a one standard deviation event reduces long-run GDP by 3.6 percentage points, and a "one-in-ten" country-year event reduces long-run GDP by 7.4% twenty years later. For countries that are frequently or persistently exposed to cyclones, these permanent losses accumulate, causing annual average growth rates to be 1-7.5 percentage points lower than simulations of "cyclone-free" counterfactuals. Across the global sample of affected countries, simulations suggest that the 2.0% average annual growth rate that we observe in the real world is depressed relative to the 3.8% growth that we would observe in a counterfactual world that had no tropical cyclones[49]. Taken together, these results suggest that the global tropical cyclone climate is likely to play an important role in determining the global distribution of countries' growth rates as well as the global rate of economic

[48] The intensification of the West Pacific is highly consistent across models, so it should be considered the most certain of these scenarios. See Appendix Figure A.5.

[49] See text above for many caveats of this result.

growth. Application of these estimates to a projection of climate change indicates that through its influence on cyclone activity, anthropogenic warming will have a substantial impact on the income trajectory of countries, with a PDV cost for individual countries that ranges from +13.1% (a benefit) to −101.5% (a loss) of current GDP.

Implications for disaster risk management policies In general, natural disaster policies have two prongs: pre-disaster risk reduction and post-disaster income-smoothing. The latter is often the focus of actual policy, however the former has received substantial recent attention as researchers demonstrate that it is sometimes highly cost-effective (Healy and Malhotra (2009), Deryugina (2011), UNISDR (2011)). The discussion of these two policy-instruments often assumes that they are substitutes for one another, in terms of raising social welfare, and that the efficient allocation of public funds should be based on their cost-efficacy. However, our results suggest that while both instruments may have positive net-present value, they are not substitutes in the long-run. Post-disaster income smoothing is achieved through borrowing, transfers and insurance mechanisms. These measures may be effective at reducing welfare losses in the short run, but they may generate no net income. Thus, if incomes decline in the long-run, then the primary welfare gains from smoothing will arise from simply *delaying* consumption losses. We observe that long-run income loses unfold gradually over the course of fifteen years, suggesting that some income smoothing measures are probably slowing the decline in national income. However, despite access to these instruments, we do not observe that populations "catch up" with their pre-disaster trajectory, suggesting that these instruments may have limited long-run impact. In contrast, pre-disaster investments that reduce risk, such as infrastructure hardening and early-warning systems, are likely to influence long-run outcomes after disaster. Many risk reduction measures are similar or identical to adaptive investments, and the results in Figure 18 suggest that adaptive behaviors are probably effective at lowering the marginal long-run effect of cyclones. Policy-makers should optimally allocate public resources between post-disaster income smoothing and pre-disaster risk reduction. If future welfare is discounted heavily, then long-run income is not important and the optimal allocation shifts towards income smoothing. As policy-makers care more about the future, then risk reduction becomes more important since its impact on future income is enduring.

Implications for economic development policies Tropical cyclone exposure effectively displaces a country's GDP trajectory in time – following cyclone exposure, a country's income does not recover to its pre-disaster trajectory but instead settles on a new trajectory that is parallel but below the original trajectory. Thus, a simple way to summarize our result is to compute how much "un-development" occurs as a result of cyclone exposure. Within the sample of cyclone-affected countries, a one standard deviation event is equal to 9.4 m/s of wind exposure which generates a long-run loss of 3.57% of GDP. Because average annual growth in this sample is 2.00% per year, each one standard deviation event effectively undoes 1.8 year's worth of economic development[50]. Using this metric, each 1 m/s marginal increase in annual wind exposure undoes 2.3 month's worth of average development. For countries endowed with cyclone climates where they are repeatedly exposed to cyclone events, there is no choice but to adapt to these adverse conditions. Here (Figure 18) and elsewhere (Hsiang & Narita

[50] An event at the 90th percentile reverses 3.7 year's worth of develoment, and an event at the 99th percentile undoes 7.5 years worth of development.

(2012), Anttila-Hughes & Hsiang (2011)) there is evidence that adaptation to cyclones is feasible, but the fact that no countries exhibit zero marginal losses indicates that the cost of additional adaptation remains binding for most populations (Hsiang & Narita (2012)). If policy-makers are able to encourage technological innovations or otherwise lower the cost of adaptive investments, this should increase populations' voluntary adoption and investment in adaptive technologies, which in turn should lower their long-run economic losses to disaster and raise their growth rate. In addition, it is possible that some populations may have underinvested in adaption because they undervalue its benefit – perhaps because it is difficult for populations to observe a return on investment for protective technologies. This study suggests that instead of conceptualizing adaptive investments as simply "protective," they can in fact be conceptualized as "revenue generating investments" since they effectively raise a population's expected future income stream.

Implications for climate change policies Optimal climate change policy balances the cost of reducing greenhouse gas emissions with the benefits of limiting global climatic changes. In practice, computing the total benefit of climate change policy requires that we identify the various pathways through which climate changes affect society and then enumerate the costs or benefits of these various impacts. It has been recognized for some time that anthropogenic climate change might alter tropical cyclone frequency or intensity (Emanuel (1999)) and recently there has been some effort to quantify the social cost of these projected changes (Nordhaus (2010), Mendelsohn et al (2012), Houser et al. (2014)), however these recent efforts have focused on the immediate destruction of assets in storms and have not accounted for their impact on long-run economic growth. The present study provides evidence that this later mechanism is economically important in scenarios of future warming, with a social cost that is larger in magnitude than the projected cost of additional asset destruction. Accounting for the effect of tropical cyclones on long-run growth will raise our estimate for the global social cost of climate change substantially. For a sense of scale, our estimates suggest that under the "Business as usual" scenario (with a 5% discount rate[51]) the PDV of lost long-run growth is $855 billion for the United States[52] (5.9% of current GDP), $299 billion for the Philippines (83.3% of current GDP), $1 trillion for South Korea (73% of current GDP), $1.4 trillion for China (12.6% of current GDP), and $4.5 trillion for Japan (101.5% of current GDP)[53] – values for other countries are tabulated in Table 4. Aggregating these estimates across all countries alters the PDV of "full mitigation" relative to "business as usual" by $9.7 trillion ($5.2 trillion without Japan). For comparison, we note that Nordhaus (2008) calculates that the total PDV of optimal global climate policy is $5 trillion (in comparison to no regulation, using a similar discount rate) which costs $2 trillion to implement, for a net gain of $3 trillion[54]. Thus, accounting for the long-run growth impact of cyclones will raise the marginal benefit of green house gas mitigation, thereby increasing the incentive for populations to undertake somewhat stronger mitigation measures. Importantly, however, because these losses are relatively focused in the coastal countries of North America and East Asia, these results are likely to influence the optimal policies of

[51]At a 3% discount rate, these values rise by a factor of 4.9.

[52]For consistency with our analysis, here we use PPP adjusted GDP for 2010 listed in the PWT.

[53]There are a small number of countries that benefit, however these gains are modest compared to losses globally (in total dollars). For example, India and Australia are by far the biggest "winners," with income trajectories that rises in PDV by $264 and $140 billion (resp.). Bangladesh receives the third largest benefit, a mere $26 billion in PDV.

[54]Nordhaus notes that under optimal management, using his model, there are $17 trillion in residual damages that remain even after optimal regulation.

Table 4: PDV of the change in countries' income trajectories resulting from the "business as usual" climate change scenario (A1B)

Country	**PDV using 5% discount rate***		
	Estimate (†billion US$)	95% confidence interval bounds	
Japan	-4,461.1	-1,813.6	-7,108.5
China	-1,364.5	-554.7	-2,174.3
South Korea	-1,026.4	-417.3	-1,635.6
Taiwan	-991.9	-403.2	-1,580.5
United States	-855.0	-347.6	-1,362.4
Hong Kong	-354.0	-143.9	-564.1
Philippines	-299.3	-121.7	-476.9
Mexico	-260.3	-105.8	-414.7
Vietnam	-160.1	-65.1	-255.1
Thailand	-140.6	-57.2	-224.0
Cuba	-40.0	-16.3	-63.7
Puerto Rico	-34.5	-14.0	-55.0
Dominican Republic	-33.0	-13.4	-52.6
Spain	-13.2	-5.4	-21.1
Guatemala	-13.2	-5.4	-21.1
Canada	-10.9	-4.4	-17.4
Indonesia	-10.9	-4.4	-17.3
Malaysia	-9.8	-4.0	-15.6
Cambodia	-9.3	-3.8	-14.8
Laos	-9.2	-3.7	-14.7
Jamaica	-7.1	-2.9	-11.2
France	-6.3	-2.6	-10.1
Portugal	-5.5	-2.2	-8.8
Singapore	-5.3	-2.1	-8.4
Honduras	-4.7	-1.9	-7.5
Haiti	-4.0	-1.6	-6.4
El Salvador	-3.6	-1.5	-5.8
Trinidad & Tobago	-3.2	-1.3	-5.0
Bahamas	-3.1	-1.3	-4.9
All others	-15.5	-6.3	-24.7
Pakistan	3.1	1.3	4.9
Sri Lanka	5.1	2.1	8.2
New Zealand	13.0	5.3	20.7
Bangladesh	26.1	10.6	41.6
Australia	140.0	56.9	223.1
India	264.2	107.4	420.9
Total losses	**-10,159**	**-4,130**	**-16,188**
Total gains	**455**	**185**	**725**
Net PDV (global)	**-9,704**	**-3,945**	**-15,463**

*Value of income stream under A1B less control scenario. †Values are PPP adjusted and based on 2010 income.

these particular countries more strongly than they influence optimal global policy.

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A APPENDIX

In the main text we showed that a marginal increase in cyclone exposure by one unit at time t led to a reduction of income by Ω_j at time $t + j$. Here we explain how we compute the present discounted value (PDV) of permanent change in cyclone risk due to climate changes, which alters the long-run income trajectory of a country.

Valuing an altered income trajectory caused by an altered cyclone climate

We did not have enough data to observe income losses more than twenty years after a cyclone event[55], so here we assume that income loss is permanent, thus $\Omega_s = \Omega_{20}$ for all $s \geq 21$. Assume a discount rate of ρ.

Letting expected cyclone exposure in the absence of anthropogenic forcing be S_0 in every period, the expected exposure of a population under climate change is

$$S(t) = S_0 + \Delta(t) \tag{A.1}$$

where $\Delta(t)$ is the total effect of all historical climate changes on S at the moment t. Before T_1, human activity has no effect so $\Delta(t) = 0$ for $t < T_1$. At some point T_2 in the future, the climate stabilizes so we set $\Delta(t) = \bar{\Delta}$ for $t > T_2$. Between T_1 and T_2, the cyclone climate exhibits transient behavior.

Our goal is to compare a cyclone-dependent income stream $Y(S_0)$ that is unaffected by climate change with a similar income stream that is affected by climate change $Y(S(t))$. A simple way to summarize the difference between these two trajectories, in a manner useful to policy, is to compute the PDV of their difference

$$PDV[Y(S_0) - Y(S(t))] = PDV[\partial Y/\partial S \times \Delta(t)] \tag{A.2}$$

which is true because the marginal impact of cyclone exposure is approximately invariant in the intensity of exposure (losses are linear), so we only need to consider the anthropogenic changes $\Delta(t)$.

To compute this value, we first evaluate the PDV of a single cyclone event with a magnitude of one at time $t = 0$, which we denote κ:

$$\kappa = \left[\sum_{j=0}^{20} \Omega_j e^{-\rho j}\right] + \frac{\Omega_{20}}{\rho} e^{-21\rho}. \tag{A.3}$$

The first term is the PDV of losses that occur in the year of the cyclone and the twenty years that follow. The second term is the PDV of the permanent income reduction Ω_{20} that is observed every period $t \geq 21$. κ is the marginal change in PDV(Y) that occurs because of a cyclone at time t if the future losses caused by that cyclone were discounted back to the moment t. Thus, the total losses from a permanent change in climate is this marginal effect κ times the change in the climate, at each

[55] Estimates with more lags (not shown) suggest that $\Omega_{30} \approx \Omega_{20}$.

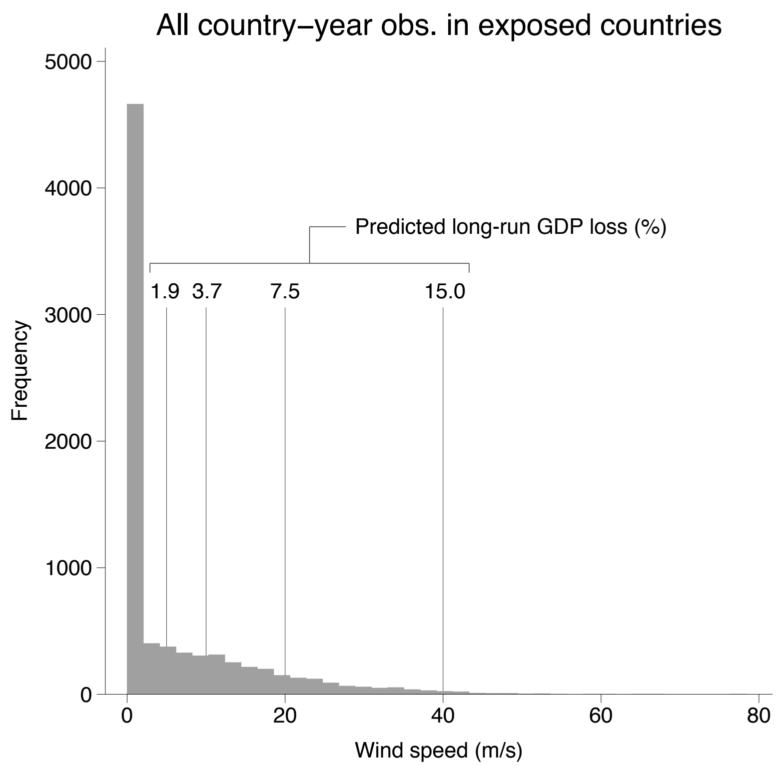
period where the climate has changed, discounted back to $t = 0$

$$PDV[\partial Y/\partial S \times \Delta(t)] = \int_{T_1}^{T_2} \kappa \Delta(t) e^{-\rho t} dt + \frac{\kappa \bar{\Delta}}{\rho} e^{-T_2 \rho}. \tag{A.4}$$

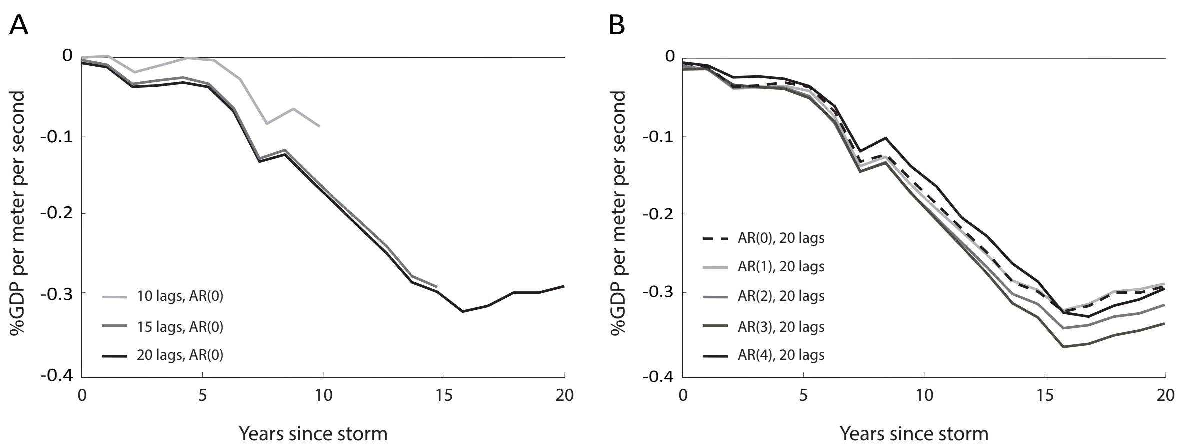
The first term is the cumulative loss that is incurred by all changes in cyclone risk that occur before the climate stabilizes. The second term is the discounted value of the permanent climate shift $\bar{\Delta}$ that is the new steady state after $t = T_2$.

Examples using generic climate scenarios To develop some intution for how the timing of events affects the PDV of cyclone climate changes, Appendix Table A.8 describes the PDV of generic changes to the current tropical cyclone climate under several different discount rates – here we focus on the 5% discount rate for succinctness[56]. We tabulate the PDV of three types of generic scenarios that are not specific to a country. The first scenario is a single 1 m/s cyclone event today, which has PDV equal to κ, i.e. -5.1% of GDP (Eq. A.3). This value is sizable because income losses from a single event are permanent relative to the counterfactual income trajectory. The second scenario is an abrupt intensification of the climate that occurs at 2090 and which persists indefinitely – a plot of $\Delta(t)$ would be a step function where the discontinuity is at $t = 2090$. The PDV of this scenario is -1.9% of GDP, equal in value to the second term in Eq. A.4. The PDV of this permanent shift in the climate is lower than the one-time event that occurs immediately only because it occurs in the distant future and is thus discounted, although the total quantity of additional cyclone risk endured in the second scenario is much larger than in the first scenario. The third generic scenario is a linear intensification of the climate that begins in 2010 and ends in 2090, where the climate stabilizes in 2090 at 1 m/s above its initial risk level in 2010 (see Figure 22 for a graphical example). The PDV of this third scenario is the sum of both terms in Eq. A.4, and its value exceeds in magnitude both the first and second scenarios. With a high discount rate (10%) the cost of this third scenario is only slightly higher in PDV than a single event today (2.3:1.9) because the costs from the gradually intensifying climate are heavily discounted, whereas for a low discount rate (1%) the PDV of this scenario is very large compared to a single event (2382:34) because the quantity of total additional risk is much larger and it is not heavily discounted. At a 5% discount rate the PDV of this scenario is still quantitatively large, amounting to -25.2% of GDP. Panel B of Figure 22 illustrates the timing of losses under this scenario with a 5% discount rate using actual climate values for the United States – most of the loss in PDV arises from the intensification of the cyclone climate that occurs during 2020-2050 because the distant future is still heavily discounted.

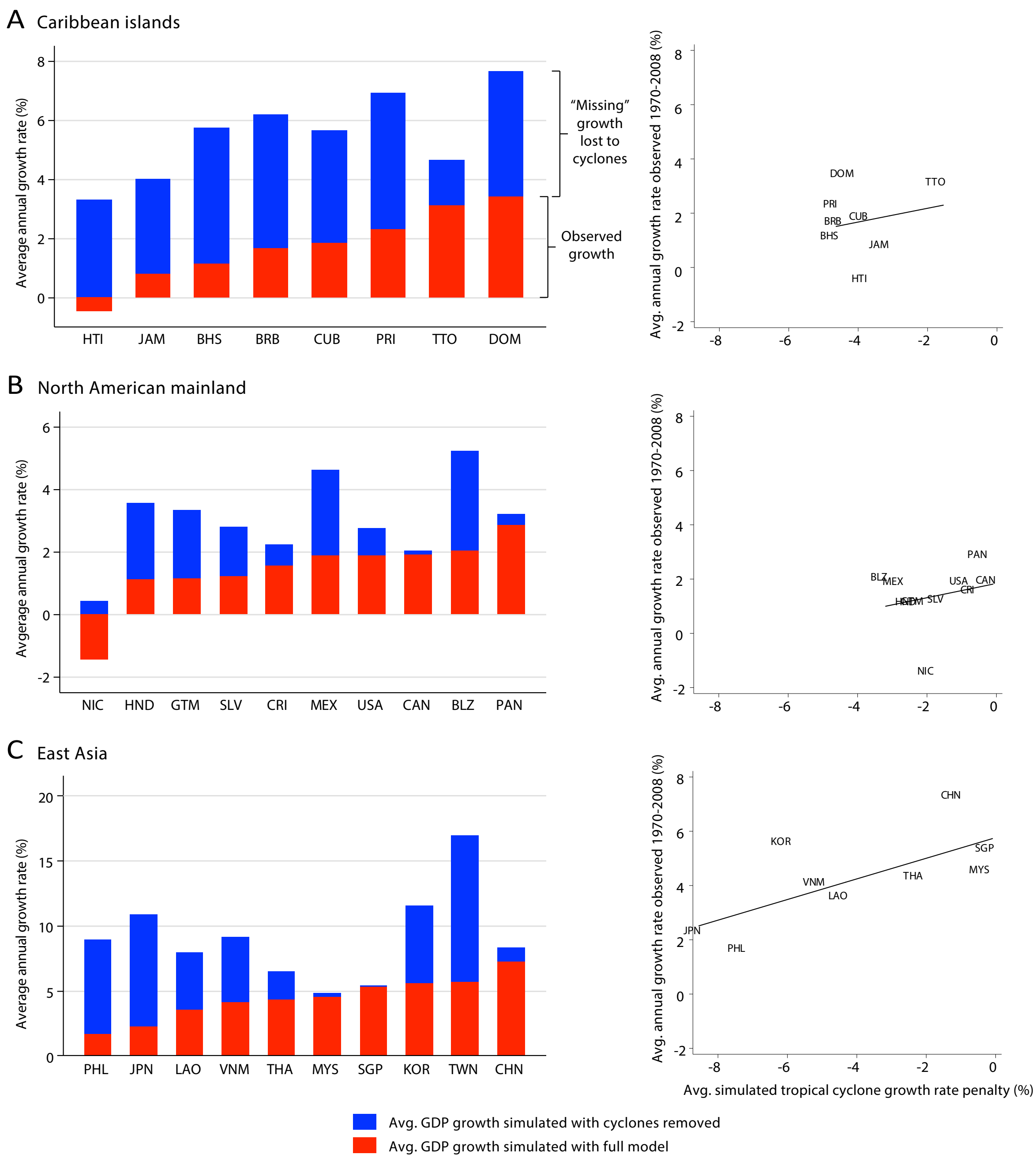
[56]Much literature has discussed what discount rates should be used for climate change projections. A 5% discount rate is at the higher end of the spectrum of values that are advocated, so we focus on it in an effort to be both conservative but reasonable. For a review and perspectives on discount rates, see Gollier (2012).



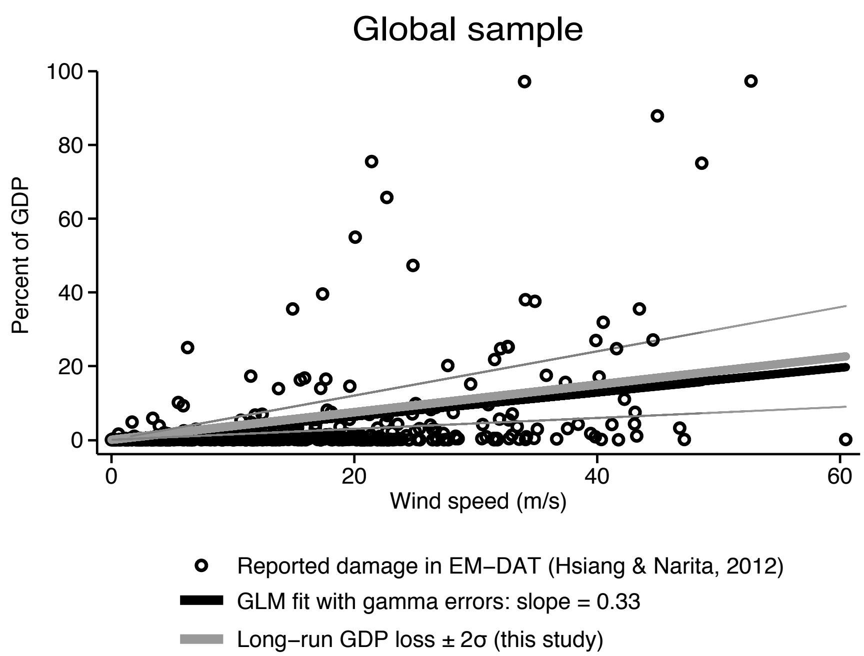
Appendix Figure A.1: Pooled distribution of country-year tropical cyclone exposure. The expected long-run GDPpc loss associated with 5, 10, 20 and 40 m/s storm events are indicated.



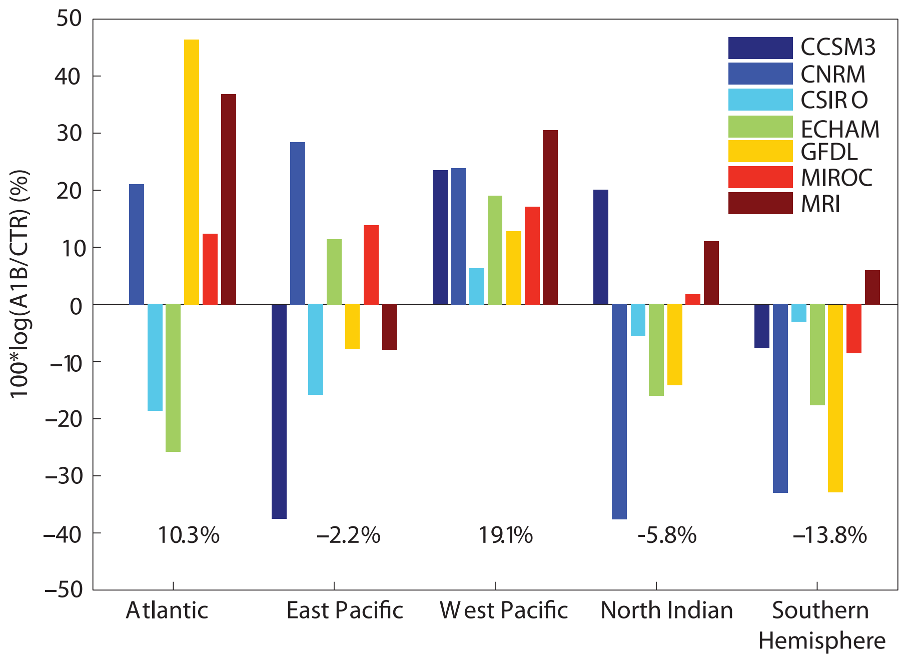
Appendix Figure A.2: A) Long-run marginal cumulative effects estimated with 10 and 15 lags, compared to the main effect estimated with 20 lags. B) Long-run marginal cumulative effects for AR(1)-AR(4) models.



Appendix Figure A.3: Left column: Average annual growth rates as observed historically (red bars, equal to simulated growth with full model) and average growth in simulations where cyclones are removed (blue bars). The difference in the height of the bars is the "missing" average annual growth loss to cyclones. Results for all countries in the simulation are tabulated in Appendix Table A.6. Right column: Within-region cross-sectional regressions of average annual growth rates as historically observed against the growth penalty (i.e. "missing growth") attributable to each country's tropical cyclone climate. Table A.7 reports coefficients and pooled estimates. Taiwan is omitted because it is an extreme outlier.



Appendix Figure A.4: Hsiang and Narita (2012) estimate the relationship between self-reported capital damages and the maximum wind speed measure used in this study.



Appendix Figure A.5: Projections for climatic intensification in basin-wide power dissipation between simulations of the twentieth-century and the period 2080-2100 under the A1B emissions scenario using seven climate models, from Emanuel et al. (2008). Percentages for each basin are the multi-model mean. Models agree strongly on the sign of West Pacific (7/7) and Oceania (6/7) projections. Models disagree more regarding North Atlantic (4/7) and North Indian (4/7) projections. Also see discussion in (Knutson et al. (2010)). Figure from Knutson et al. (2010).

Appendix Table A.1: Summary statistics for key variables in cyclone-exposed countries

Variable	Mean	Std. Dev.	Min.	Max.	N
Economic Characteristics					
Log GDPpc (Penn World Tables)	8.093	1.235	4.913	11.637	4914
Log GDPpc (World Development Indicators)	7.366	1.462	4.084	10.876	4248
Population (thousands)	32864	124191	7	1317066	6017
Small Island Developing State dummy	0.306	0.461	0	1	7905
Below median income (1970) dummy	0.643	0.479	0	1	5508
Physical Characteristics					
Tropical cyclones					
Wind speed (meters per second)	5.869	9.379	0	78.344	7905
Energy (standard deviations)	0.386	†1.271	0	19.41	7905
Log(land area)	9.606	3.984	-1.386	16.101	7905
Latitude (degrees north of Equator)	8.319	19.598	-41.577	59.388	7905

†The standard deviation of standardized *energy* is not equal to one because these summary statistics are computed for exposed countries only.

Appendix Table A.2: Results for all dependent-independent variable pairs

	(1)	(2)	(3)	(4)
Dependent variable	Growth (%)			
Independent variable	Wind speed (m/s)		Energy (sd)	
Growth data source	PWT	WDI	PWT	WDI
Marginal cumulative effect of 1 additional unit of exposure				
1 years	-0.0509**	-0.0241	-0.334**	-0.191
	(0.0208)	(0.0218)	(0.166)	(0.164)
2 years	-0.0584**	-0.0512**	-0.358*	-0.405**
	(0.0259)	(0.0249)	(0.186)	(0.190)
3 years	-0.0876***	-0.0798***	-0.654***	-0.629***
	(0.0303)	(0.0275)	(0.214)	(0.205)
4 years	-0.0903***	-0.105***	-0.688***	-0.844***
	(0.0349)	(0.0292)	(0.242)	(0.221)
5 years	-0.0895**	-0.129***	-0.722**	-1.052***
	(0.0427)	(0.0322)	(0.289)	(0.235)
6 years	-0.0974**	-0.147***	-0.716**	-1.095***
	(0.0473)	(0.0372)	(0.318)	(0.272)
7 years	-0.133**	-0.188***	-0.796**	-1.419***
	(0.0535)	(0.0444)	(0.355)	(0.330)
8 years	-0.197***	-0.232***	-1.118***	-1.746***
	(0.0591)	(0.0488)	(0.392)	(0.358)
9 years	-0.190***	-0.225***	-1.204***	-1.859***
	(0.0647)	(0.0524)	(0.435)	(0.399)
10 years	-0.223***	-0.272***	-1.484***	-2.160***
	(0.0711)	(0.0582)	(0.461)	(0.424)
11 years	-0.257***	-0.297***	-1.695***	-2.316***
	(0.0747)	(0.0623)	(0.486)	(0.457)
12 years	-0.292***	-0.327***	-1.813***	-2.538***
	(0.0797)	(0.0660)	(0.509)	(0.486)
13 years	-0.325***	-0.349***	-1.876***	-2.633***
	(0.0837)	(0.0702)	(0.534)	(0.498)
14 years	-0.364***	-0.368***	-2.033***	-2.761***
	(0.0893)	(0.0772)	(0.571)	(0.542)
15 years	-0.378***	-0.383***	-2.069***	-2.851***
	(0.0938)	(0.0820)	(0.594)	(0.568)
16 years	-0.405***	-0.403***	-2.221***	-3.061***
	(0.0975)	(0.0879)	(0.617)	(0.599)
17 years	-0.398***	-0.415***	-2.153***	-3.146***
	(0.102)	(0.0910)	(0.643)	(0.619)
18 years	-0.384***	-0.419***	-2.038***	-3.142***
	(0.104)	(0.0955)	(0.672)	(0.647)
19 years	-0.383***	-0.387***	-1.909***	-3.037***
	(0.109)	(0.100)	(0.692)	(0.669)
20 years	-0.374***	-0.379***	-1.825**	-3.090***
	(0.113)	(0.105)	(0.733)	(0.700)
Observations	6415	6952	6415	6952
Adjusted R^2	0.144	0.191	0.144	0.191

All models contain country fixed effects, year fixed effects, and country-specific linear trends. Standard errors in parentheses are robust to spatial (1000km) and serial (10-year) correlation. Each column displays coefficents from our model with a different data pairing. Column (1) replicates column (2) of Table A.3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A.3: Long-run growth vs. wind speed with weaker and stronger trend assumptions

	(1)	(2)	(3)
Dependent variable	Growth (%) from PWT		
Independent variable	Wind speed		
Marginal cumulative effects of 1 additional m/s exposure			
5 years	-0.0944**	-0.0895**	-0.0938**
	(0.0392)	(0.0427)	(0.0456)
10 years	-0.211***	-0.223***	-0.215***
	(0.0605)	(0.0711)	(0.0731)
15 years	-0.306***	-0.378***	-0.376***
	(0.0734)	(0.0938)	(0.0986)
20 years	-0.247***	-0.374***	-0.383***
	(0.0854)	(0.113)	(0.122)
Country FE	Y	Y	Y
Year FE	Y	Y	
Region × year FE			Y
Country-specific linear trend†		Y	Y
Observations	6415	6415	6415
Adjusted R^2	0.122	0.144	0.157

Standard errors in parentheses are robust to spatial (1000km) and serial (10-year) correlation. Lagged cumulative effects of wind speed every 5 years are displayed, but effects of all years are estimated. †A country-specific linear trend with country fixed effects in the growth regression translates into a country-specific quadratic trend in cumulative growth (i.e. income). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A.4: Controlling for endogenous economic factors

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Growth (%) from PWT					
Sample restrictions	Pooled exposed and unexposed countries					Exposed only‡
Marginal cumulative effect of 1 additional m/s exposure						
5 years	-0.0895**	-0.0766*	-0.0896**	-0.0826**	-0.0689	-0.0577
	(0.0427)	(0.0430)	(0.0427)	(0.0417)	(0.0420)	(0.0412)
10 years	-0.223***	-0.225***	-0.223***	-0.202***	-0.202***	-0.182***
	(0.0711)	(0.0689)	(0.0711)	(0.0702)	(0.0681)	(0.0681)
15 years	-0.378***	-0.439***	-0.377***	-0.346***	-0.402***	-0.376***
	(0.0938)	(0.0930)	(0.0939)	(0.0930)	(0.0920)	(0.0916)
20 years	-0.374***	-0.512***	-0.373***	-0.322***	-0.453***	-0.411***
	(0.113)	(0.113)	(0.113)	(0.112)	(0.112)	(0.111)
$ln(GDPpc)_{t-1}$†		-14.52***			-14.64***	-13.99***
		(1.541)			(1.543)	(1.506)
$Pop.Growth_{t-1}$			-8.508		-9.101	0.803
			(11.30)		(10.74)	(13.97)
$Openness_{t-1}$				0.0321***	0.0357***	0.0307***
				(0.0110)	(0.0101)	(0.00982)
Observations	6415	6415	6415	6415	6415	3834
Adjusted R^2	0.144	0.206	0.144	0.148	0.211	0.226

All models contain country fixed effects, year fixed effects, and country-specific linear trends. "Exposed" countries are those countries that are ever exposed to tropical cyclones in the sample. Standard errors in parentheses are robust to spatial (1000km) and serial (10-year) correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. †The coefficient on lagged income is larger in magnitude than standard estimates because standard models do no account for country-specific linear trends in growth rates – to verify that standard estimates are obtained when these trends are dropped, see Appendix Table A.5. ‡Dropping countries that are never exposed to tropical cyclones in the sample.

Appendix Table A.5: Convergence behavior with no linear time-trend

	(1)	(2)	(3)	(4)
Dependent variable	Growth (%) from PWT			
Country sample	All	Exposed	All	Exposed
Marginal cumulative effect of 1 additional m/s exposure				
5 years	-0.0944**	-0.0822**	-0.0662*	-0.0570
	(0.0392)	(0.0390)	(0.0396)	(0.0392)
10 years	-0.211***	-0.190***	-0.181***	-0.163***
	(0.0605)	(0.0616)	(0.0608)	(0.0613)
15 years	-0.306***	-0.282***	-0.316***	-0.294***
	(0.0734)	(0.0744)	(0.0740)	(0.0746)
20 years	-0.247***	-0.212**	-0.302***	-0.268***
	(0.0854)	(0.0870)	(0.0856)	(0.0869)
$ln(GDPpc)_{t-1}$			-4.015***	-4.022***
			(0.555)	(0.588)
Observations	6415	3834	6415	3834
Adjusted R^2	0.122	0.150	0.139	0.171

All models contain country fixed effects, year fixed effects, and country-specific linear trends. "Exposed" countries are those countries that are ever exposed to tropical cyclones in the sample. Standard errors in parentheses are robust to spatial (1000km) and serial (10-year) correlation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A.6: Observed and simulated country-specific growth rates with and without cyclones

Country	Prediction with full model* (%)	Prediction with cyclones removed (%)	Cyclone climate growth penalty (%)	Country	Prediction with full model* (%)	Prediction with cyclones removed (%)	Cyclone climate growth penalty (%)
ARG	1.11	1.11	0.00	JOR	0.78	0.78	0.00
AUS	2.12	3.77	-1.65	JPN	2.29	10.84	-8.55
AUT	2.47	2.47	0.00	KEN	0.16	0.16	0.00
BDI	0.65	0.65	0.00	KOR	5.59	11.55	-5.96
BEL	2.25	2.25	0.00	LKA	3.39	5.05	-1.66
BEN	0.50	0.50	0.00	LSO	2.30	2.30	0.00
BFA	1.17	1.17	0.00	LUX	3.54	3.54	0.00
BGD	1.48	4.83	-3.35	MAR	2.29	2.36	-0.07
BOL	0.68	0.68	0.00	MDG	-0.34	4.06	-4.41
BRA	2.02	2.03	0.00	MEX	1.87	4.62	-2.75
BRB	1.67	6.19	-4.52	MLI	2.03	2.03	0.00
BWA	6.36	6.42	-0.06	MOZ	1.35	2.48	-1.13
CAF	-1.26	-1.26	0.00	MRT	0.82	0.84	-0.02
CAN	1.92	2.02	-0.10	MUS	3.90	11.52	-7.62
CHE	1.31	1.31	0.00	MWI	0.19	0.36	-0.17
CHL	2.60	2.60	0.00	MYS	4.54	4.79	-0.25
CHN	7.30	8.38	-1.08	NAM	0.87	0.90	-0.03
CIV	-0.17	-0.17	0.00	NER	-0.54	-0.54	0.00
CMR	0.96	0.96	0.00	NGA	1.28	1.28	0.00
COG	1.49	1.49	0.00	NIC	-1.43	0.43	-1.87
COL	2.44	2.48	-0.04	NLD	2.00	2.00	0.00
COM	-0.54	1.78	-2.32	NOR	2.81	2.81	0.00
CPV	2.74	4.96	-2.23	NPL	1.34	1.53	-0.19
CRI	1.56	2.23	-0.66	NZL	1.31	2.62	-1.31
CYP	3.09	3.09	0.00	PAK	2.10	2.27	-0.17
DNK	1.86	1.86	0.00	PAN	2.86	3.20	-0.34
DOM	3.42	7.64	-4.22	PER	1.00	1.00	0.00
DZA	1.27	1.27	0.00	PHL	1.65	8.93	-7.28
ECU	1.86	1.86	0.00	PNG	1.90	2.17	-0.27
EGY	3.37	3.37	0.00	PRI	2.29	6.93	-4.64
ESP	2.34	2.51	-0.17	PRT	2.82	3.22	-0.40
ETH	0.78	0.79	-0.01	PRY	1.70	1.70	0.00
FIN	2.57	2.57	0.00	RWA	0.65	0.65	0.00
FJI	1.70	6.24	-4.54	SEN	0.53	0.93	-0.40
FRA	1.94	1.99	-0.05	SGP	5.33	5.42	-0.09
GAB	0.60	0.60	0.00	SLE	-0.14	-0.13	-0.01
GBR	2.12	2.12	0.00	SLV	1.23	2.79	-1.57
GHA	1.40	1.40	0.00	SWE	1.83	1.83	0.00
GIN	-0.25	-0.19	-0.06	SYC	4.44	5.79	-1.35
GMB	1.21	1.72	-0.51	SYR	1.53	1.53	0.00
GNB	1.95	2.36	-0.42	TCD	0.80	0.80	0.00
GNQ	8.90	8.90	0.00	TGO	-1.46	-1.46	0.00
GRC	2.34	2.34	0.00	THA	4.31	6.48	-2.17
GTM	1.14	3.33	-2.19	TTO	3.12	4.66	-1.55
HKG	4.49	14.74	-10.25	TUN	2.80	2.80	0.00
HND	1.13	3.54	-2.41	TUR	2.26	2.26	0.00
HTI	-0.46	3.33	-3.79	TWN	5.69	16.88	-11.19
IDN	4.06	4.17	-0.10	TZA	1.54	1.57	-0.02
IND	3.18	4.75	-1.57	UGA	0.77	0.77	0.00
IRL	3.33	3.33	0.00	URY	2.13	2.13	0.00
IRN	0.80	0.80	0.00	USA	1.89	2.76	-0.88
ISL	2.98	2.98	0.00	VEN	0.42	0.59	-0.18
ISR	2.02	2.02	0.00	ZAF	1.12	1.14	-0.02
ITA	1.96	1.96	0.00	ZMB	-0.57	-0.57	0.00
JAM	0.81	4.00	-3.19	ZWE	-0.82	-0.59	-0.23

*By construction, observed growth rates are the same as predictions with the full model.

Appendix Table A.7: Cyclone climate as a predictor of average growth

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Average annual growth rate observed 1970-2008 (%)					
Independent variable	Simulated growth penalty from cyclone climate (%)					
Cross sectional coefficient	0.382***	0.358***	0.259	0.254	0.263	0.380***
	[0.127]	[0.133]	[0.274]	[0.827]	[0.411]	[0.143]
Observations	34	27	18	8	10	9
Whithin-region R^2	0.275	0.265	0.053	0.044	0.061	0.479
	Regions in sample					
East Asia	Y	Y				Y
N. America mainland	Y	Y	Y		Y	
Caribbean islands	Y	Y	Y	Y		
S. Asia	Y					
Oceania	Y					

Regressor is the average difference between annual growth predicted with the full model and the model where tropical cyclone exposure is set to zero. Models with more than one region in the sample include region fixed effects. Observed growth rates are from the PWT. Also see Figure A.3. Bootstrapped standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A.8: PDV of changes to the global tropical cyclone climate under generic climate changes

	PDV as percentage of current GDP				
Discount rate:	1.0%	3.0%	5.0%	7.0%	10.0%
Generic climate scenarios (standard errors in parentheses)					
A single +1 m/s tropical cyclone event today	-34.49 (-10.39)	-9.86 (-2.97)	-5.12 (-1.55)	-3.20 (-0.98)	-1.86 (-0.58)
An abrupt +1 m/s climate intensification in 2090	-1549.93 (-466.84)	-29.81 (-8.97)	-1.88 (-0.57)	-0.17 (-0.05)	-0.01 (0.00)
A linear climate intensification to +1 m/s in 2090†	-2382.10 (-717.49)	-124.95 (-37.61)	-25.19 (-7.63)	-8.13 (-2.49)	-2.32 (-0.73)