The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth*

Solomon M. Hsiang† | **Amir S. Jina**‡

UC Berkeley | Columbia University

NBER | UC Berkeley

Abstract

Do natural disasters have a causal effect on economic development? Reconstructing every country's physical exposure to the universe of tropical cyclones during 1950-2008, we exploit year-to-year variation in cyclone strikes to identify the effect of disasters on long-run growth. The data reject long-standing hypotheses that disasters stimulate growth via "creative destruction" 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. This result is globally valid, holding for countries of all types, and is supported by non-income variables as well as global patterns of climate-based adaptation. National income loss arises 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.

PRELIMINARY DRAFT

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†Email: shsiang@berkeley.edu

‡Email: asj2122@columbia.edu

1 Introduction

Natural disasters occupy a unique position in our collective consciousness, commanding tremendous attention from the public, the media, policy-makers and historians. However, despite this interest, we know very little about their long-term impact on societies. Here we examine whether one of the most frequent forms of disasters, tropical cyclones, have a long-run effect on economic development. The short-run effect of disasters on income growth has been widely studied (e.g. Hsiang (2010); Strobl (2011); Deryugina (2011)), but credibly identifying a long-run effect remains an unsolved challenge.

In this paper, we exploit year-to-year variation in each country's physical exposure to cyclones to identify their long-run impact on economic growth. Using this approach, we obtain estimates that are both economically large and statistically precise: each additional meter per second[1] of wind exposure lowers 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.

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. Figure 1 schematically illustrates these hypotheses:

1. The **"creative destruction" hypothesis** (I in Figure 1) 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); United Nations and World Bank (2010)). This notion is partially supported by Belasen and Polachek (2008), Hsiang (2010) and Deryugina (2011) who find that short-run output in the construction industry may rise after disaster, presumably because demand rises, however this effect is short-lived (1-2 years) and does not seem to influence the broader economy.

2. The **"build back better" hypothesis** (II in Figure 1) argues that growth may suffer initially, since lives may be lost and productive capital destroyed, however the gradual replacement of these 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); United Nations and World Bank (2010); Field et al. (2012)). Similarly, it has also been argued that the loss of physical capital encourages households to invest relatively more heavily in human capital since it is more durable, improving prospects for long-run growth (Skidmore & Toya (2002)); although recent evidence suggests that human capital investments may actually decline in the wake of disaster (Maccini and Yang (2009); Banerjee, Duflo, Postel-Vinay and Watts (2010); Anttila-Hughes and Hsiang (2011)).

3. The **"recovery to trend" hypothesis** (III in Figure 1) 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 critical rebound may

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

occur because the marginal product of capital will rise when capital and labor become relatively scarce after disaster, causing individuals and wealth to migrate into devastated locations until output recovers to the regional trend (United Nations and World Bank (2010); Miguel and Roland (2011)). Strömberg (2007), Yang (2008) and Deryugina (2011) observe that natural disasters tend to cause transfers of wealth into the affected region, providing support to the logic underlying this hypothesis, however the long-run effect of these transfers on growth is unknown. Smith, Carbon, Pope, Hallstrom and Darden (2006), Vigdor (2008), Belasen and Polachek (2009), Hornbeck (2009), Strobl (2011), and Boustan, Kahn and Rhode (2012) provide evidence that changes in wages and population movements within the United States may be triggered by natural disaster, but their collective support for this hypothesis is ambiguous since wage increases and population inflow occur roughly as often as decline and outflow. Davis and Weinstein (2002) and Miguel and Roland (2011) find support for this hypothesis in the context of wartime bombing, however wars are unlikely to be good analogs for natural disasters because they are triggered endogenously, a person (the enemy) can be unambiguously blamed as the proximate cause of destruction, and, most importantly, they occur only once.

4. Finally, the **"no recovery" hypothesis** (IV in Figure 1) argues that disasters temporarily slow growth by destroying capital, but no rebound occurs because the various recovery mechanisms above fail to outweigh the direct negative effect of losing capital (United Nations and World Bank (2010); Field et al. (2012)). In addition to the direct impact of capital losses, it is also thought that disasters may generate enduring economic impacts by permanently altering the preferences of affected individuals (Banerjee and Mullainathan (2010); Cameron and Shaw 2011), by motivating populations to irreversibly disinvest in durable human or physical capital (Udry (1994); Jacoby and Skoufias (1997); Duflo (2000); Maccini and Yang (2009); Banerjee, Duflo, Postel-Vinay and Watts (2010); Anttila-Hughes and Hsiang (2011)) or by triggering political actions that have lasting economic consequences (Besley and Burgess (2002); Healy and Malhotra (2009); Burke et al. (2009); Burke (2012); Hsiang, Meng and Cane (2011)). According to this hypothesis, post-disaster output may continue to grow, however it remains permanently lower than its pre-disaster trajectory.

Recent reviews of the literature argue that the long-run effect of disaster remains a central open question because it directly informs the design of domestic and international policies governing post-disaster recovery, pre-disaster risk management, economic development in disaster-prone environments and global climate change; yet recent attempts have not convincingly demonstrated whether any of the four hypotheses above hold generally (United Nations and World Bank (2010); Cavallo and Noy (2011); UNISDR (2011); Kellenberg and Mobarak (2011); Field et al. (2012)). Skidmore and Toya (2002) used cross-sectional correlations to argue that disasters are beneficial for a country's long-run growth, supporting the "creative destruction" and "build back better" hypotheses. However the associations that they estimate are undoubtedly affected by omitted variables bias, so it is difficult to know if they represent a causal relationship (Holland (1986), Freedman (1991), Green (2003), Angrist and Pischke (2008)). In an effort to address this issue, recent work by Raddatz (2009) and Cavallo, Galiani, Noy and Pantano (2010) exploit year-to-year variation of self-reported disaster exposure to estimate the growth effect of disaster during the ten years that follow. Both studies suggest that growth effects over this window tend to be negative in the short-run, however their long-run estimates are imprecise and cannot distinguish between the "build back better", "full recovery" or "no recovery" hypotheses. This failure to eliminate hypotheses is theoretically unsatisfying, however the indeterminacy is likely to be resolved with better data. The quality of these estimates is affected by the endogenous nature of their independent variables: self-reported disaster counts and losses, respectively, taken from the Emergency Events Database (EM-DAT). 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 (2012a)), factors which also affect growth and thus might confound these results. Furthermore, recent comparisons of the EM-DAT file to geophysical records indicates that it is contaminated by extraordinarily large temporal biases that arise from rapidly changing disaster-monitoring networks (Hsiang and Narita (2012b)).

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, typhoons, cyclones and tropical storms, and use a physical model to simulate 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[2].

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. These results allow us to conclusively reject the "creative destruction", the "build back better" and the "recovery to trend" hypotheses, leaving only the "no recovery" hypothesis unfalsified. Our conclusion that no recovery occurs is robust, passing numerous specification and data checks, and strikingly general: we observe "no recovery" 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. Furthermore, the long-run response of alternative macroeconomic measures, as well as evidence of climate-based adaptation, corroborate this central finding.

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

[2] Our approach is identical to the "ideal but unattainable" method outlined by Noy (2009), who used EM-DAT data as an independent variable and simply 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

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 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 (PDV, using a 5% discount rate) of losses rise by 6% of current GDP for the United States, 13% of GDP for China, 17% of GDP for Mexico, 73% of GDP for South Korea, 83% of GDP for the Philippines and 102% of GDP for Japan. In total, 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.

Background on 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[3]. Roughly 35% of the global population is seriously affected by tropical cyclones (Hsiang and Narita (2012b)), 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[4], 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 critically on the unpredictable year-to-year variation in the intensity of each country's cyclone exposure.

To identify the effect of cyclones on growth, we index total cyclone exposure according a location's exposure to cyclone-induced winds. Intense winds at the core of a storm are one of its most destructive features, however the wind field generates heavy rainfall as well as sea level surges along the coast, both of which may cause substantial damage. We do not characterize countries' exposure to these other processes because they are more heavily influenced by idiosyncratic geographic features, making them more difficult to model. However, in our econometric analysis, our indices of wind exposure will capture the effects of these other processes to the extent that they are correlated with surface winds.

2 Data

Our central innovation is our construction of a novel data file describing physical measures of cyclone exposure, which we link to standard macroeconomic datasets. Because macroeconomic data are available at the country-by-year level, linking it to cyclone data requires that cyclone exposure be aggregated across storms within a year and across locations within a country. We follow the approach of Hsiang (2010) and compute cyclone exposure *per unit area* so that exposure levels in countries of different physical sizes will be properly scaled. Converting cyclone exposure to a scale-free intensive variable is theoretically consistent with our use of the standard *per capita* normalization for macroeconomic variables, which produces similarly scale-free variables[5] (see Appendix Figure A.1 for a graphical

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

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

[5]Hsiang and Narita (2012a) derive a theoretical justification for this approach.

explanation). Using intensive 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 (2012a); Hsiang and Narita (2012b)) and at the level of both provinces and larger administrative regions using Filipino household data (Anttila-Hughes and Hsiang (2011)). As one would expect when using scale-free intensive variables, in all of these cases the estimated effect-sizes were invariant in the geographic size of the observational units.

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

Tropical cyclone data

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, Kruk, Levinson, and Gibney (2009)) as a translating vortex using the Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model developed in Hsiang (2010). LICRICE reconstructs cyclone wind fields, adjusting their shape and amplitude based on the observations in IBTrACS and parametrizations developed in the atmospheric sciences. Figure 2 displays an example snapshot of a cyclone wind field reconstructed by LICRICE and Figure 3 illustrates how LICRICE uses this wind field to reconstruct a country's surface-level exposure during a single storm event.

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 point observations that are recorded every six hours for each storm (Appendix Figure A.2 displays the raw reconstruction data for every year over the entire globe). When we average pixel-level exposure across all 59 years of data, we recover the "cyclone-climate" of each pixel, which we display in Figure 4. 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. Mali) because tropical cyclones are driven towards land by the westward blowing winds that dominate atmospheric circulations over regions where these storms form.

We utilize two wind indices, based on 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[6]. Storms with more intense winds dissipate more energy, as do storms that remain at a fixed location for long periods of time. 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 quantity. However, the units are the relatively unintuitive *meters-cubed per seconds-squared*

[6]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)).

(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") experienced over the course of all storms in a given year, which was first introduced in Hsiang and Narita (2012a). 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[7]. 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.

Both wind speed and energy are spatially averaged[8] over all pixels in a country[9], so the country-by-year statistics are substantially less extreme than the exposure one would measure within the most violent regions of a storm. Figure 5 displays the distribution of country-by-year wind speed observations for each year[10], illustrating both the within-country variation that we use to identify cyclone impacts as well as cross-country variation in cyclone-climates. 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 (2012a), probably because its distribution is less skewed than energy. For related reasons but in different contexts, Hsiang and Narita (2012b) 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. For reference, Hsiang and Narita (2012b) provides documentation of both wind speed and energy at both the pixel and country-by-year level.

Economic data

We obtain gross domestic product (GDP) data for 1970-2008 from the Penn World Tables[11] (PWT) (Summers and Heston (1991)) as well as the World Development Indicators (WDI) file (World Bank (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. We also obtain various other macroeconomic measures from the WDI file (see Table 1).

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

[8] 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. 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.

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

[10] Figure A.3 shows the same distribution differentiated by specific countries.

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

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 (2012)), 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)).

3 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 a linear convolution of contemporaneous and historical tropical cyclone exposure S out to a maximum lag length k. 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 (2001)). 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[12] (Barro and Sala-i-Martin (2003)). 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 temperature (Hsiang (2010)). Indexing countries by i and years by t, this approach leads us to the flexible and parsimonious model:

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

where the parameters of interest are the coefficients β. We estimate Equation 1 using ordinary least squares (OLS) and follow 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 (Conley (1999)). Because the timing, location and intensity of cyclone exposure is unpredictable and stochastic across years, we assume that S is exogenous, allowing the coefficients β to be identified. Furthermore, it is unlikely that social, political or economic events within a country systematically influence our measurement of cyclone exposure because the LICRICE reconstruction of S primarily relies on satellite observations.

We estimate Equation 1 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 1, we construct the cumulative effect

[12] Including both a country fixed effect and a country-specific trend in a growth regression allows the trajectory of income in each country to exhibit an independent intercept, an independent slope and an independent curvature.

of a cyclone j years after exposure via the summation

$$\Omega_j = \sum_{L=0}^{j} \beta_L. \tag{2}$$

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 1 with fewer lags and focusing only on the years during and just following cyclone exposure (Albala-Bertrand (1993); Benson and Clay (2004); Caselli and Malhotra (2004); Horchrainer (2009); Loayza Olaberria, Rigolini and Christiaensen (2009); Dercon and Outes (2009); Noy (2009); Fomby, Ikeda and Loayza (2009); Belasen and Polachek (2009); Raddatz (2009); Hsiang (2010); Cavallo, Galiani, Noy and Pantano (2010); Strobl (2011); Deryugina (2011)). 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, our second essential innovation is to examine a model that spans two full decades ($k = 20$), the longest lag length for which our estimates seem reliable (given that our panel is only 39 years long) and for which we do not have to drop any observations (since our cyclone data reconstruction begins in 1950). We have experimented with shorter (down to 5 years) and longer (up to 30 years) maximum lag lengths (k) and observe no appreciable change in our results.

4 Results

We first establish that tropical cyclones have a large and robust negative effect on long-run GDP. 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.

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

The first panel of Figure 6 presents our main result: the long-run effect of tropical cyclones on GDP relative to a country's pre-disaster baseline trend[13]. The plot depicts $\Omega_{t\in[-5,20]}$ after Equation 1 is estimated using OLS. 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 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,

[13] 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.

generating a loss of $9.4 \times 0.38 = 3.57$ percentage points two decades later. A "one-in-ten" country-year event[14] 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%. To succinctly summarize the size of our main result and the frequency of these storms, Figure 7 displays the distribution of country-by-year cyclone observations[15] 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" or "build back better") or recover to their pre-disaster trajectory ("recovery to trend") within twenty years. 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 specifications, alternative data sets, randomization tests, and subsampling of our data.

Nonparametric time controls In order to produce any 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 or if we introduce region-by-year fixed effects, as shown in columns 1 and 3 of Table 2. 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 effects and country-specific trends (column 2 of Table 2) 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 6.

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 6 presents these alternative estimates. Under all four pair-wise combinations of the data, we obtain essentially the same result, although estimates using energy as the independent variable tend to have smaller standard errors. We present exact parameter estimates for several lags in Table 3 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

[14] The 90th percentile in wind speed is 19.5 m/s and the 99th percentile 39.2 m/s.
[15] For country-specific distributions, refer to Figure A.3.

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.

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 1. 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 1-2. We conduct this randomization in three different ways (see Appendix Figure A.4 for a graphical explanation):

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 8 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 1 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 (2012a) 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. Yet when Hsiang (2010) and Antilla-Hughes and Hsiang (2011) use LICRICE to examine short-run income losses at the national and household level, they find that both are linear in energy and wind speed, respectively. As it remains unexplained why immediate damages from storms should be nonlinear when income loss is linear[16] it is important that we examine whether our *linear* model of long-run growth is justified. To test the linearity of the long-run growth effect,

[16] 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.

we separately estimate the marginal effect of cyclone exposure within three different exposure levels of wind speed: 0–10, 10–20 and > 20 m/s. Figure 9 displays the long-run marginal effect of cyclone exposure for all three types of events. These estimates are somewhat noisier than earlier estimates, since the number of storm events underlying each estimate is one-third of the original sample and the variance in the independent variable is smaller, however the point estimates are near one another and we see no significant or systematic changes in these marginal effects as storm intensity grows. The long-run growth effect of cyclone exposure appears to be approximately linear in cyclone intensity.

Climatological controls We include a variety of controls for time-varying characteristics of countries and find no evidence that they affect our results. We are particularly concerned about climatological confounders (Auffhammer, Hsiang, Schlenker and Sobel (2012)), since the intensity and distribution of tropical cyclones are influenced by global climatic patterns that also may affect economic outcomes[17]. In Table 4 we account for country-level exposure to changes in temperature and rainfall and find that neither significantly influences our estimates. Accounting for climatological controls systematically increases the magnitude of the long-run growth effect ($< 20\%$), but this adjustment is not statistically significant. In Table 4, we present estimates for both the full sample of countries as well as for a sample that is restricted to only those countries that are ever hit by tropical cyclones ("exposed"), to check whether the influence of climatological controls changes between exposed and unexposed countries. The results in both samples are essentially identical.

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[18], 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. Thus, we only present these results as a robustness check and do not think that they should be interpreted causally. In Table 5 we account for lagged income[19], population growth and trade openness, and find that our parameter estimates remain virtually unchanged.

Subsamples of the data In Figure 10, we check whether specific subgroups of countries are driving our result and find that our estimates are globally generalizable. 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 in the first panel where we divide countries into terciles based on their surface area (km^2) and observe that their long-run growth responses are all similar to the average response (the largest countries exhibit a positive point estimate for intermediate lag lengths, but none of these estimates are statistically significant). In the second panel we stratifying the sample according to whether they are above and below the median income in 1970, however we find

[17] 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)).

[18] For examples, see Sachs, Warner, Aslund and Fischer (1995), Barrow (1998) and Sala-i-Martin (1997).

[19] 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, something which is not done in traditional models. In Appendix Table A.1, we demonstrate that if we remove these country-specific trends from the model then we obtain more familiar estimates for convergence rates.

that the two groups respond almost identically. In the third 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 (2012a), that the response to cyclones in these three geographic regions are similar.

Other long-run macroeconomic impacts of 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 1-2 replacing GDP with other microeconomic variables. We plot the long-run effects Ω in the panels of Figure 11. 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 the top panel of Figure 11, 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 (2012a)), but we lack the data to test this hypothesis.

Consumption and Investment If populations insure themselves, they may smooth their consumption to insulate themselves from transient income losses[20] (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 the lower panel of Figure 11, we observe this pattern: the magnitude and dynamics of the consumption response closely matches that of the income response. Figure 11 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 12, 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 should have no effect on distant economies that consume exported goods[21].

[20] It is worth noting that recent evidence from the Philippines indicates that households struggle to smooth consumption across the transient component of cyclones-induce 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)).

[21] 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

Government reserves Government reserves decline in the long-run (Figure 12); 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); UNISDR (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 12, 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[22].

Evidence of adaptation to disaster-prone environments

As illustrated in Figure 4, 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 (2012a)). 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[23]. 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 actually strikes. Denoting a country's optimal level of adaptive effort e^* and income Y, the above logic predicts

$$\frac{\partial e^*}{\partial \bar{S}} > 0 \tag{3}$$

production of exports temporarily declines, similar to the temperature-related findings of Jones and Olken (2010).

[22]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."

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

where $\bar{S}$ is expected storm exposure, a summary statistic for a location's typhoon-climate[24]. 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

$$\frac{\partial}{\partial e} \cdot \left(-\frac{\partial Y(e)}{\partial S}\right) < 0. \tag{4}$$

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 $\Omega = \partial Y/\partial S$, we can multiply Equations 3 and 4 to obtain

$$\frac{\partial}{\partial \bar{S}} \cdot \frac{\partial Y(e^*)}{\partial S} = \frac{\partial \Omega(e^*)}{\partial \bar{S}} > 0 \tag{5}$$

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 (2012a).

Cross-Sectional Evidence of Adaptation We test Equation 5 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 1-2 for each quintile separately and display the marginal long-run growth effect of disaster ($\partial\Omega(e^*)/\partial S$) in Figure 13. Consistent with Equation 5, 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.

Before continuing, it is important to note that 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 6. This has two implications. First, the average effect presented in Figure 6 basically describes the effect of cyclones on the highly adapted and regularly exposed populations[25], so it is a good approximation for the average economic impact of most cyclones observed on the planet. Second, 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

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

[25] 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.

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 $e^{\star}$ (Hsiang and Narita (2012a)).

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 illustrated in Figures 4 and A.3, 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 14 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 6), so detecting the cumulative effect of cyclones by visually examining GDP time-series should be nearly impossible. Consider Figure 14: 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 have no 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 1) 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 1

$$\Delta \ln(GDP)_{i,t} = f(\mathbf{S_{i,t}}) + g_{i,t} + \epsilon_{i,t}, \tag{6}$$

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 (Table 2, column 2), we predict "actual" historical growth for each country by using all the terms of Equation 6. We then construct a "cyclone-free" growth history for each country by dropping $f(.)$ from the model while keeping g unchanged[26]. 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 15 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 that face a variety of cyclone climates[27] (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

[26]This is equivalent to setting storm exposure $S_{i,t} = 0$ for all observations, since f is linear in S.

[27]Equation 6 predicts the long term evolution of income well (when all terms are retained), regardless of the cyclone climate in each country. Results are presented for all countries with non-missing 1970 GDP in Appendix Figures A.5-A.6.

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 on their average growth rate in Appendix Table A.2.

We summarize the total effect of cyclones on global economic growth in Figure 16 where the top panel plots the distribution of annual country-by-year growth rates with and without cyclones included in the model. 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 the lower panel of Figure 16. 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[28] and without cyclones – the difference between these two numbers is growth that is "missing," which we attribute to each country's cyclone climate. In Figure 17 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 (also see Appendix Figure A.7). 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

[28] 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.

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 Figure 18 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 Table 6 we present coefficients for this regression, including region fixed effects to account for the large differences in average growth rates between regions. In this simple cross-sectional model, average growth tends to fall 0.38% per year for each 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[29] (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 may be unobservable factors that limit growth in certain countries, so it may be impossible for some countries 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) 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.

Comparisons with previous studies

While several studies have examined different impacts of disasters, few can be directly compared to our results. However, two prior studies combine cyclone metrics from LICRICE with alternative data

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

sets to examine short-run economic losses, so we use these earlier studies as benchmarks to consider whether the size of our estimates are reasonable. Hsiang and Narita (2012a) examine how the direct, self-reported, short-run economic damages in the Emergency Events Database (EM-DAT) respond to country-level maximum wind speed in a global sample of countries. A linearization of their result indicates that direct, short-run damages increase by roughly 0.33% of GDP per m/s on average, which is similar in magnitude to our estimate of 0.37% of GDP per m/s in long-run losses (Figure 19, top panel). Anttila-Hughes and Hsiang (2011) examine household data from the Philippines to identify short-run income losses using province-by-year variation in wind speed. They estimate that an average household suffers short-run income losses of 6.6% in the average year, which is similar in magnitude to the average 7.5% annual loss of long-run income that we estimate the Philippines suffers as a country (Figure 19, lower panel). Without a theory relating short and long-run income losses after disaster, we refrain from speculating whether the short-run losses identified in these two earlier studies represent the exact same income losses that we observe in this study. However, the *magnitude* of the short and long-run losses are similar, suggesting that the long-run estimates we present here may be reasonably sized.

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 (2012a)). 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[30]. However, these statistics are global statistics and stronger patterns are expected at the basin level in some cases. For example, there is relatively 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 the "business as usual" scenario (A1B).

Valuing an altered income trajectory caused by an altered cyclone climate

Above 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 $t+j$. We did not have enough data to observe income losses more than twenty years after a cyclone event[31], so here we assume that income loss is permanent, thus $\Omega_s = \Omega_{20}$ for all $s \geq 21$. Let there be a discount rate ρ.

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

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

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

$$S(t) = S_0 + \delta(t) \tag{7}$$

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 that is unaffected by climate change with a similar income stream that is affected by climate change. 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

$$PDV[Y(S_0) - Y(S(t))] = PDV[\partial Y/\partial S \times \delta(t)] \tag{8}$$

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:

$$\kappa = \left[\sum_{j=0}^{20} \Omega_j e^{-\rho j}\right] + \frac{\Omega_{20}}{\rho} e^{-21\rho}. \tag{9}$$

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

$$PDV[\partial Y/\partial S \times \delta(t)] = \int_{T_1}^{T_2} \kappa\delta(t)e^{-\rho t}dt + \frac{\kappa\bar{\delta}}{\rho}e^{-T_2\rho}. \tag{10}$$

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 $t = T_2$.

Generic climate scenarios Table 7 describes the PDV of changes to the current tropical cyclone climate under several different discount rates – here we focus on the 5% discount rate for succinctness[32]. In the top panel, 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. 9). This value is sizable because income losses from a single event are permanent relative

[32] 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 perspectives on discount rates, see (**?**).

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. 10. 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 Appendix Figure A.9 for a graphical example). The PDV of this third scenario is the sum of both terms in Eq. 10, and its value exceeds in magnitude of 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[33].

Application to the A1B "Business as usual" scenario To apply quantities to Equation 10, 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.8 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[34]. 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[35].

The lower panels of Table 7 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 is 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[36] (right column). Anthropogenic climate change is expected to cause moderate intensification of North Atlantic cyclone activity[37] (+10.3%), which has a sizable negative NPV for many countries (we again focus on the 5% discount rate). Caribbean islands lose the largest

[33]Panel B of Appendix Figure A.9 illustrates the timing of losses under this scenario with a 5% discount rate – 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.

[34]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.

[35]Appendix Figure A.9 provides a schematic for how estimates from Emanuel et al (2008) are converted to a cyclone climate trajectory, which is then valued at each moment in time.

[36]These estimates are a linear rescaling of the third generic scenario (Eq. 10) where $\bar{\delta}$ is set to the fractional intensification of basin-level activity times each country's baseline climatology.

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

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 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[38] (+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.

5 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 (United Nations and World Bank (2010); Cavallo and Noy (2011); UNISDR (2011); Kellenberg and Mobarak (2011); Field et al. (2012)). 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

[38] 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.8.

the 3.8% growth that we would observe in a counterfactual world that had no tropical cyclones[39]. Taken together, these results suggest that the global tropical cyclone climate are likely to play an important role in determining the global distribution of countries' growth rates as well as the global rate of economic 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 13 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

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

effectively undoes 1.8 year's worth of economic development[40]. 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 13) and elsewhere (Hsiang & Narita (2012a), 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 (2012a)). 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)), however these recent efforts have focused exclusively 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[41]) the PDV of lost long-run growth is \$855 billion for the United States (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)[42] – values for other countries are tabulated in Appendix Table A.3. 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

[40] 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.

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

[42] 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.

trillion[43]. 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 these particular countries more strongly than they influence optimal global policy.

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

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FIGURES & TABLES

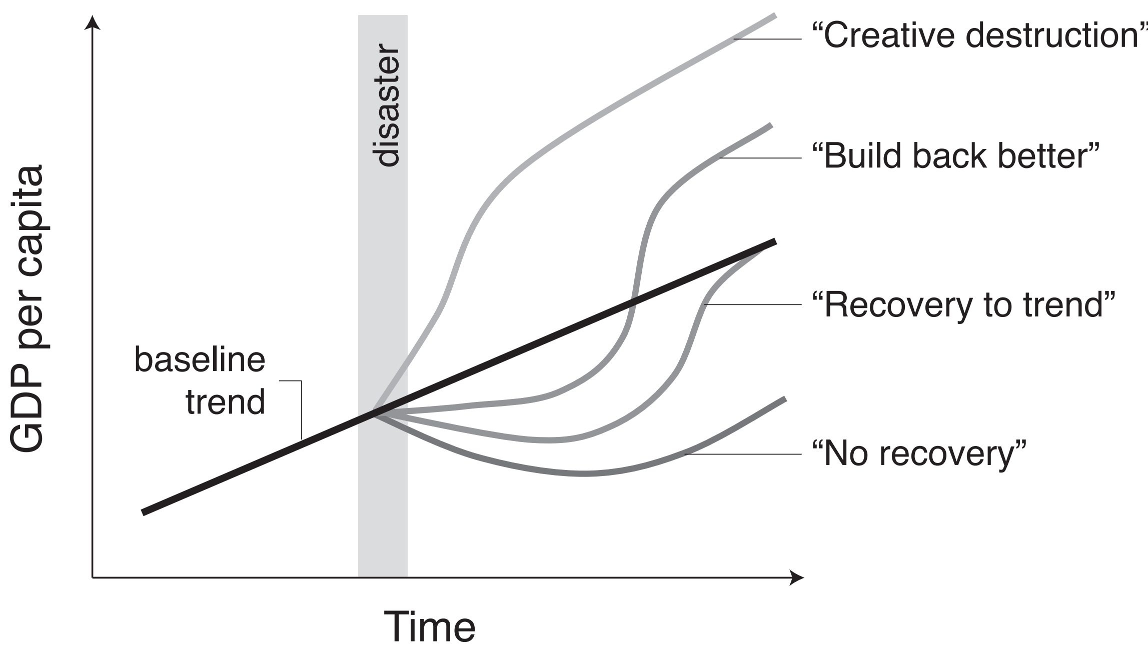


Figure 1: Four hypotheses, proposed in the literature, that describe the long-term evolution of GDPpc following a natural disaster.

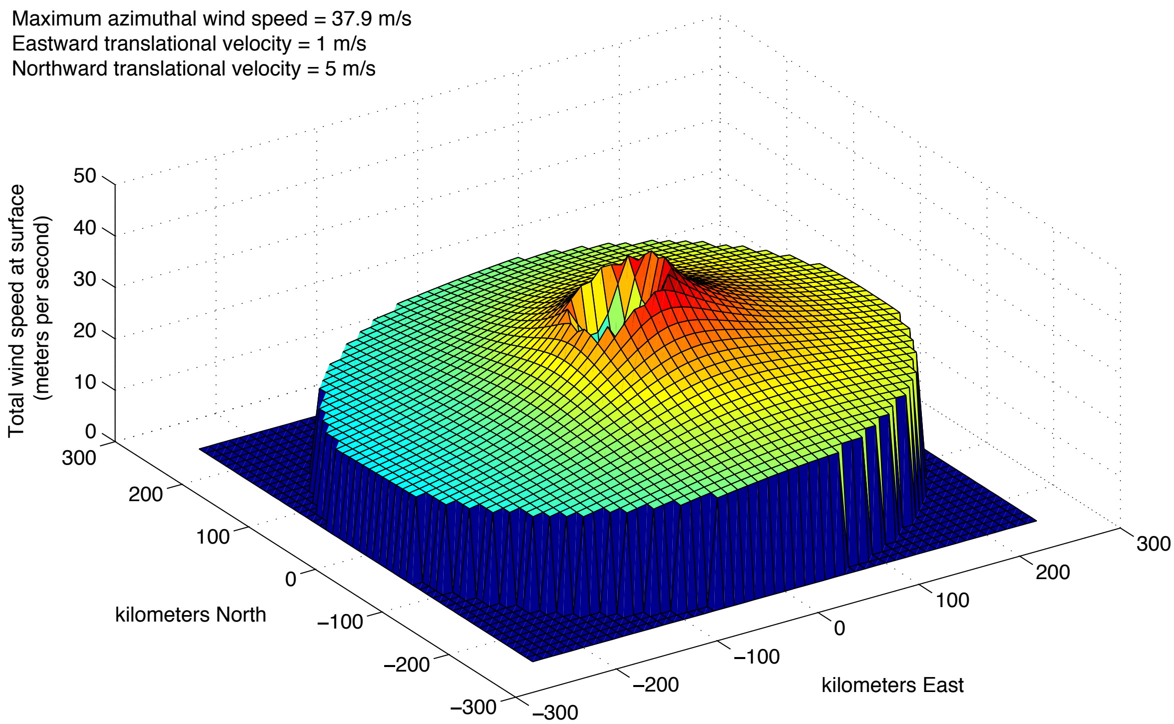


Figure 2: An example of the physically derived wind field used in the LICRICE model to reconstruct surface-level exposure to tropical cyclone winds. The wind field is parametrized using meteorological observations from the IBTrACS dataset. This particular example is a Category 1 storm traveling north-northeast.

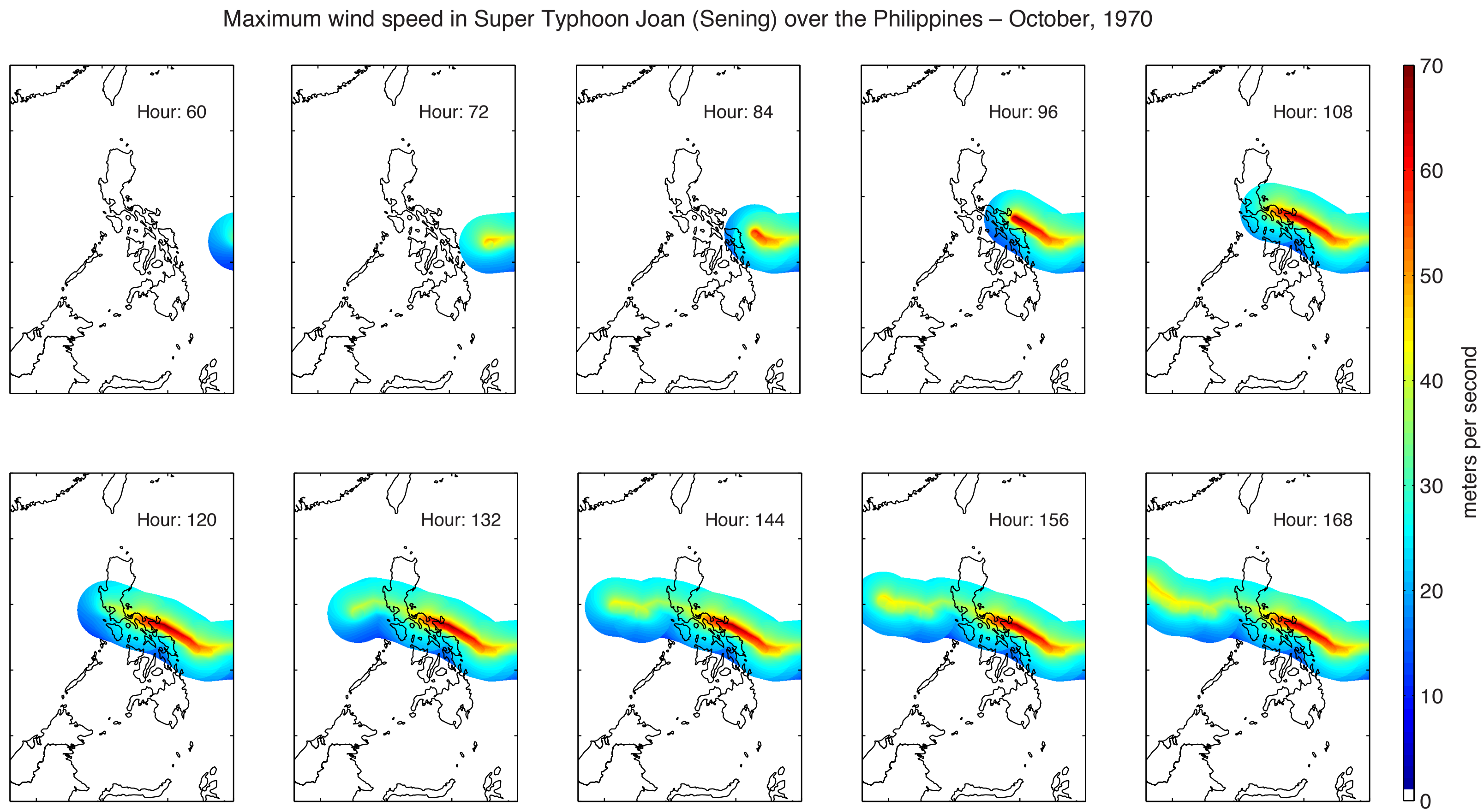


Figure 3: An example LICRICE reconstruction of location-specific tropical cyclone maximum wind speed exposure throughout the evolution of Typhoon Joan as it made landfall over the Philippines in October of 1970.

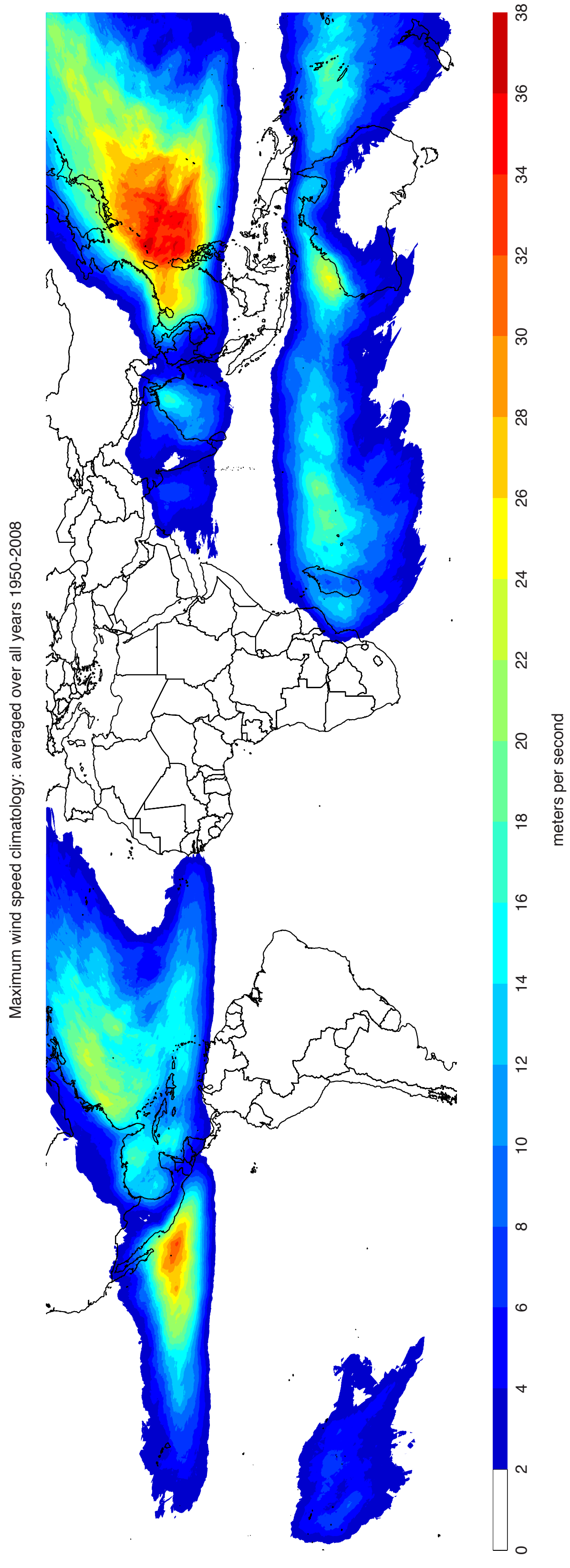


Figure 4: Global tropical cyclone exposure climatology derived from LICRICE. Colors denote the average (across years) maximum wind speed for all tropical cyclone events during 1950-2008. See Appendix Figure A.2 for year-by-year data.

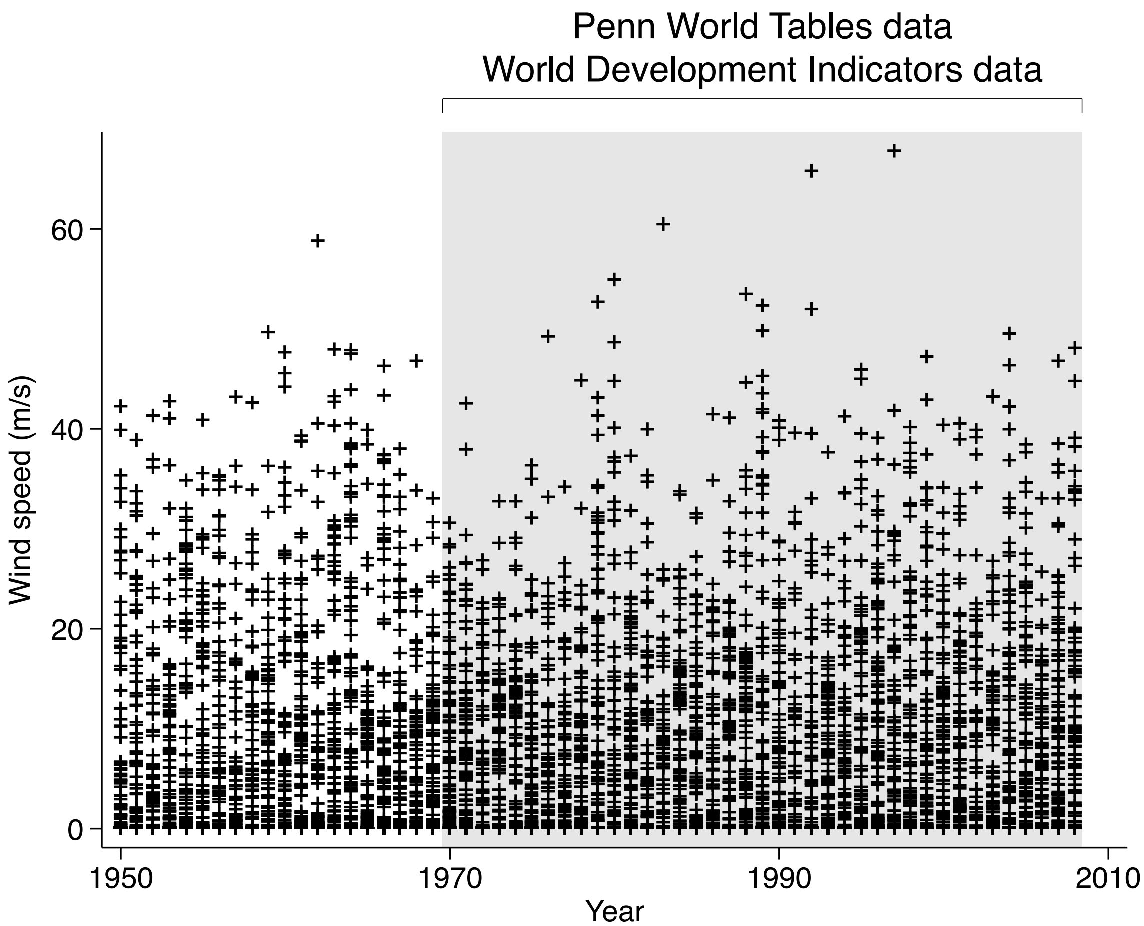


Figure 5: Wind speed observations aggregated to the country-by-year level. Sample years with economic data are shaded. Because our model includes twenty lags, cyclone exposure in 1950 influences economic outcomes in 1970. See Appendix Figure A.1 for a graphical explanation of how and why a spatial average is used for aggregating cyclone exposure.

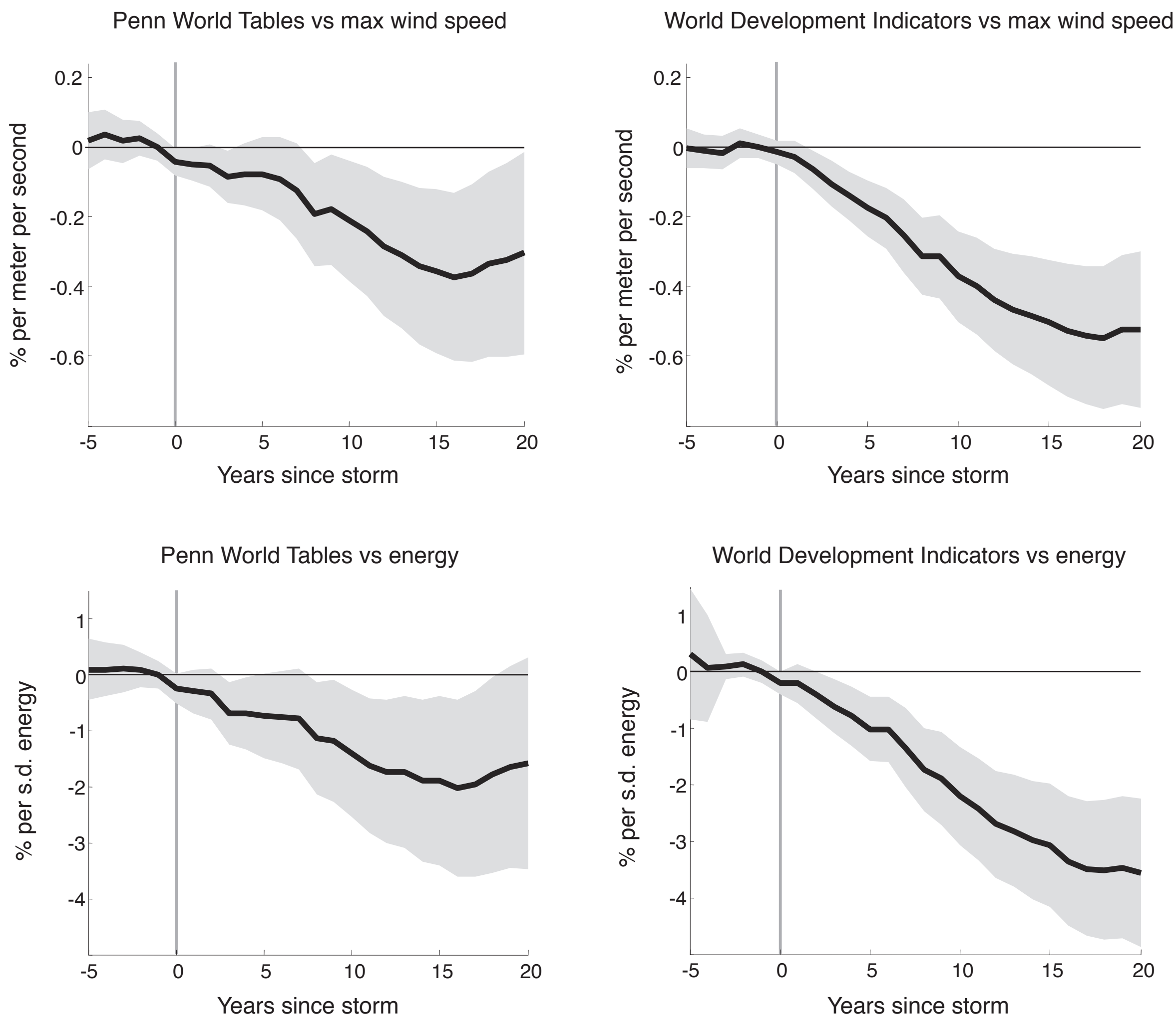


Figure 6: The marginal cumulative effect of tropical cyclone exposure on long-run GDPpc growth. A zero-effect would indicate that a country follows its baseline trajectory after it was exposed to a cyclone. Each panel uses a different pairing of dependent variable data source and a different measure of cyclone exposure. 95% confidence intervals (robust to spatial and serial correlation) are shaded. Table 3 reports exact estimates.

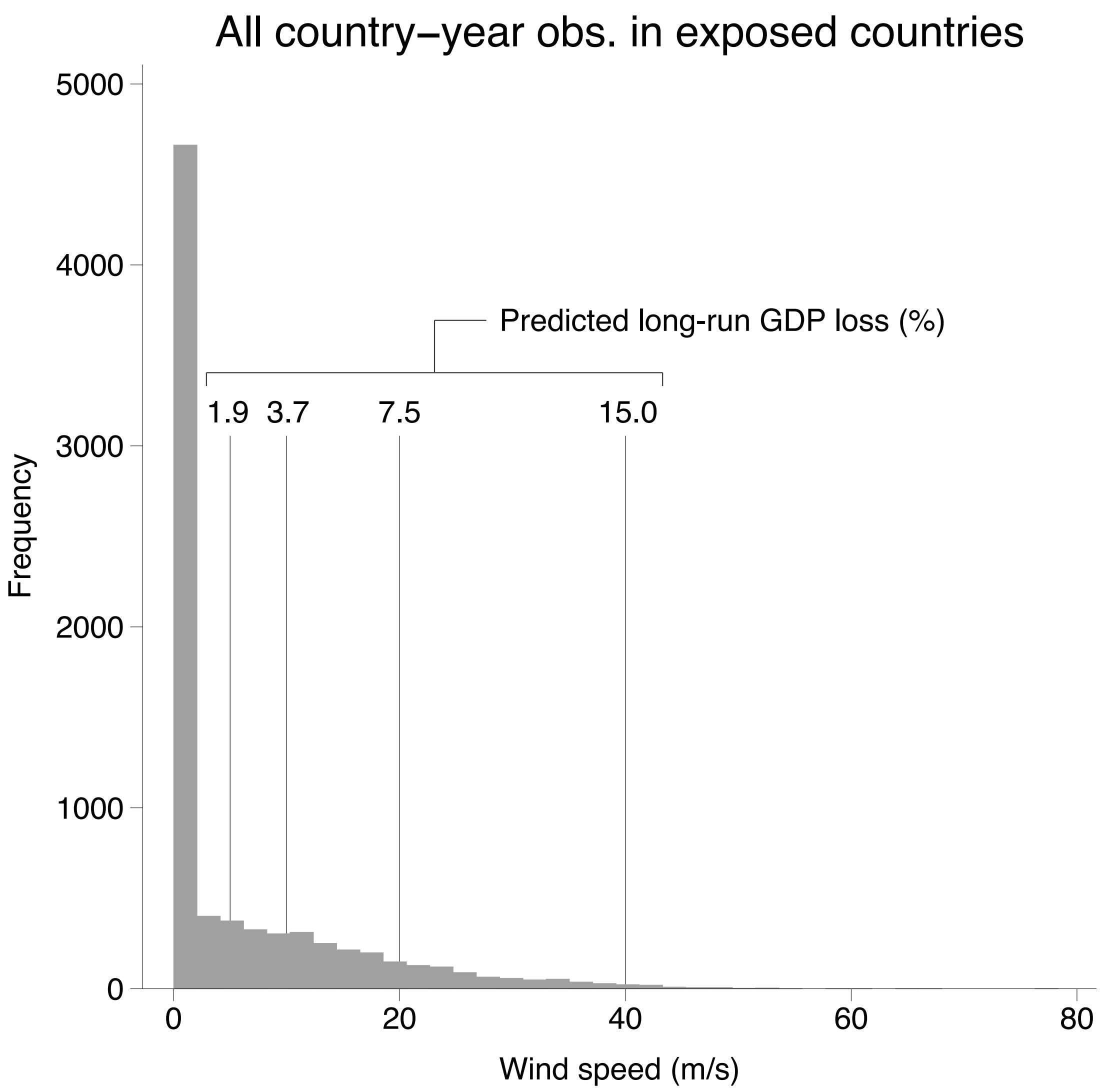


Figure 7: Pooled distribution of country-year tropical cyclone exposure. The expected long-run GDPpc loss associated with 5, 10, 20 and 40 m/s storm events are indicated.

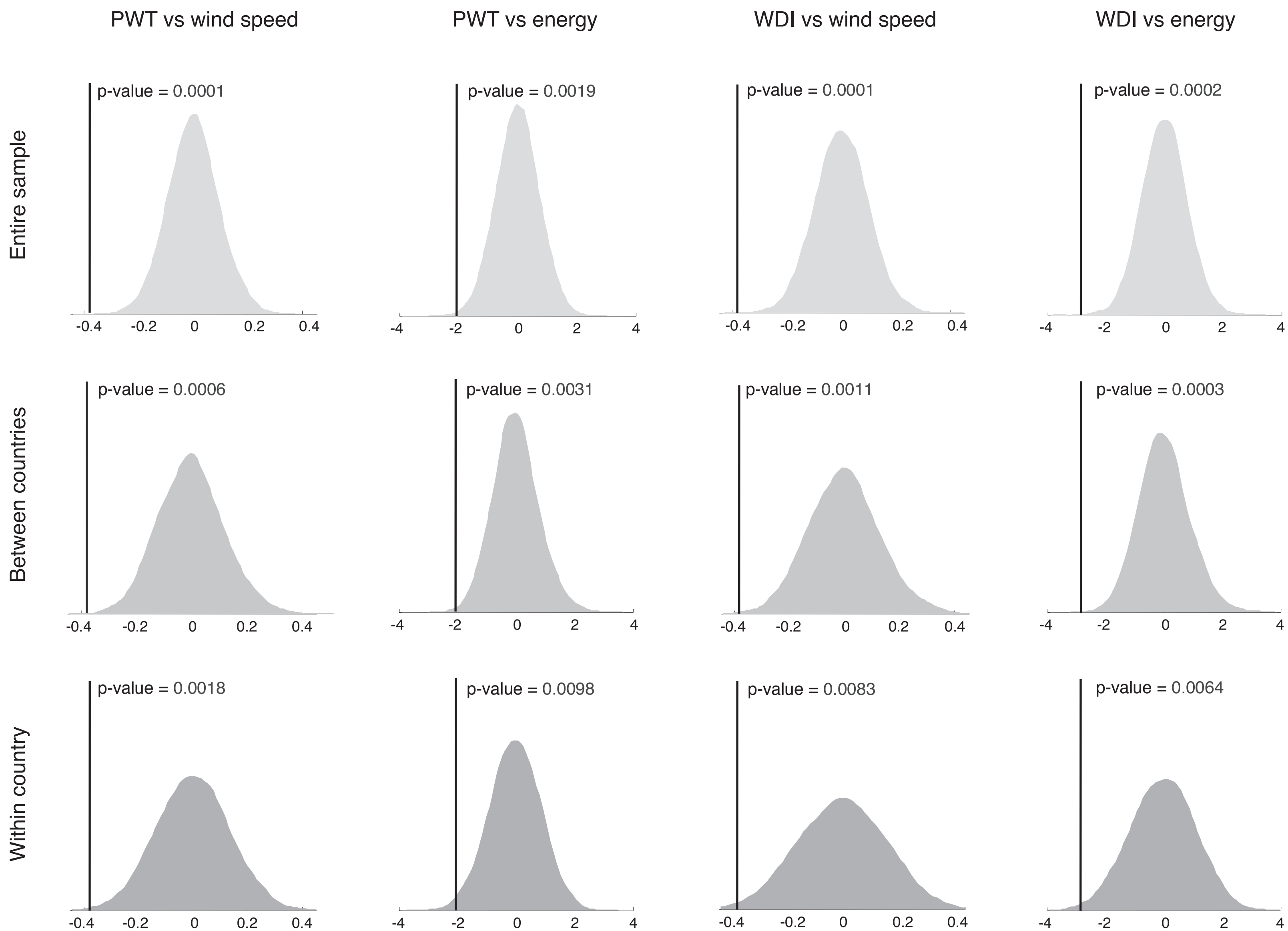


Figure 8: Distribution of point estimates for 15-year lag determined by re-estimating Equations (1)-(2) on randomized placebo datasets. Each distribution corresponds to the different dependent-independent variable pairing (columns) for one of three different randomization schemes (rows, see Appendix Figure A.4 for a graphical depiction). 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.

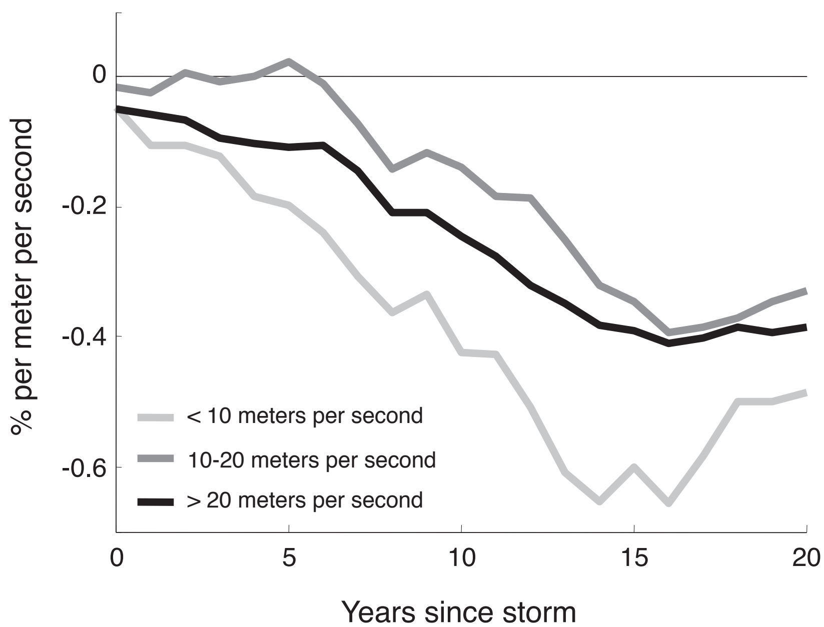


Figure 9: Long-run marginal cumulative effects of cyclone exposure for small (<10 m/s), medium (10-20 m/s), and large (>20 m/s) exposure levels.

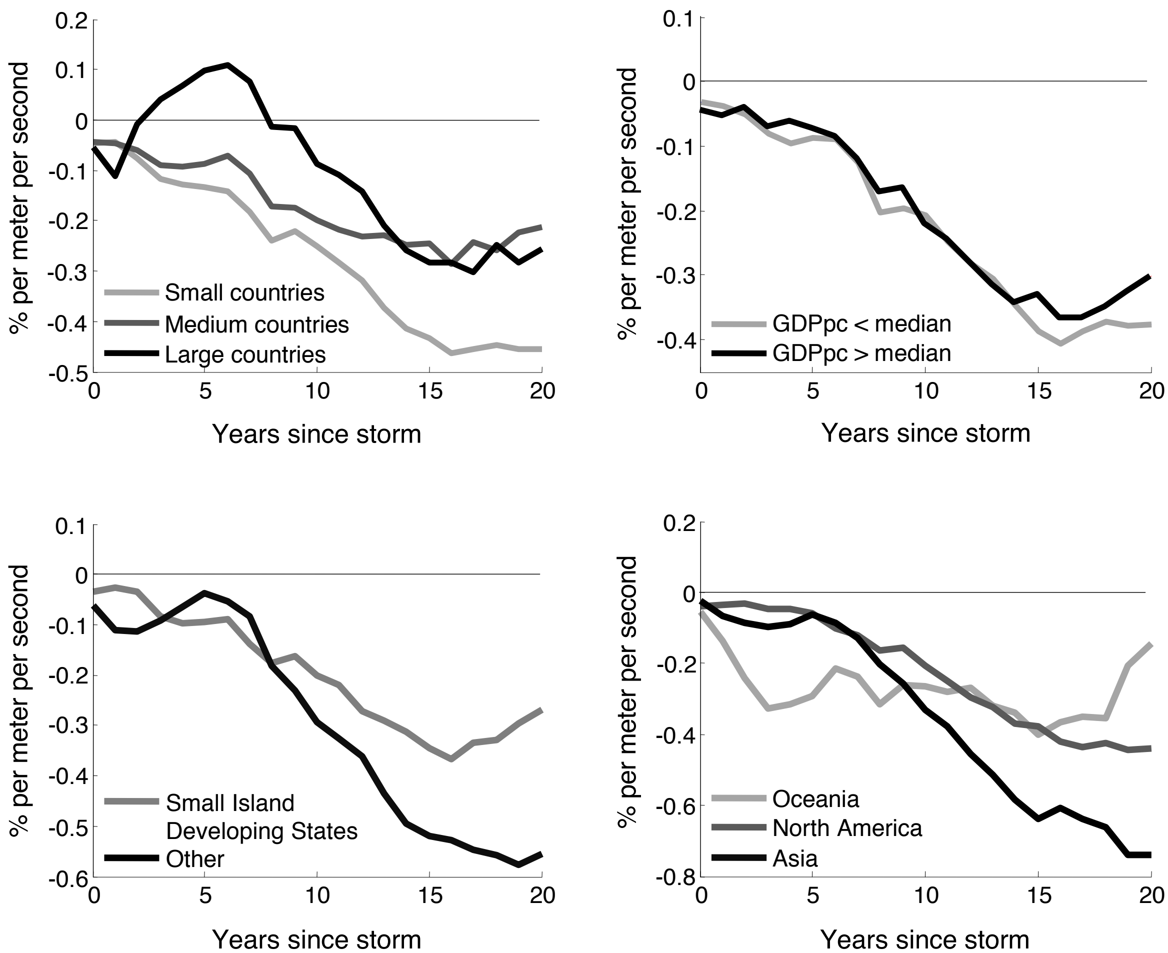


Figure 10: The estimated effect of cyclones on GDPpc for subsamples stratified by country size, income in 1970, Small Island Developing State (SIDS) status, and region.

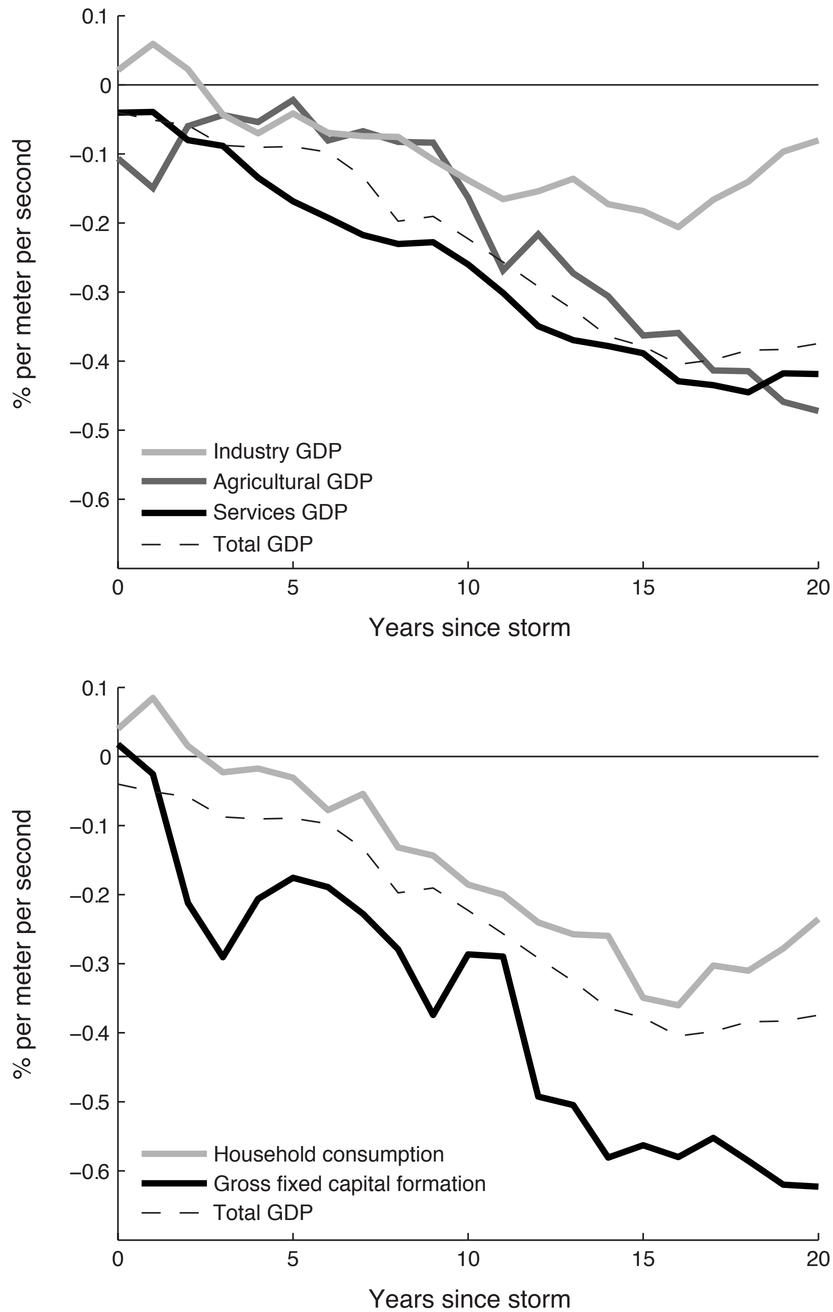


Figure 11: The estimated effect of cyclones on different components of GDP (top) and on consumption and capital formation (bottom). Dashed line is the effect on total GDP for comparison.

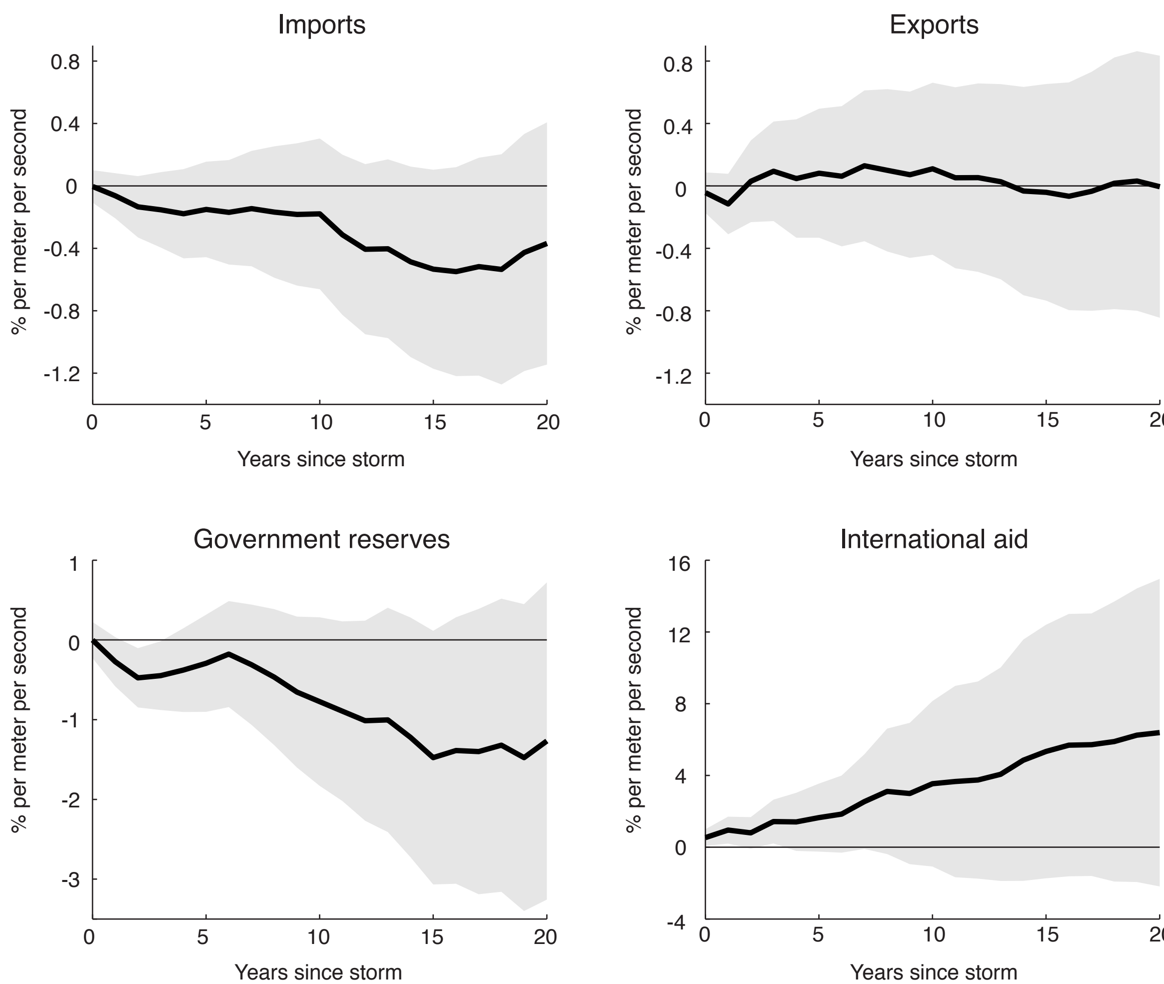


Figure 12: The estimated effect of cyclones on long-run growth of imports, exports, government reserves and international aid. 95% confidence intervals are shaded.

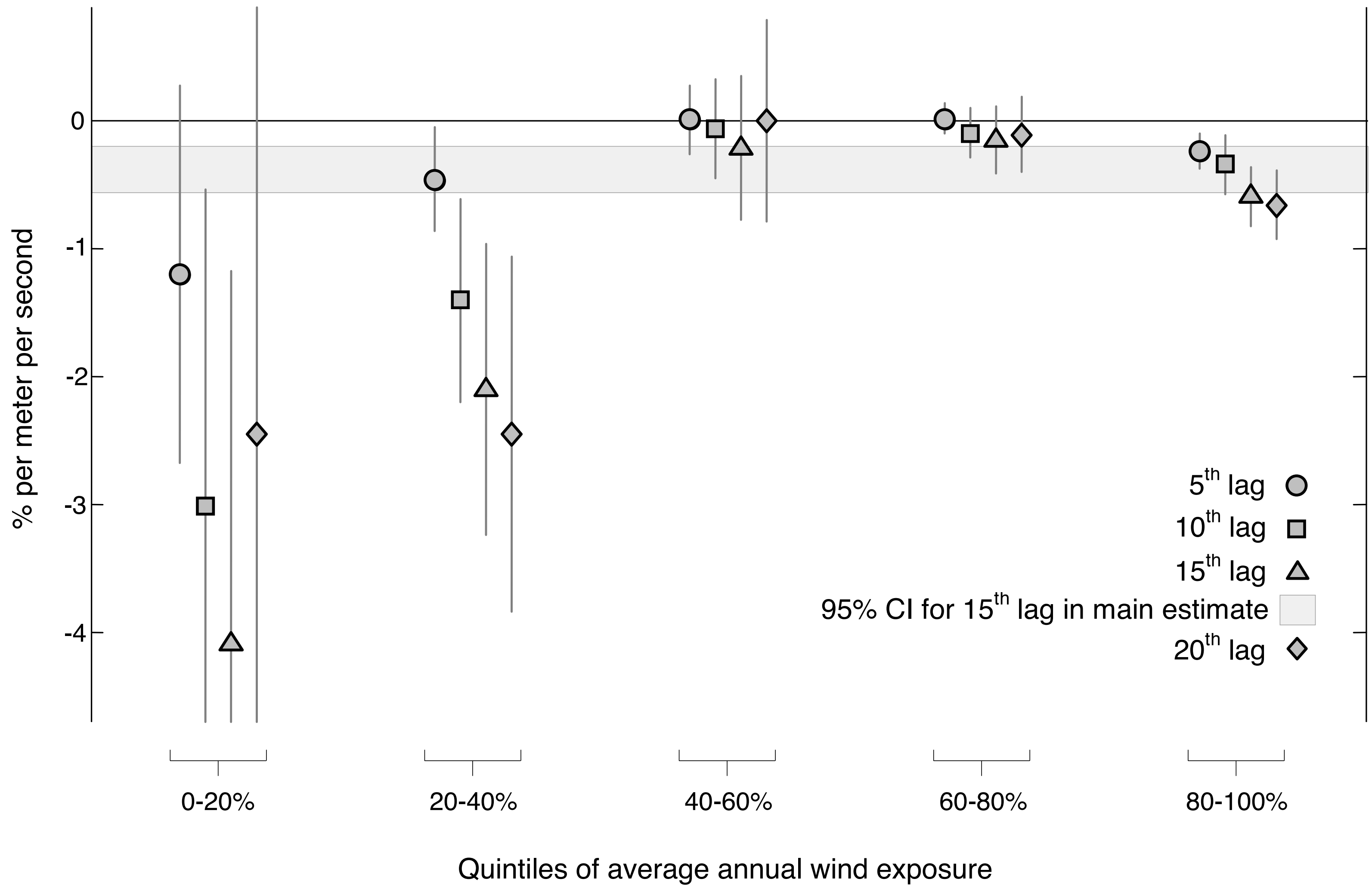


Figure 13: The cumulative GDPpc response to TC exposure, stratified by countries' cyclone climate (defined as average exposure over all years). For each quintile, four lagged effects are shown (5-, 10-, 15-, and 20-year effects). Vertical lines represent the 95% confidence intervals. The grey horizontal bar shows the confidence interval of the 15th-lag in our main (pooled) estimate. Note: African countries are excluded.

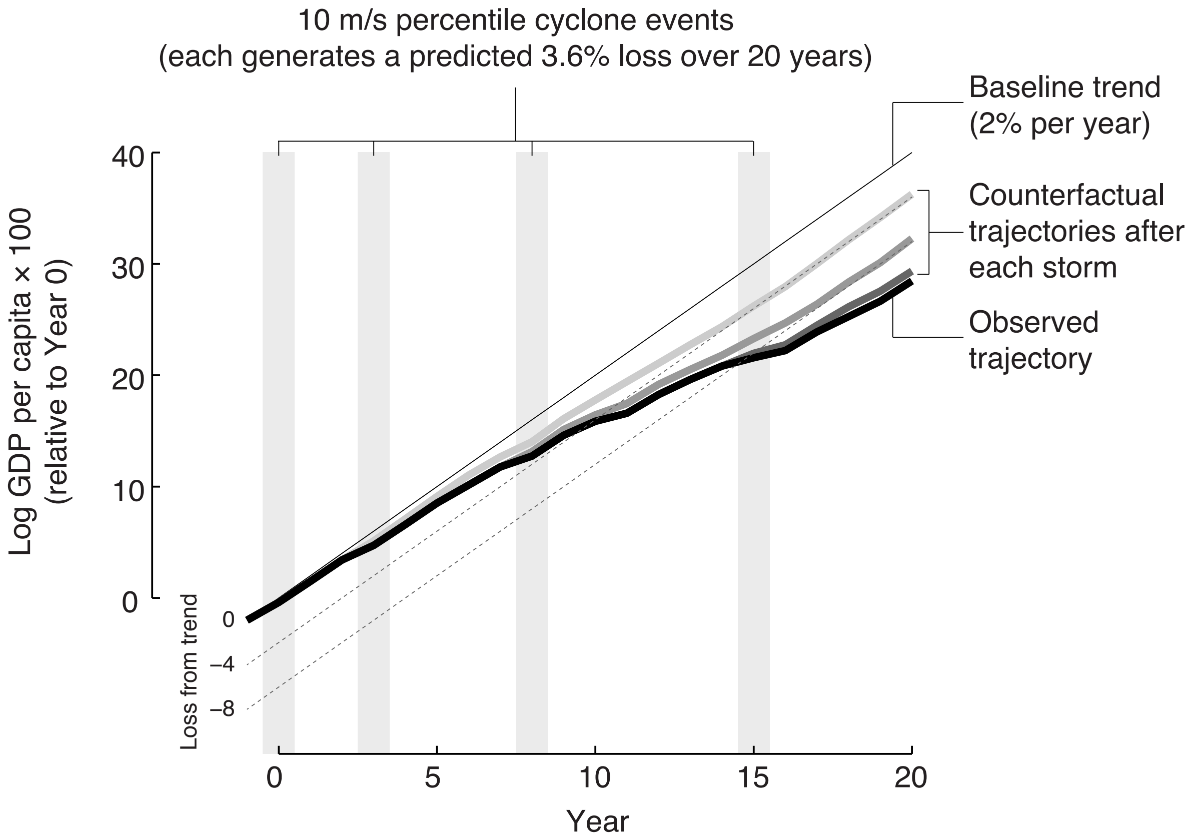


Figure 14: An example GDPpc trajectory in the presence of repeated TC exposure. We set exposure to 10 m/s in years 0, 3, 8, and 15. The penalty to income increases with each event, leading to a substantial divergence from the pre-disaster trend in income growth. The counterfactual trajectories that the 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.

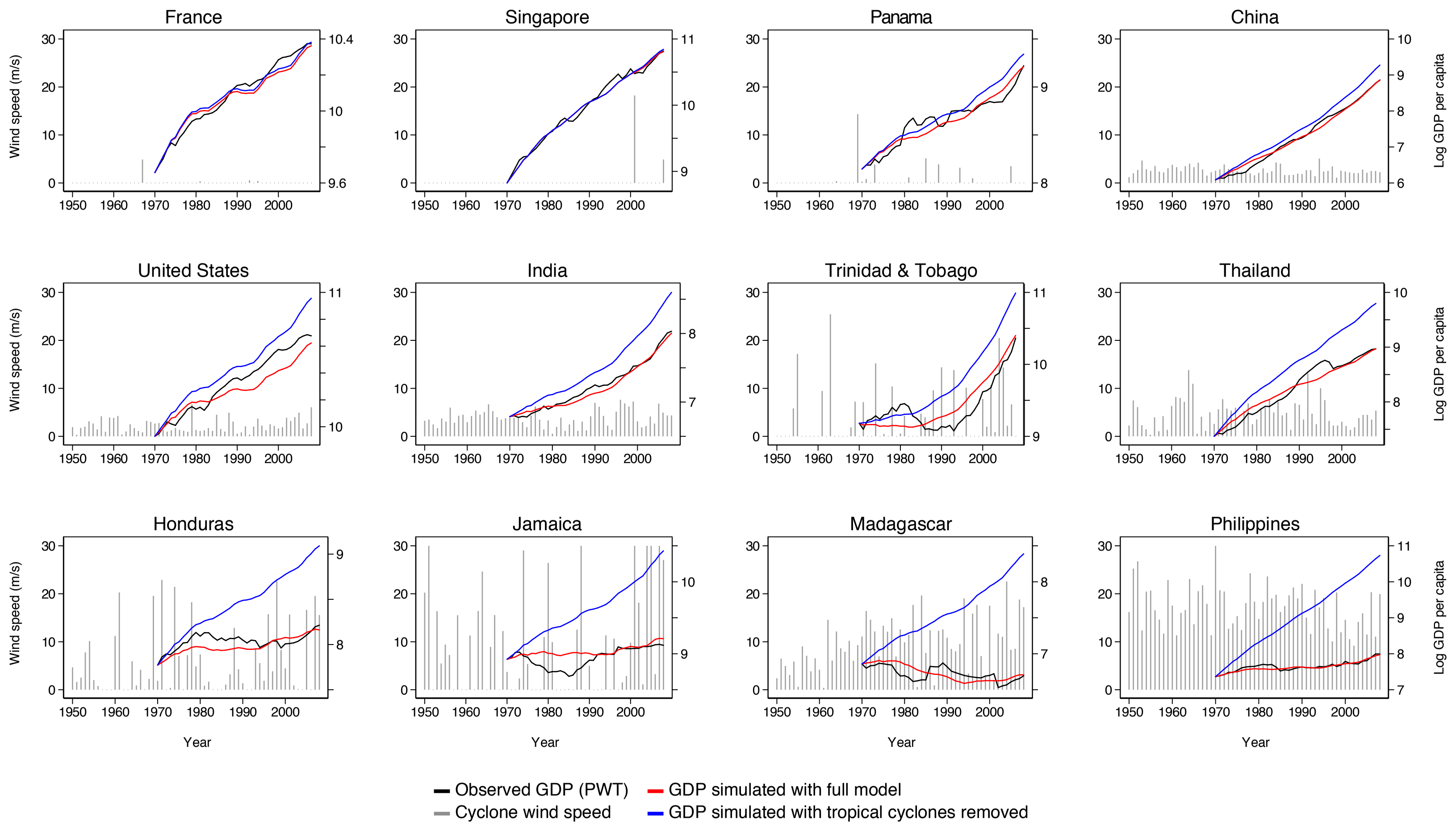


Figure 15: Simulations of log GDPpc growth with (red) and without (blue) tropical cyclone exposure. Observed log GDPpc is black and cyclone exposure in each year are vertical grey lines. Countries are presented in ascending order based on their average tropical cyclone exposure, from low (France, top 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. Plots for all countries are shown in Appendix Figures A.5-A.6

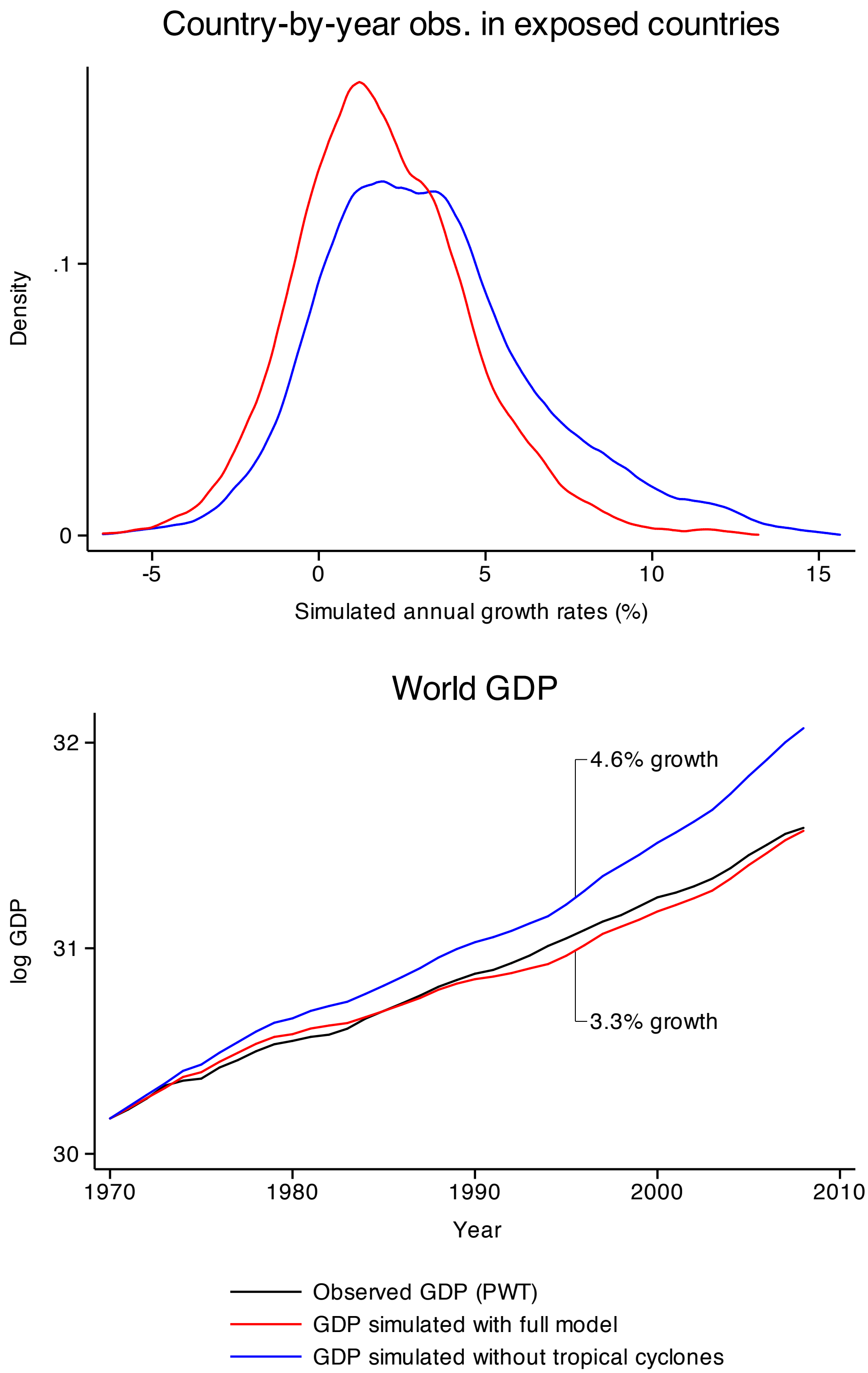


Figure 16: Top: The global distribution of predicted annual growth rates for exposed countries using the complete growth model (red) and the model where historical cyclone exposure is removed (blue) during 1970-2008. Bottom: the observed trajectory of World GDP (black, 3.5% growth) and simulated trajectories with and without tropical cyclones included in the model. Japan, Taiwan and Hong-Kong are not included in these plots (see text).

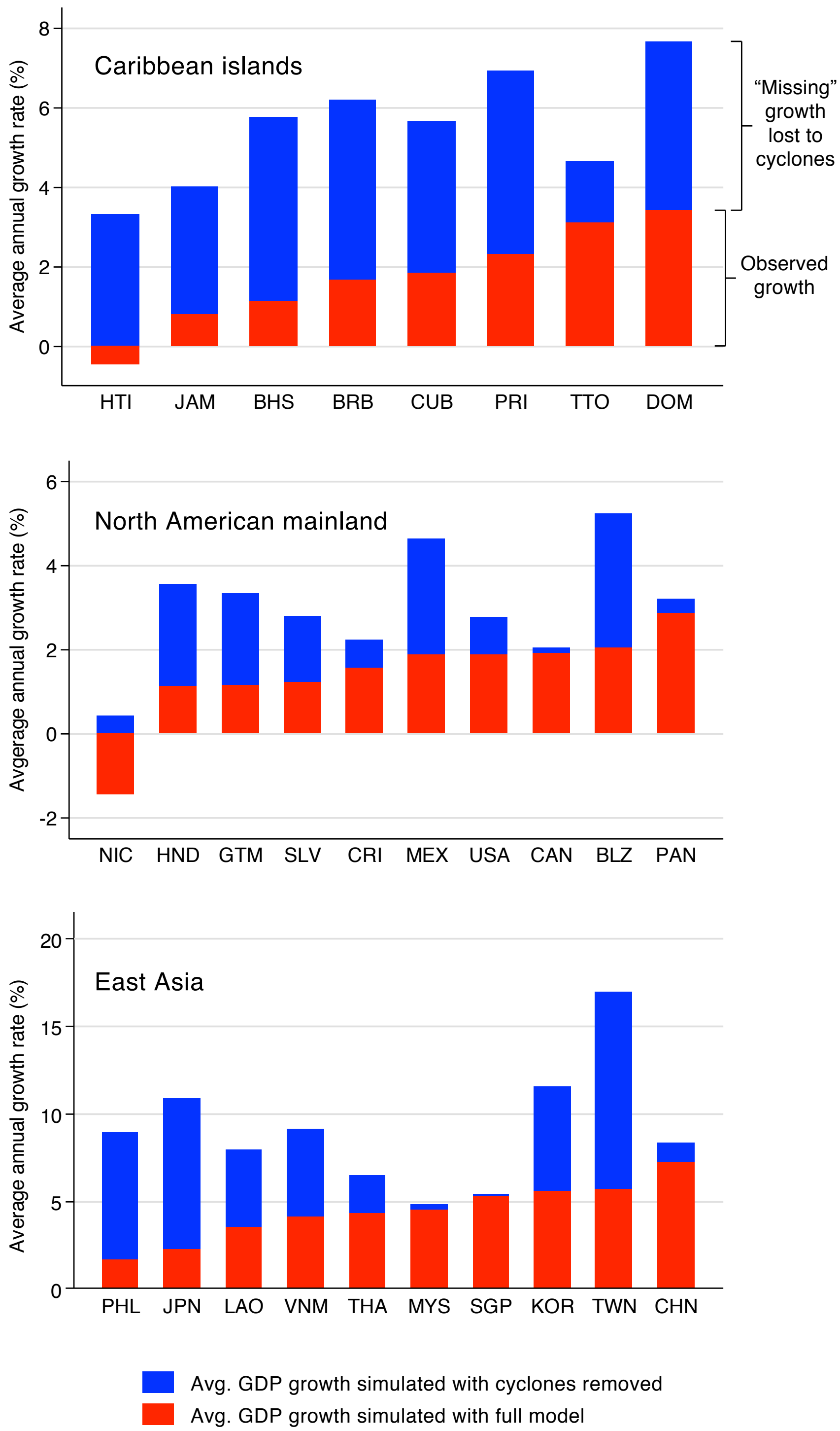


Figure 17: Average annual growth rates as observed historically (red bars, equal to simulated growth with full model) and average growth in simulations where cyclones are removed (blue bars). The difference in the height of the bars is the "missing" average annual growth loss to cyclones. See also Appendix Figure A.7. Results for all countries in the simulation are tabulated in Appendix Table A.2

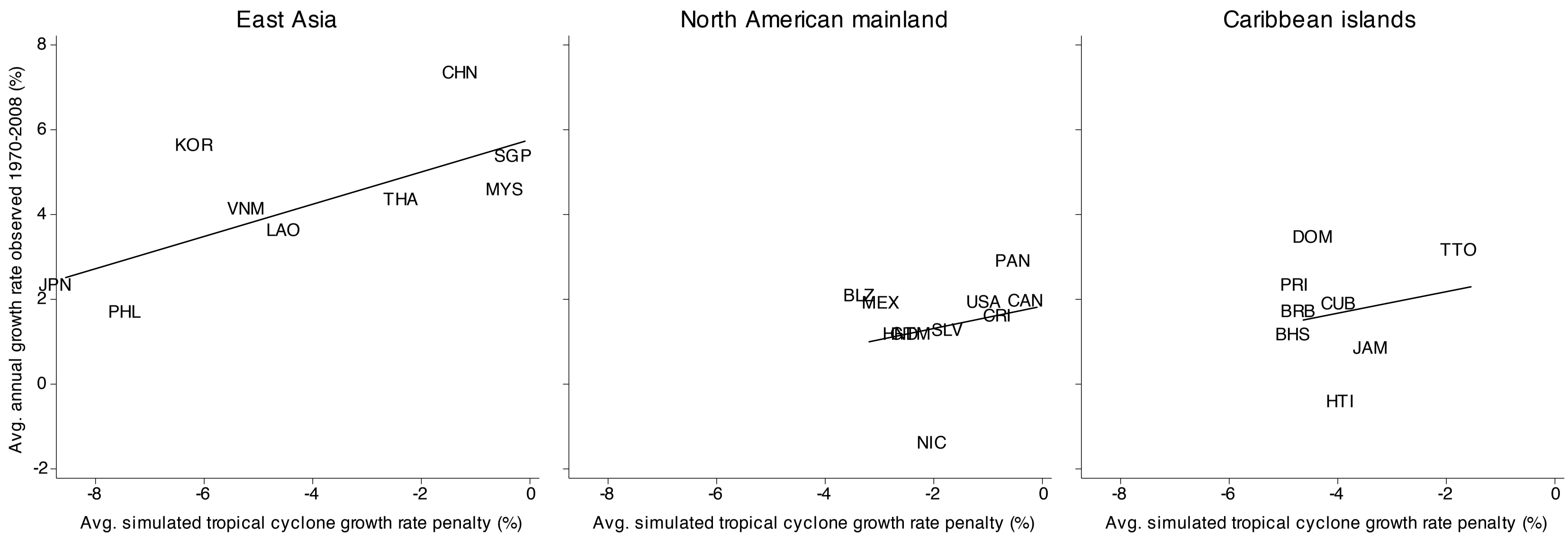


Figure 18: Within-region cross-sectional regressions of average annual growth rates as historically observed against the growth penalty (i.e. "missing growth") attributable to each country's tropical cyclone climate. Table 6 reports coefficients and pooled estimates. Taiwan is omitted because it is an extreme outlier.

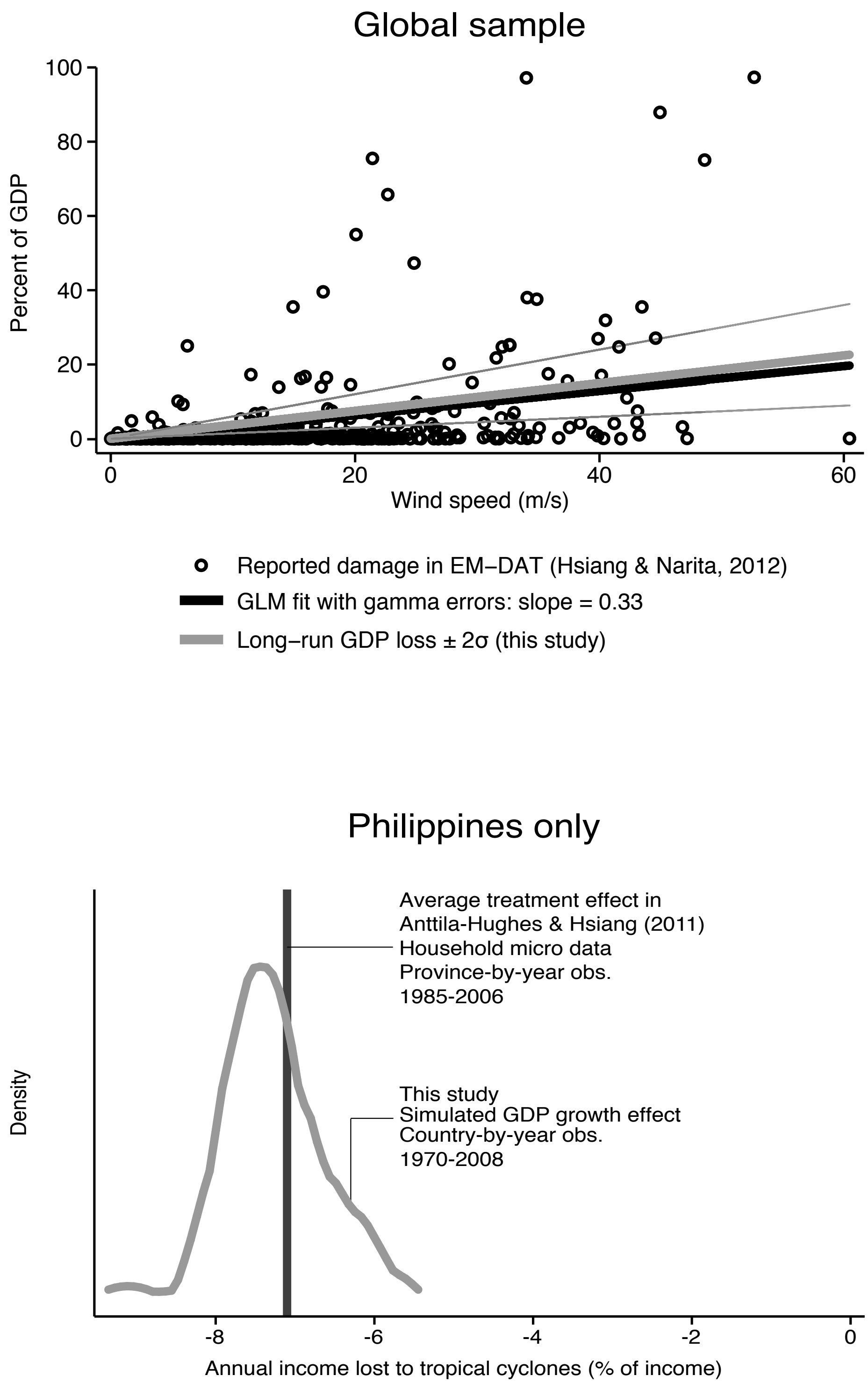


Figure 19: Quantitative comparison of our results to related estimates in the literature. Top: Hsiang and Narita (2012a) estimate the relationship between self-reported capital damages and the maximum wind speed measure used in this study. Bottom: Anttila-Hughes and Hsiang (2011) estimate the average income lost to Filipino households due to tropical cyclone exposure in the prior year.

Table 1: Summary statistics for exposed countries

Variable	Mean	Std. Dev.	Min.	Max.	N
Economic Characteristics					
GDPpc (Penn World Tables)	8.093	1.235	4.913	11.637	4914
GDPpc (World Development Indicators)	7.366	1.462	4.084	10.876	4248
Population (thousands)	32863.599	124191.223	7.251	1317066	6017
Population Growth	0.021	0.019	-0.313	0.569	5914
Economic Openness Index	72.676	50.727	1.035	443.08	4914
Aid per capita	2.733	2.033	-6.37	9.397	4151
Small Island Developing State	0.306	0.461	0	1	7905
Below median income (1970)	0.643	0.479	0	1	5508
Agriculture (pc)	5.105	0.751	-0.067	7.079	3169
Industry (pc)	5.879	1.653	2.239	10.455	3128
Services (pc)	6.44	1.537	1.914	10.187	3022
Physical Characteristics					
Tropical cyclone *Wind speed* (meters per second)	5.869	9.379	0	78.344	7905
Tropical cyclone *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)	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.

Table 2: Long-run growth vs. wind speed with alterations to non-parametric time controls

	(1)	(2)	(3)
Dependent variable	Growth (%) from PWT		
Independent variable	Wind speed		
Marginal cumulative effect of 1 additional m/s exposure			
1 year	-0.0532***	-0.0509**	-0.0609***
	(0.0200)	(0.0208)	(0.0216)
2 years	-0.0602**	-0.0584**	-0.0830***
	(0.0250)	(0.0259)	(0.0277)
3 years	-0.0914***	-0.0876***	-0.0994***
	(0.0290)	(0.0303)	(0.0317)
4 years	-0.0952***	-0.0903***	-0.0995***
	(0.0323)	(0.0349)	(0.0367)
5 years	-0.0944**	-0.0895**	-0.0938**
	(0.0392)	(0.0427)	(0.0456)
6 years	-0.101**	-0.0974**	-0.105**
	(0.0428)	(0.0473)	(0.0511)
7 years	-0.135***	-0.133**	-0.143**
	(0.0484)	(0.0535)	(0.0564)
8 years	-0.196***	-0.197***	-0.187***
	(0.0516)	(0.0591)	(0.0609)
9 years	-0.185***	-0.190***	-0.182***
	(0.0560)	(0.0647)	(0.0663)
10 years	-0.211***	-0.223***	-0.215***
	(0.0605)	(0.0711)	(0.0731)
11 years	-0.236***	-0.257***	-0.241***
	(0.0631)	(0.0747)	(0.0776)
12 years	-0.261***	-0.292***	-0.277***
	(0.0643)	(0.0797)	(0.0842)
13 years	-0.281***	-0.325***	-0.319***
	(0.0686)	(0.0837)	(0.0892)
14 years	-0.305***	-0.364***	-0.358***
	(0.0712)	(0.0893)	(0.0931)
15 years	-0.306***	-0.378***	-0.376***
	(0.0734)	(0.0938)	(0.0986)
16 years	-0.318***	-0.405***	-0.402***
	(0.0741)	(0.0975)	(0.103)
17 years	-0.299***	-0.398***	-0.401***
	(0.0773)	(0.102)	(0.108)
18 years	-0.274***	-0.384***	-0.391***
	(0.0802)	(0.104)	(0.113)
19 years	-0.265***	-0.383***	-0.389***
	(0.0839)	(0.109)	(0.117)
20 years	-0.247***	-0.374***	-0.383***
	(0.0854)	(0.113)	(0.122)
Country FE	Y	Y	Y
Year FE	Y	Y	
Region X 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 coefficients of wind speed are displayed. †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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: 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)
5 years	-0.0895**	-0.129***	-0.722**	-1.052***
	(0.0427)	(0.0322)	(0.289)	(0.235)
10 years	-0.223***	-0.272***	-1.484***	-2.160***
	(0.0711)	(0.0582)	(0.461)	(0.424)
15 years	-0.378***	-0.383***	-2.069***	-2.851***
	(0.0938)	(0.0820)	(0.594)	(0.568)
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 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Controlling for climatic variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Growth (%) from PWT							
Country sample	All	Exposed	All	Exposed	All	Exposed	All	Exposed
Marginal cumulative effect of 1 additional m/s exposure								
5 years	-0.0895**	-0.0811*	-0.0861*	-0.0965**	-0.0952**	-0.0790*	-0.0846*	-0.0864*
	(0.0427)	(0.0423)	(0.0449)	(0.0450)	(0.0451)	(0.0451)	(0.0452)	(0.0454)
10 years	-0.223***	-0.209***	-0.230***	-0.252***	-0.252***	-0.213***	-0.229***	-0.229***
	(0.0711)	(0.0718)	(0.0734)	(0.0755)	(0.0756)	(0.0777)	(0.0744)	(0.0771)
15 years	-0.378***	-0.363***	-0.395***	-0.432***	-0.423***	-0.373***	-0.392***	-0.395***
	(0.0938)	(0.0940)	(0.0993)	(0.100)	(0.101)	(0.103)	(0.1000)	(0.102)
20 years	-0.374***	-0.349***	-0.415***	-0.449***	-0.444***	-0.377***	-0.414***	-0.408***
	(0.113)	(0.114)	(0.122)	(0.123)	(0.123)	(0.125)	(0.122)	(0.123)
Precipitation controls			Y	Y			Y	Y
Temperature controls					Y	Y	Y	Y
Observations	6415	3834	6259	3678	6259	3678	6259	3678
Adjusted R^2	0.144	0.167	0.139	0.156	0.139	0.158	0.139	0.157

All models contain country fixed effects, year fixed effects, and country-specific linear trends. Temperature (in degrees Celsius) and precipitation (in mm/month) are spatially averaged over each country-year in the sample and are each allowed to influence growth linearly. "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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Controlling for endogenous economic factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	Growth (%) from PWT									
Country sample	All	Exposed	All	Exposed	All	Exposed	All	Exposed	All	Exposed
Marginal cumulative effect of 1 additional m/s exposure										
5 years	-0.0895**	-0.0811*	-0.0766*	-0.0638	-0.0896**	-0.0813*	-0.0826**	-0.0723*	-0.0689	-0.0577
	(0.0427)	(0.0423)	(0.0430)	(0.0420)	(0.0427)	(0.0424)	(0.0417)	(0.0412)	(0.0420)	(0.0412)
10 years	-0.223***	-0.209***	-0.225***	-0.202***	-0.223***	-0.210***	-0.202***	-0.182**	-0.202***	-0.182***
	(0.0711)	(0.0718)	(0.0689)	(0.0688)	(0.0711)	(0.0718)	(0.0702)	(0.0708)	(0.0681)	(0.0681)
15 years	-0.378***	-0.363***	-0.439***	-0.408***	-0.377***	-0.364***	-0.346***	-0.321***	-0.402***	-0.376***
	(0.0938)	(0.0940)	(0.0930)	(0.0928)	(0.0939)	(0.0940)	(0.0930)	(0.0925)	(0.0920)	(0.0916)
20 years	-0.374***	-0.349***	-0.512***	-0.462***	-0.373***	-0.351***	-0.322***	-0.284**	-0.453***	-0.411***
	(0.113)	(0.114)	(0.113)	(0.113)	(0.113)	(0.114)	(0.112)	(0.111)	(0.112)	(0.111)
$ln(GDPpc)_{t-1}{}^{\dagger}$			-14.52***	-14.31***					-14.64***	-13.99***
			(1.541)	(1.520)					(1.543)	(1.506)
$Pop.Growth_{t-1}$					-8.508	7.386			-9.101	0.803
					(11.30)	(14.59)			(10.74)	(13.97)
$Openness_{t-1}$							0.0321***	0.0417***	0.0357***	0.0307***
							(0.0110)	(0.0106)	(0.0101)	(0.00982)
Observations	6415	3834	6415	3834	6415	3834	6415	3834	6415	3834
Adjusted R^2	0.144	0.167	0.206	0.223	0.144	0.167	0.148	0.173	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.1.

Table 6: 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 18. Bootstrapped standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 7: PDV of changes to the global tropical cyclone climate under "business as usual" (A1B)

	PDV as percentage of current GDP					
Discount rate:	1.0%	3.0%	5.0%	7.0%	10.0%	
Generic climate scenarios						
A single +1 m/s tropical cyclone event today	-34	-9.86	-5.12	-3.20	-1.86	
An abrupt +1 m/s climate intensification in 2090	-1550	-29.81	-1.88	-0.17	-0.01	
A linear climate intensification to +1 m/s in 2090†	-2382	-124.95	-25.19	-8.13	-2.32	
North Atlantic: linear increase up to +10.3% in 2090						Current climate (m/s)
BHS	-3048	-160	-32.2	-10.4	-3.0	12.4
BLZ	-2029	-106	-21.5	-6.9	-2.0	8.3
CRI	-304	-16	-3.2	-1.0	-0.3	1.2
CUB	-2673	-140	-28.3	-9.1	-2.6	10.9
DOM	-2738	-144	-29.0	-9.3	-2.7	11.2
GTM	-1304	-68	-13.8	-4.5	-1.3	5.3
HND	-1455	-76	-15.4	-5.0	-1.4	5.9
HTI	-2625	-138	-27.8	-9.0	-2.6	10.7
JAM	-2420	-127	-25.6	-8.3	-2.4	9.9
MEX	-1629	-85	-17.2	-5.6	-1.6	6.6
NIC	-1081	-57	-11.4	-3.7	-1.1	4.4
TTO	-950	-50	-10.0	-3.2	-0.9	3.9
USA	-560	-29	-5.9	-1.9	-0.5	2.3
West Pacific: linear increase up to +19.1% in 2090						
CHN	-1194	-63	-12.6	-4.1	-1.2	2.6
JPN	-9600	-504	-101.5	-32.8	-9.4	21.1
KOR	-6937	-364	-73.4	-23.7	-6.8	15.2
LAO	-4492	-236	-47.5	-15.3	-4.4	9.9
MYS	-235	-12	-2.5	-0.8	-0.2	0.5
PHL	-7878	-413	-83.3	-26.9	-7.7	17.3
THA	-2176	-114	-23.0	-7.4	-2.1	4.8
VNM	-5291	-278	-56.0	-18.1	-5.2	11.6
Oceania: linear decrease down to -13.8% in 2090						
AUS	1238	65	13.1	4.2	1.2	3.8
IDN	71	4	0.7	0.2	0.1	0.2
NZL	904	47	9.6	3.1	0.9	2.7
PNG	194	10	2.0	0.7	0.2	0.6
North Indian: linear decrease down to -5.8% in 2090						
BGD	1054	55	11.1	3.6	1.0	7.6
IND	533	28	5.6	1.8	0.5	3.9
LKA	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.8). Estimates using the 5% discount rate are converted to 2010 US$ in Appendix Table A.3. †See Figure A.9 for a graphical explanation of this calculation.

A APPENDIX TABLES & FIGURES

Appendix Table A.1: 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.2: Observed and simulated country-specific growth rates with and without cyclones

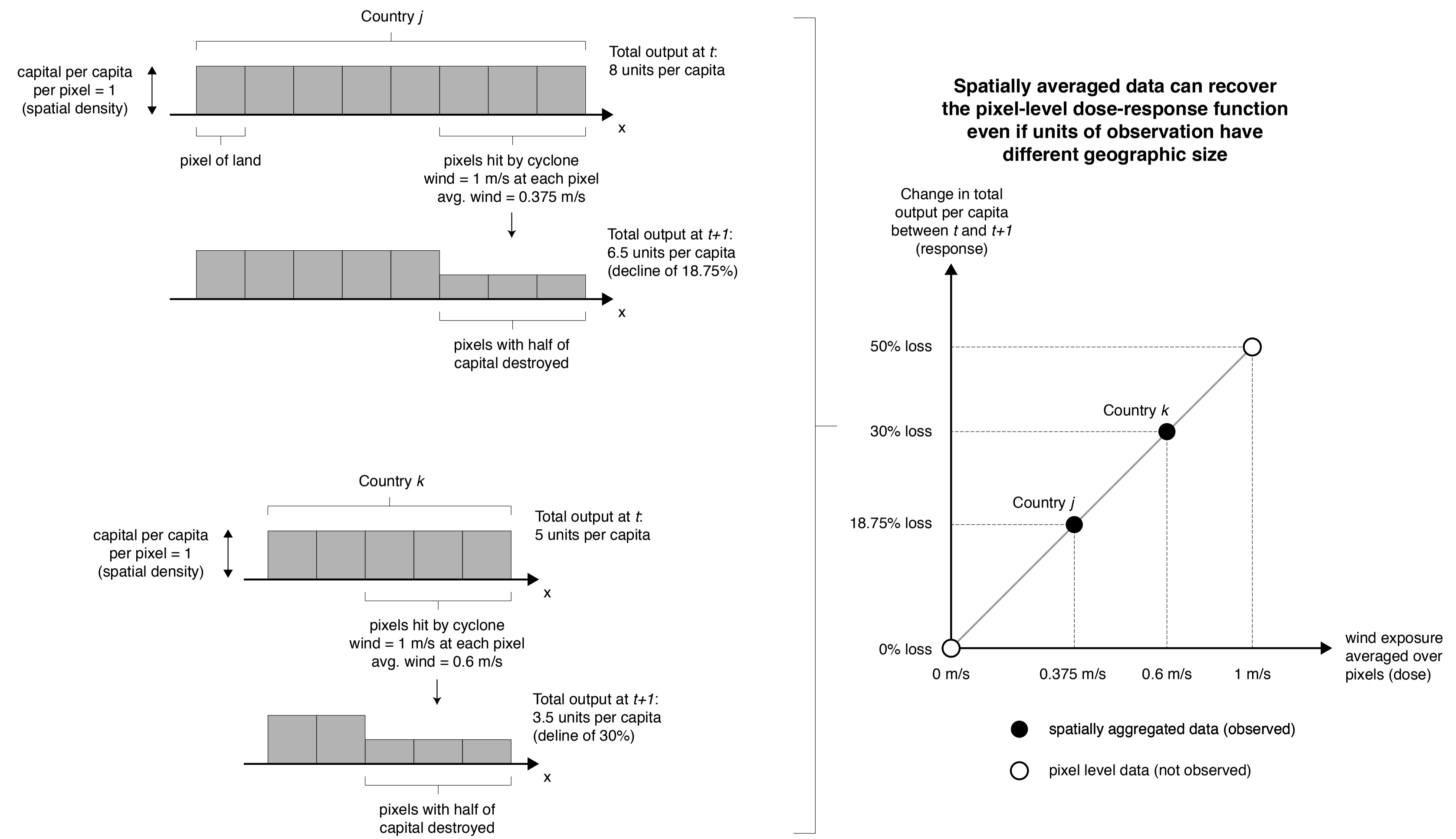
Country	Prediction with full model* (%)	Prediction with cyclones removed (%)	Cyclone climate growth penalty (%)	Country	Prediction with full model* (%)	Prediction with cyclones removed (%)	Cyclone climate growth penalty (%)
ARG	1.11	1.11	0.00	JOR	0.78	0.78	0.00
AUS	2.12	3.77	-1.65	JPN	2.29	10.84	-8.55
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.3: PDV of the change in countries' income trajectories resulting from the "business as usual" climate change scenario (A1B)

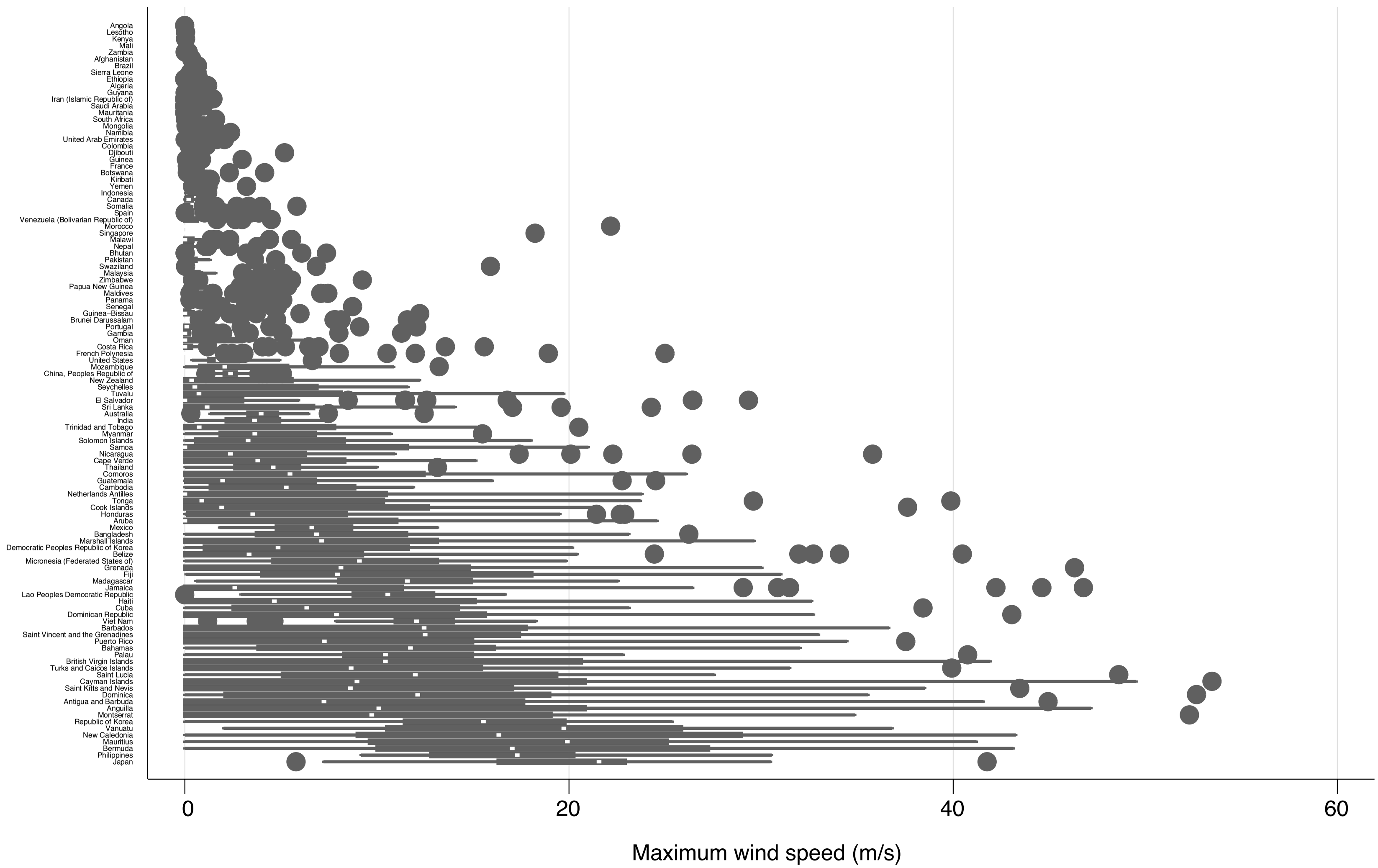
Country	PDV* (†billion US$)
Japan	-4,461.1
China	-1,364.5
Republic of Korea	-1,026.4
Taiwan	-991.9
United States	-855.0
Hong Kong	-354.0
Philippines	-299.3
Mexico	-260.3
Vietnam	-160.1
Thailand	-140.6
Cuba	-40.0
Puerto Rico	-34.5
Dominican Republic	-33.0
Spain	-13.2
Guatemala	-13.2
Canada	-10.9
Indonesia	-10.9
Malaysia	-9.8
Cambodia	-9.3
Laos	-9.2
Jamaica	-7.1
France	-6.3
Portugal	-5.5
Singapore	-5.3
Honduras	-4.7
Haiti	-4.0
El Salvador	-3.6
Trinidad & Tobago	-3.2
Bahamas	-3.1
All others	-15.5
Pakistan	3.1
Sri Lanka	5.1
New Zealand	13.0
Bangladesh	26.1
Australia	140.0
India	264.2
Total losses	**-10,159**
Total gains	**455**
Net PDV (global)	**-9,704**

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

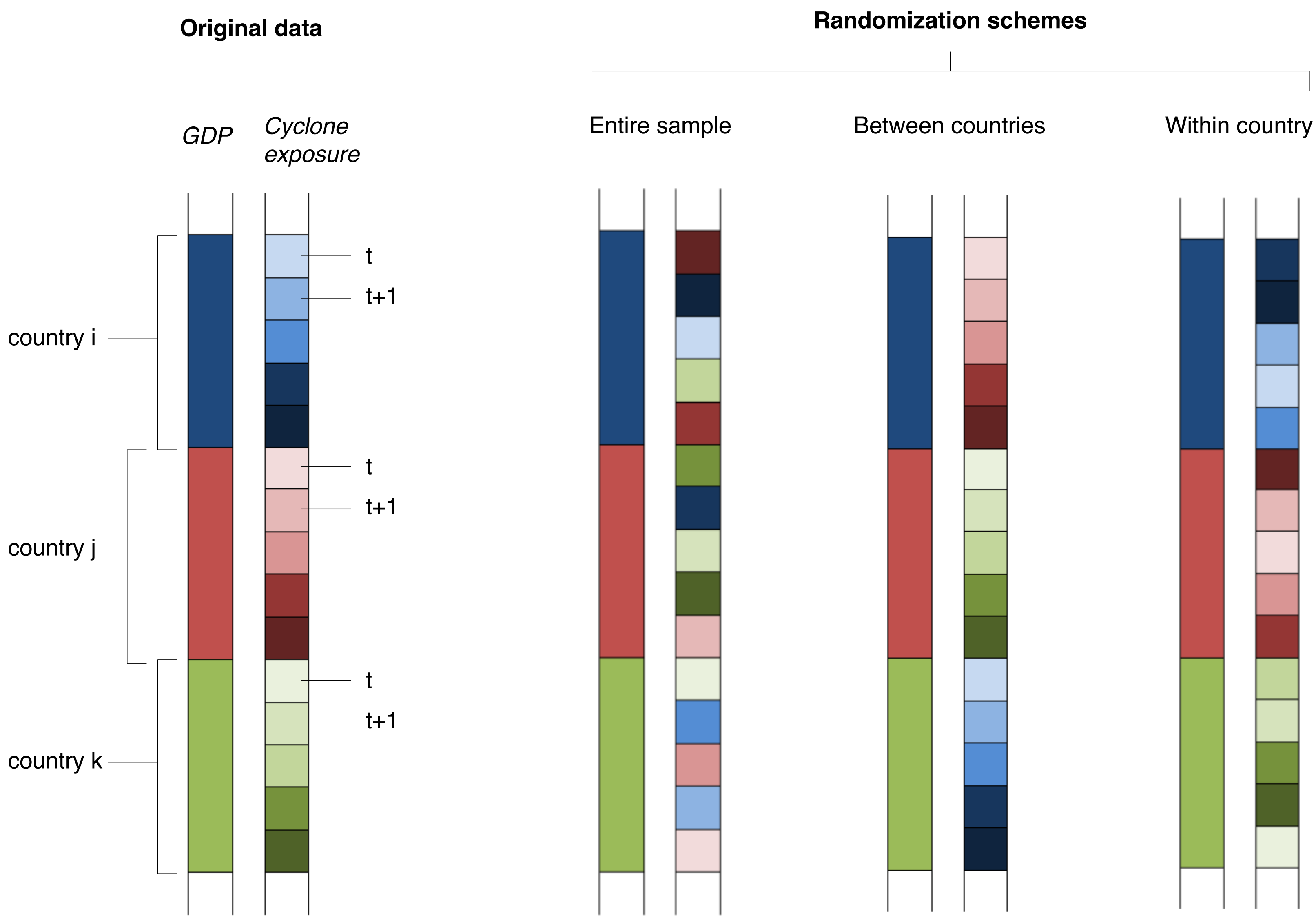


Appendix Figure A.1: If each unit of capital has an independent probability of loss that is a function of wind speed exposure, than a spatially-averaged measure of wind exposure will recover this unit-level relationship and can be used to compare countries of unequal geographic size. In this heuristic example, two countries (each of which is one-dimensional in space) differ in size. j occupies eight pixels while k occupies five. In both countries, a cyclone strikes three pixels with uniform winds (1 m/s) and some capital in these affected pixels is lost (50% in each pixel). By aggregating wind exposure to the country-level using a spatial average, we account for the fact that a relatively smaller fraction of j's pixels (37.5%) were affected by the cyclone in comparison to k (60%). When we compare the change in aggregate output of j with that of k, we are comparing intensive variables that correspond to area-averaged wind speed exposure, which is also an intensive variable. Because we are comparing two intensive variables that are independent of country size, we are able to recover the dose-response function at the pixel level using this aggregated data (right).

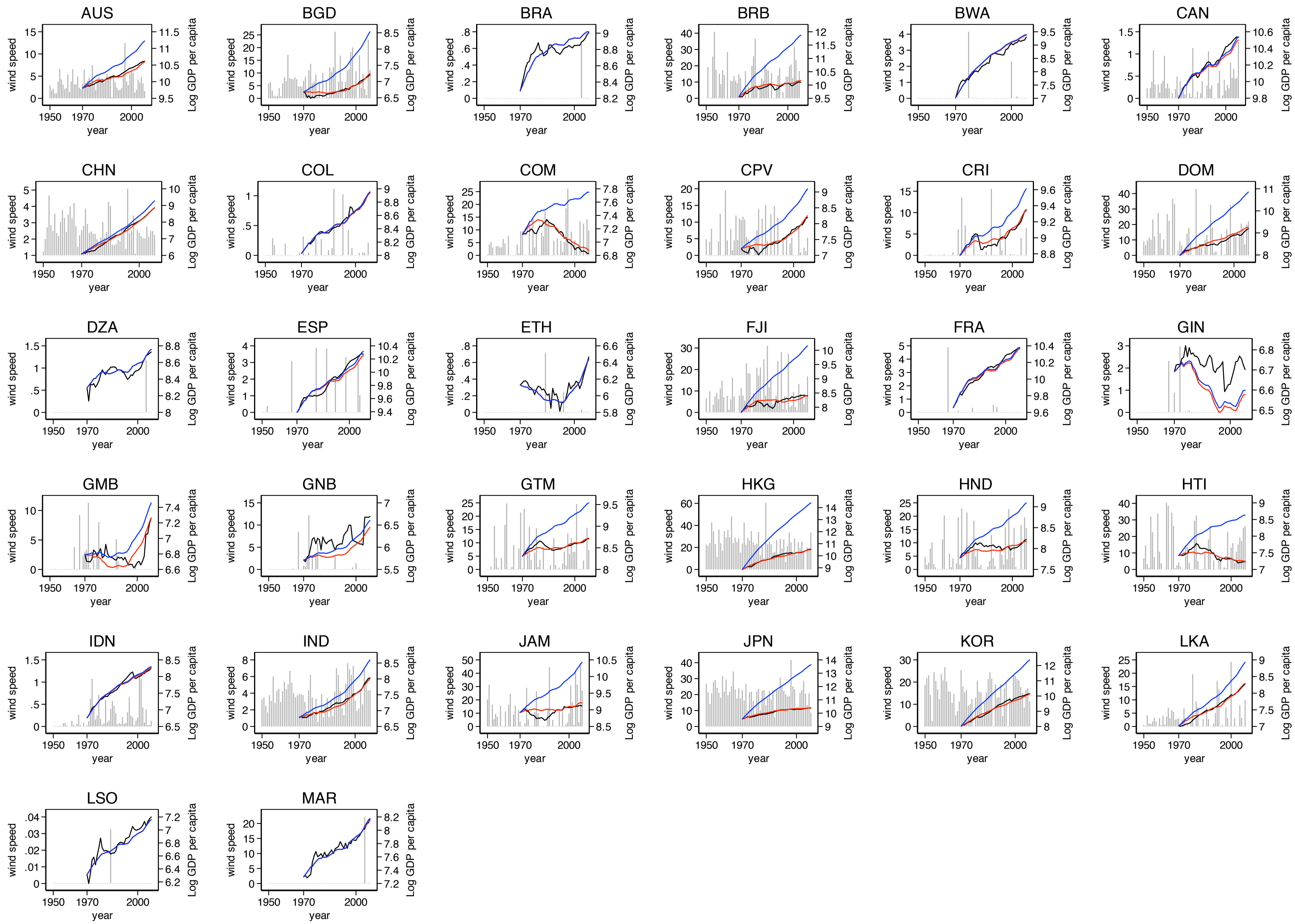
Appendix Figure A.2: Global tropical cyclone exposure displayed as maximum wind speed, for each year in the dataset. These pixel-level fields are aggregated up to country-by-year observations



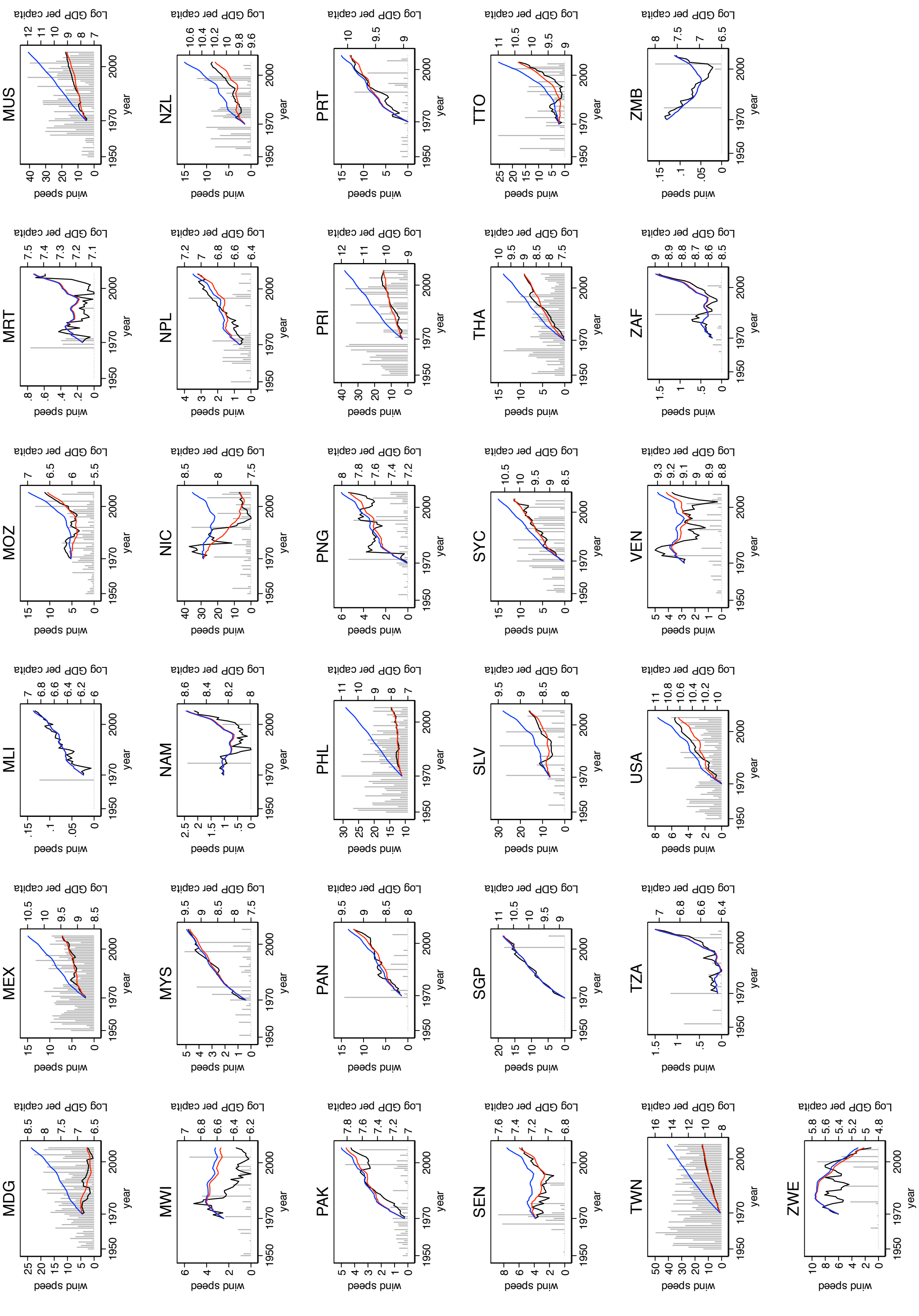
Appendix Figure A.3: Country-year distribution of maximum wind speed for exposed countries (1950-2008). Boxes are inter-quartile ranges, white bars are medians and dots are outliers. Countries are ordered by their mean cyclone exposure.



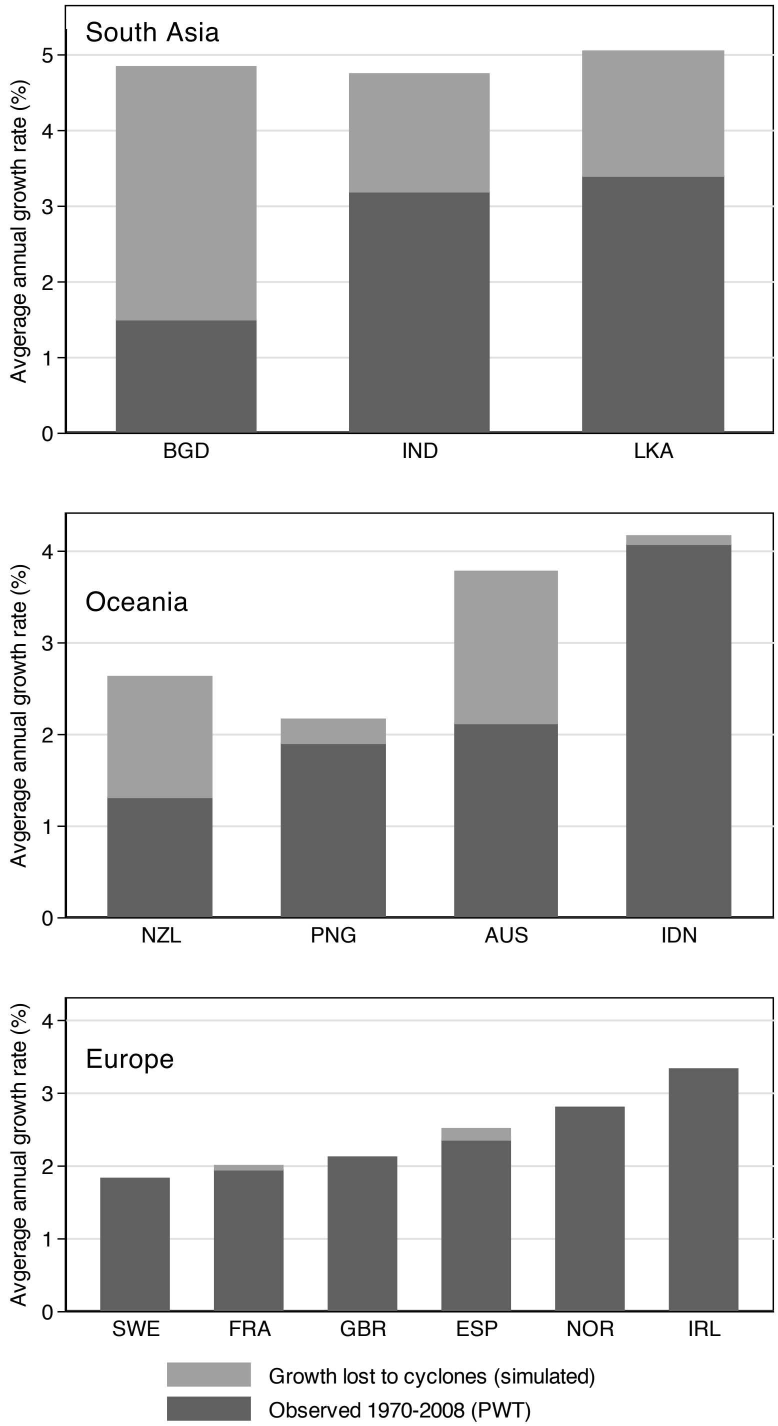
Appendix Figure A.4: Three randomization tests were used as placebos. GDP growth was held fixed for each country-by-year observation at the true value. TC exposure was randomly re-organized according to three different schemes. "Entire sample" randomization reassigned TC exposure to a country-by-year observation anywhere in the sample, without replacement. "Between country" randomization held the order of TC observations fixed, but randomly assigned the entire TC series to any country. "Within country" randomization assigned TC observations to the true country, however they were randomly reordered.



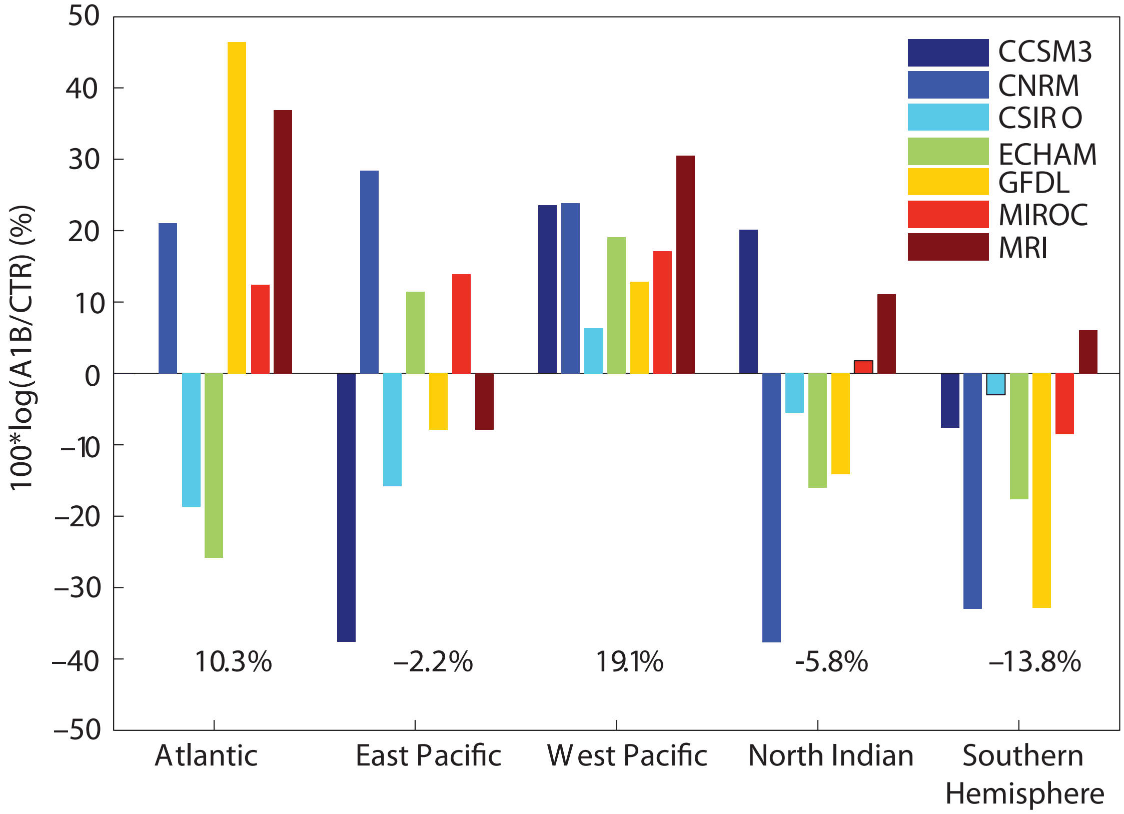
Appendix Figure A.5: Simulations of log GDPpc with (red) and without (blue) tropical cyclones for exposed countries (right axis). Vertical grey bars display each country's wind exposure in each year (left axis).



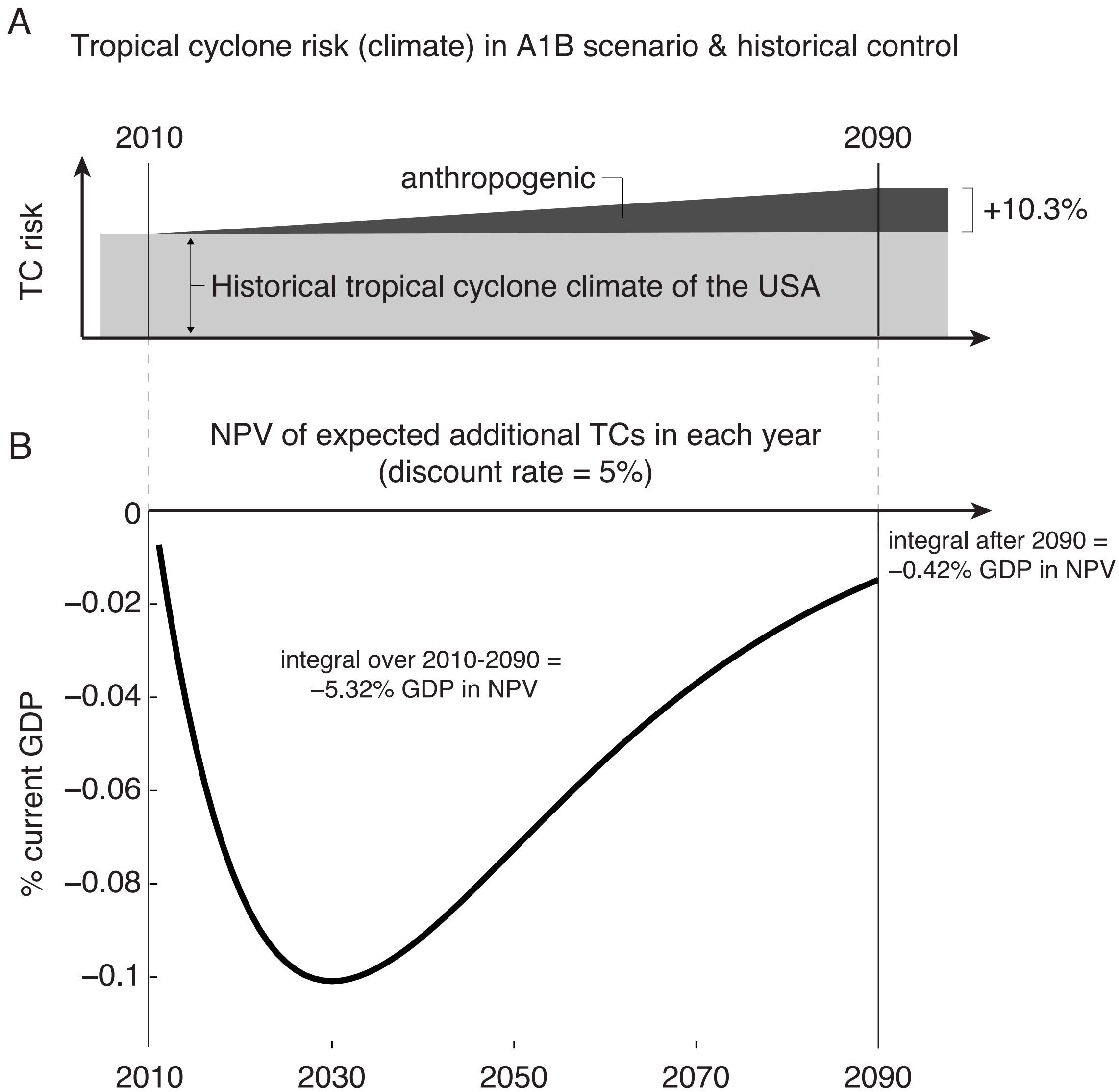
Appendix Figure A.6: Figure A.5 continued.



Appendix Figure A.7: Average annual growth rates as observed historically (dark bars, equal to simulated growth with full model) and average growth in simulations where cyclones are removed (light bars). The difference in the height of the bars is the "missing" average annual growth loss to cyclones.



Appendix Figure A.8: 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 (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 Figure A.9: Example calculation of NPV of changes to the tropical cyclone climate of the United States under "Business as usual" (as tabulated in Table 7). (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.