Climate Shocks, Cyclones, and Economic Growth: Bridging the Micro-Macro Gap

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Abstract

This paper proposes a joint empirical-structural approach to quantify the impacts of cyclone risks on economic growth and welfare. First, we review prior reduced-form approaches in a harmonized global dataset and through a theory lens. Second, we estimate cyclone impacts on structural determinants of growth (total factor productivity, capital losses, fatalities) to quantify a stochastic endogenous growth cyclone-economy model for 40 vulnerable countries. Third, we study climate change impacts on cyclone risk. The results suggest negative but mostly modest impacts of risk changes on growth, but substantial welfare losses for many countries, especially in the Caribbean and the United States.

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1 Introduction

What are the macroeconomic consequences of climate change? A rapidly growing body of empirical work has associated weather events such as temperature anomalies and tropical storms with large impacts on aggregate output. While many of these studies seek to inform estimates of the social costs of climate change, their findings have often been slow to be incorporated into macroeconomic climate-economy models. On the one hand, there are still fundamental questions about the methodologies and interpretation of this empirical work (see, e.g., Newell et al., 2021; Carleton and Greenstone, 2020). Indeed, for tropical storms the empirical literature has found a wide range of results, including positive (e.g., Skidmore and Toya, 2002), mixed (e.g., Noy, 2009), small negative (e.g., Strobl, 2011), and very large negative (e.g., Hsiang and Jina, 2014) effects on growth. On the other hand, it is often unclear how to map reduced-form evidence into structural models. Given that climate-economy models are used to quantify the social cost of carbon emissions (Greenstone, Kopits, and Wolverton, 2013), and given that empirically estimated output impacts could add significantly to these costs (e.g., Moore and Diaz, 2015), this "micro-macro" gap represents both an important academic and policy concern.

This paper proposes a novel joint empirical-structural approach to overcome this gap in the context of *tropical cyclones* (i.e., hurricanes, typhoons). Cyclones are the leading cause of natural disaster damages world-wide.[1] A large empirical literature has investigated the impacts of tropical cyclones on economic growth (e.g., Skidmore and Toya, 2002; Noy, 2009; Loayza et al., 2009; Raddatz 2009; Strobl, 2011; Fomby, Ikeda, and Loayza, 2013; McDermott et al., 2014; Hsiang and Jina, 2014; Eliott et al., 2015; see also review by Kousky, 2014; etc.). Importantly, cyclone impacts are projected to increase in the coming decades due to global changes (e.g,. Nordhaus, 2010b; Mendelsohn et al., 2012; Ranson et al., 2014). Our contribution to this literature is twofold.

First, we review competing prior empirical approaches to quantifying cyclone impacts on economic growth. We assemble a modern dataset encompassing meteorological measures of the full history of cyclones around the globe from 1970-2015 in order to revisit prior approaches in a harmonized sample. On the one hand, we find that key divergent prior findings can be reconciled based on methodological differences in estimation. On the other hand, through the lens of macroeconomic theory, we also show that prior reduced-form approaches cannot capture the full impacts of future cyclone risk changes on growth and welfare. For example, panel fixed-effects models may isolate the direct output losses from cyclone strikes, but fail to capture long-run and indirect impacts of cyclone *risk* on margins such as savings and investment behavior.

[1] Comparing overall natural event losses worldwide (1998-2008) from cyclones to earthquakes/tsunamis, convective storms, winter storms, floods, and heatwaves/fires in MunichRe's NatCatService database.

Second, we propose a novel approach which combines empirical estimation with the structure of a model to account for both direct and indirect impacts and to quantify the welfare costs of cyclone risk. On the empirical side, we first quantify cyclone impacts on the *structural determinants of growth*, rather than on growth itself. Specifically, we estimate cyclone strike impacts on total factor productivity (TFP), capital destruction, and fatalities within our global panel. On the modeling side, we present a stochastic endogenous growth cyclone-climate-economy model. Our framework builds closely on Krebs (2003ab, 2006; see also Krebs et al., 2015) who studies the implications of business cycles and idiosyncratic human capital risks for growth, and welfare. One key feature of the model is that it makes an explicit distinction between climate and weather: Households face repeated risks to their physical and human capital from cyclone strikes (weather), whose probability distribution is determined by the climate. This setup enables us to directly calibrate cyclone impacts to the plausibly causally identified estimates from panel (weather) regressions. In addition, the model structure enables us to account for household responses to changing cyclone risks (climate) through changes in savings and asset allocations. Our approach thus meets the three goals for modern climate impact quantification as proposed by Auffhammer (2018) and Greenstone (2016): (i) plausibly causally identified empirical impact estimates, (ii) accounting for adaptation through endogenous adjustments in savings and investments, and (iii) computing welfare costs of changes in climatic risks.

We quantify our cyclone-climate-economy model separately for each of 40 cyclone-vulnerable nations. The calibration includes country-specific probability distributions current and future cyclone intensity which we estimate based on 68,000 synthetic storm track simulations from Emanuel et al. (2008) and grounded in historical best track cyclone data. We use the model to quantify the growth and welfare impacts of both present-day and future cyclone risk distributions.

Our main finding is that cyclone risk changes from global warming are projected to impose significant welfare costs on many countries. Even under a moderate emissions scenario, welfare losses are estimated to reach up to a 5% balanced growth path consumption equivalent loss in the most vulnerable countries (e.g., St. Vincent and the Grenadines). Interestingly, though the most negatively impacted countries are generally poor and/or small island states (e.g., Belize, Haiti, Comoros, etc.), the United States is also among the top ten impacted countries. This result is informed by prior empirical work identifying the United States as an outlier in cyclone vulnerability conditional on its income levels and exposure (e.g., Bakkensen and Mendelsohn, 2016), and highlights the importance of work investigating the determinants of adaptation to storms in the United States (e.g., Fried, 2021).

We also find negative impacts of cyclone risk on average economic growth. This finding is distinct from the negative impacts of cyclone strikes on short-run growth that has been documented empirically, and which our model replicates. Present-day cyclone risks are estimated to decrease average annual growth rates by between 0.01 and 0.1 percentage points in the ten most vulnerable countries in our sample. One reason why these figures may appear smaller than some prior empirical estimates is that our model accounts for both direct and indirect effects of storms. Indeed, we find that behavioral adjustments to changes in storm risk can mitigate their negative growth impacts by up to 30-40%.

Our analysis complements several recent literature advancements on the quantitative modeling of natural disasters and the macroeconomy. Perhaps most closely related in methodology, Fried (2021) presents a dynamic general equilibrium model of the U.S. economy where heterogeneous households face risks of capital destruction from storms. She presents an original calibration using U.S. Federal Emergency Management Agency (FEMA) disaster assistance across regions, and utilizes the model to quantify adaptation capital, FEMA policy effects, and the role of adaptation in mitigating welfare costs from future storm intensity increases. Hallegatte et al. (2007) develop a 'non-equilibrium dynamic model' (NEDyM) of disasters and apply it to extreme weather events (albeit not cyclones)[2] in Europe. NEDyM builds on a Solow growth model with limits on reconstruction investment and non-clearing short-run labor and goods markets. As both our model structure and research goals are fundamentally different, we abstract from some of the important nuances featured in these studies, and focus instead on detailed linkages to empirical reduced-form approaches and long-run growth impacts under aggregate risk.[3,4] Conceptually, our analysis is also informed by a vast literature in macroeconomics on the effects of uninsurable risks on economic growth and welfare (e.g., Bewley, 1977; Lucas, 1987; Ayiagari, 1994; Krebs, 2003ab, etc.). In recent years, several theoretical studies have considered natural disaster risks and growth in particular (e.g., Ikefuji and Horii, 2012; Müller-Fürstenberger and Schumacher, 2015; Bretschger and Vinogradova, 2016; Akao and Sakamoto, 2013).[5]

More broadly, our analysis also relates to a parallel literature on temperature shocks and economic growth. Several influential empirical studies have argued that temperature shocks

[2] Hallegatte (2009) combines empirical direct cyclone impact estimates for the United States with estimates of the relationship between direct and indirect losses (based on a case study applying an Input-Output model to Hurricane Katrina's sectoral impacts) to project total economic losses from hurricanes in the United States both with and without climate change-induced hurricane intensity increases.

[3] For example, besides structural differences, Fried (2021) features no aggregate risk from storms in the United States. In contrast, we study aggregate growth impacts of cyclone risk across 40 vulnerable countries. Similarly, Hallegatte et al. (2007) focus on short-run transitional additions to overall disaster costs. In contrast, our focus is on long-run growth effects through changes in asset allocations and savings rates, which are exogenous in NEDyM.

[4] Another related study by Narita, Tol, and Anthoff (2009) use the FUND integrated assessment model to project direct cyclone damage impacts on the social cost of carbon, but not on the macroeconomy.

[5] Some studies have considered the macroeconomic impacts of rare disaster risk (e.g., Barro, 2006; Pindyck and Wang, 2013). Cyclones are typically not examples of such rare disasters, however, as they are both common in many countries and physically limited (Emanuel and Holland, 2011). Pindyck and Wang (2013) define catastrophic shocks as reducing capital by "more than 10 or 15 percent." In our data, even the 95th percentile of capital destruction is only 2.8 percent.

affect economic growth (e.g., Bansal and Ochoa, 2011; Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015; Colacito, Hoffman, Phan, 2018; etc.). Though the robustness and interpretation of these results remains subject to an active debate (e.g., Newell et al., 2021; Kalkuhl and Wenz, 2020), there have been efforts to incorporate these findings into climate-economic models. One pioneering analysis by Moore and Diaz (2015) seeks to incorporate Dell et al.'s (2012) findings into the seminal DICE model (Nordhaus, 2017). As *output growth* impact estimates do not provide a clear mapping into macroeconomic models, Moore and Diaz (2015) consider calibrating either TFP growth or capital depreciation to match reduced-form estimates. While both mechanisms lead to an increase in the social cost of carbon, the choice between them appears quantitatively significant.[6] A similar issue arises in Fankhauser and Tol (2005) and Dietz and Stern (2015), who extend DICE to an endogenous long-run growth framework with capital- or investment-based knowledge spillovers. Absent empirical guidance, they also consider a capital depreciation specification and a TFP depreciation specification. Notably, the optimal carbon price in 2015 is 55% higher with the TFP specification, again highlighting the critical importance of understanding impact channels. In order to overcome these ambiguities, we propose a joint empirical-structural approach that directly estimates cyclone impacts on the determinants of growth.[7,8]

The remainder of this paper proceeds as follows. Section 2 describes our data and presents our review of reduced-form approaches to quantifying cyclone impacts on economic growth. Section 3 presents our stochastic endogenous growth cyclone–climate-economy model. Section 4 details our quantification of the model, including the empirical estimation of cyclone strike impacts on TFP, capital destruction, and fatalities and our estimation of cyclone risk probability distributions. Finally, Section 5 presents our modeling results, and Section 6 concludes.

[6] More and Diaz (2015) ultimately focus on the TFP pathway. Supplementary results for the depreciation pathway suggest broadly similar patterns but a significantly higher social cost of carbon. Gauging visually from the relevant graphs, the SCC appears to reach well over $1,500+ per ton by 2080 for depreciation damages, compared to around $1,000 per ton for the TFP pathway in the benchmark.

[7] Alternative approaches include, e.g., Bansal and Ochoa (2011) who present a Long-Run Risk model calibrated to their own estimates of temperature shock growth impacts. Consumption growth is a given process in this model; that is, it is not a production-based growth model, thus side-stepping questions of impact mechanisms.

[8] A growing number of studies present climate-economy models with growth impacts but without focus on empirical connections. Bretschger and Valente (2011) provide a theoretical foundation for climate change growth impacts through multiple channels (capital and TFP depreciation). Lemoine (2019) presents an endowment economy with temperature impacts on consumption growth to study the implications of uncertainty for the social cost of carbon. Of course there is also a broader theoretical literature on the environment and endogenous growth (e.g,. Bovenberg and Smulders, 1995).

2 Revisiting Empirical Approaches

2.1 Data

The first step in our analysis is to compile a harmonized global panel of cyclones and relevant economic indicators at the country-year level.

Cyclone Data: Building on best practices in the literature (Hsiang and Jina, 2014), we gather historical global tropical cyclone tracks from the International Best Track Archive for Climate Stewardship (IBTrACS; Knapp et al., 2010). Considered the most comprehensive record of global historical tropical cyclone tracks by the World Meteorological Organization, IBTrACS contains best track records of cyclone position and intensity characteristics collected from meteorological agencies across the world. We focus on 1970-2015, the post-satellite era for which cyclones have been most reliably tracked. For all 3,346 cyclone landfalls during this period, we calculate cyclone intensity metrics including annual maximum wind speed at landfall (in knots) and annual energy (the sum of cubes of wind speeds recorded within a country), a metric based on the power dissipation index developed by Emanuel (2008).[9] We process the tracks in ArcGIS and aggregate data up to the country-year level.[10] Importantly, we divide all meteorological cyclone intensity measures by country land areas in order to account for potential heterogeneity in macroeconomic relevance of cyclones for countries of different sizes. Next, in order to estimate future changes in cyclone risks, we incorporate 68,000 simulated *future* tropical cyclone tracks based on advancements in climatological research by Kerry Emanuel and co-authors (Emanuel, 2008; Emanuel, Sundararajan, and Williams, 2008). These synthetic tracks and their usage are described in detail in Section 4.3.

Macroeconomic Indicators: We collect annual national-level macroeconomic indicators including real GDP (2011 $US), physical and human capital stocks, and population from the Penn World Tables 9.0 ("PWT", Feenstra et al., 2015). Though not directly used in our analysis, we further obtain World Bank data (from World Development Indicators) on several other macroeconomic indicators (gross capital formation and imports, foreign direct investment, and government surplus all as percentage of GDP) included in analyses such as Noy (2009) in order to construct a comparable sample based on data availability (described in Section 2.2).

Geography: Country areas and absolute latitudes are collected from the Harvard WorldMap.

[9] Given that some cyclone wind speeds are listed as zero while a cyclone necessarily has non-zero wind speeds, we interpolate missing wind speeds from minimum pressure readings following Atkinson and Holliday (1977). For a minority of observations missing both wind and pressure, we assume a wind speed of 35 knots for categorized cyclones and 25 knots for tropical depressions. Lastly, we convert 1 minute sustained wind speeds to 10 minute sustained wind speeds for unit consistency.

[10] We process the data without a dedicated wind-field model. For recent advancements on such modeling, see, e.g., Strobl (2011), Hsiang and Narita (2012), Hsiang and Jina (2014).

We also collect information on countries' populations living below five meters of elevation from the Low Elevation Coastal Zone Urban-Rural Population and Land Area Estimates from the Center for International Earth Science Information Network (CIESIN) at Columbia University and as published through the Socioeconomic Data and Applications Center (SEDAC).

Institutions: In line with the broader disasters literature (e.g., Noy, 2009; McDermott et al., 2014), we consider the World Bank's measure of *domestic credit provided by the financial sector* (as a percentage of GDP) as a proxy for financial market development. We also collect World Bank data on countries' "Statistical Capacity Ratings."

Cyclone Damages: Finally, we obtain cyclone damage estimates from two sources. Our benchmark measure of property damages and fatalities is gathered from EMDAT, the International Disaster Database (Guha-Sapir et al., 2016). EMDAT is the most comprehensive publicly available database on disaster losses and arguably the most widely used in the literature (e.g., Skidmore and Toya, 2002; Raddatz, 2007; Noy, 2009; Hsiang and Narita, 2012; etc.). At the same time, EMDAT data are subject to certain data quality caveats (e.g., Hsiang and Narita, 2012). While comparative analyses with proprietary damage data from global re-insurance companies fail to indicate that these would necessarily dominate EMDAT data coverage (Guha-Sapir et al., 2002), for robustness, we also consider damage estimates from MunichRe. We specifically use country-year aggregates of total direct losses from cyclones as computed by Neumayer, Plumper, and Barthel (2014) from the MunichRe database.

2.2 Estimation

The most common empirical approach to studying natural disaster impacts on growth is to use panel variation. Conceptually, this approach captures the impact of cyclone *strikes* on realized growth. This literature has documented a range of results, with most finding negative effects of varying magnitude and duration (see, e.g., Kousky, 2014) but some finding no impacts in all but the most extreme disasters (Cavallo et al., 2013).[11] As a first step we thus consider a panel specification similar to Hsiang and Jina (2014) in our harmonized global sample:

$$g_{j,t} = \gamma_j + \delta_t + (\theta_j \cdot t) + \sum_{l=0}^{L} \beta_{1+l}\varepsilon_{j,t-l} + \beta_{Int}(q_{j,t} \cdot \varepsilon_{j,t}) + \epsilon_{j,t} \tag{1}$$

Here, $g_{j,t}$ is a country's annual real GDP per capita growth rate, γ_j are country fixed-effects,

[11] Prior research has already identified study design features which can contribute to differences in results. For example, Loayza et al. (2009) document heterogeneous impacts across disaster types (e.g., earthquakes versus storms). Different proxies for disaster intensity (e.g., property damages versus fatalities) have also been shown to yield different results (Noy, 2009). Given our focus on one disaster type, cyclones, and one intensity measure type, meteorological, these factors cannot account for differences in results in our setting.

$(\theta_j \cdot t)$ are country-specific linear time trends, and $\varepsilon_{j,t-l}$ are cyclone realization measures up to lag L. Our preferred cyclone intensity measure $\varepsilon_{j,t}$ is maximum sustained cyclone wind speed per square kilometer of land area. However, parts of our analysis also consider the number of cyclone landfalls per land area or cyclone energy (the sum of cubes of maximum wind speeds in a given country-year). Online Appendix Table A0 presents summary statistics for each of these measures. Our output growth panel regressions focus on contemporaneous impacts ($L = 0$), but we consider richer lag structures in our main empirical impact channel estimation in Section 4. The empirical literature has frequently found that disaster impacts vary with country characteristics, particularly the level of development and the quality of (financial) institutions (e.g., Kahn, 2005; Loayza et al., 2009; Noy, 2009; Raddatz 2009; Fomby, Ikeda, and Loayza, 2013; McDermott et al., 2014). Specification (1) consequently allows for the impact of cyclones to vary with covariates $q_{j,t}$, specifically domestic credit or lagged GDP per capita.[12] Standard errors $\epsilon_{j,t}$ are heteroskedasticity-robust and clustered at the country level.

In reviewing the literature, we document another potential source of variation in results: sample composition based on macroeconomic control variable availability. That is, prior studies differ in the control variables they consider. One classic example, Noy (2009), includes a rich set of controls such as government budget surplus and foreign exchange reserves, permitting a final sample of 109 countries. Numerous other recent studies end up with similar or smaller samples,[13] whereas, e.g., Cavallo et al. (2013) use a synthetic controls approach and construct certain variables permitting a sample of 196 countries. In order to gauge whether such sample differences may be contributing to differences in studies' results, we estimate (1) for two samples: (i) "Unfiltered" includes all available countries (182 countries), whereas (ii) "Has Controls" includes only country-years for which control variables used by Noy (2009) and others are available.[14] We do *not* actually include those controls in the regressions so as to isolate sample effects.

Table 1 presents the results for landfall counts and maximum wind speed per square kilometer as intensity metrics. Results for energy are presented in the Online Appendix (Table A1). First, the results generally confirm that cyclone *strikes* have a negative effect on contemporaneous economic growth. Second, the statistical precision of these results differs notably across

[12] We lag GDP to avoid endogeneity to the year t disaster realization, but consider contemporaneous credit as it reduces impacts precisely through its response to disasters.

[13] For example, Loyaza et al. (2012) have a sample of 94 countries and Fomby et al. (2013) study 84 countries.

[14] We specifically define a sample of country-years that have data on gross capital formation, domestic credit, imports as percentage of GDP, foreign direct investment, government surplus, and countries that have at any point had institutional quality ratings from the *International Country Risk Guide* (ICRG). This sample does *not* match Noy's exactly due to changes in source databases over time. We also do not purchase the *ICRG* data and utilize public metadata instead (URL: https://epub.prsgroup.com/available-countries). If countries have entered this database since the time of Noy's (2009) analysis, they may also change the relative samples. Importantly, our goal is not to replicate Noy's sample per se, but to demonstrate how a representative example of standard controls can affect the sample precision and results.

the unfiltered and data-restricted country samples. In the unfiltered sample, contemporaneous cyclone impacts are precisely estimated only for energy, whereas they are generally significantly different from zero in the data-restricted sample, broadly in line with some of the underlying heterogeneity in the literature.[15] As shown in the Online Appendix (Table A2), countries in the restricted sample feature significantly higher average statistical capacity, lower volatility in GDP growth, and larger average populations than the unfiltered sample, likely contributing to the difference in precision of the estimated results. Finally, in line with prior studies, we see that these negative growth impacts are generally lower in countries with better financial institutions (proxied by domestic credit, Columns (2) and (5)) and higher levels of development (Columns (3) and (6)).

[15] For example, studies such as Noy (2009) have found significant negative effects of disasters on growth, whereas Cavallo et al. (2013) do not except in the largest disasters. Of course, there are many other methodological differences across these and other studies, and it is beyond the scope of our study to formally decompose differences in results across these factors.

Table 1: Panel Analysis: Cyclone Strikes and Growth

Dependent Variable:	Real GDP/Capita Growth$_{j,t}$					
	Unfiltered			Has Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
#Landfalls/sqkm$_{j,t}$	0.637	-1.970	-19.395	-67.112**	-472.355**	-1,212.980***
	(1.282)	(20.518)	(33.566)	(29.058)	(191.126)	(427.418)
Credit$_{j,t}\cdot$(#Landfalls/sqkm$_{j,t}$)		0.010			5.370**	
		(0.273)			(2.669)	
$\ln\left(\text{GDP p.c.}\right)_{j,t-1}\cdot$(#Landfalls/sqkm$_{j,t}$)			1.962			115.904***
			(3.308)			(41.925)
Domestic Credit$_{j,t}$		-0.000			-0.000**	
		(0.000)			(0.000)	
$\ln\left(\text{GDP p.c.}\right)_{j,t-1}$			-0.103***			-0.220***
			(0.013)			(0.033)
Adj. R-Squared	0.110	0.0985	0.165	0.177	0.201	0.277
Max. Wind/sqkm$_{j,t}$	0.004	-0.899	-2.708	-2.280***	-3.731**	-5.183
	(0.050)	(1.202)	(2.065)	(0.298)	(1.821)	(9.959)
Credit$_{j,t}\cdot$(Max. Wind/sqkm$_{j,t}$)		0.010			0.020	
		(0.015)			(0.023)	
$\ln\left(\text{GDP p.c.}\right)_{j,t-1}\cdot$(Max. Wind/sqkm$_{j,t}$)			0.275			0.306
			(0.207)			(0.993)
Domestic Credit$_{j,t}$		-0.000			-0.000**	
		(0.000)			(0.000)	
$\ln\left(\text{GDP p.c.}\right)_{j,t-1}$			-0.103***			-0.219***
			(0.013)			(0.033)
Adj. R-Squared	0.110	0.0993	0.166	0.178	0.200	0.278
Observations	7,573	5,690	7,573	1,978	1,978	1,978
#Countries	182	171	182	116	116	116
Country F.E.s:	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s:	Yes	Yes	Yes	Yes	Yes	Yes
Country-Trends:	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Cluster	Country	Country	Country	Country	Country	Country

Table presents regression of countries' real GDP per capita growth rate in year t on number of cyclone landfalls per sqkm. (top panel) or max. wind speed per sqkm. in year t plus controls for lagged natural log of real GDP per capita in level and interacted with storms (Cols.3, 6) or domestic credit provided by financial sector (%GDP) in level and interacted with storms (Cols. 2, 5). All regressions include country fixed effects, year fixed effects, country-specific linear time trends, and a constant. Standard errors are heteroskedasticity-robust and clustered at the country level. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

An alternative approach to analyzing the association between natural disasters and economic growth has been cross-sectional analysis. Though less common, this approach is used in one of the most widely cited papers in the literature by Skidmore and Toya (2002).[16] Their study

[16] Another cross-sectional study by Hsiang and Jina (2015) documents a negative cross-sectional relationship

regresses countries' average 1960-90 growth rates on disaster metrics such as the average number of climatic events per year. In stark contrast to the panel literature, Skidmore and Toya (2002) find a *positive* correlation between disasters and growth. We show in the Online Appendix that this surprising result survives in our harmonized modern dataset. That is, in the same global analysis that yields a negative panel impact estimate of cyclone strikes on growth, we find a positive correlation between average cyclone risk and growth. We next describe potential reasons for this divergence and the shortcomings of both panel and cross-sectional methods for quantifying the full impacts of cyclone risk changes.

2.3 Discussion

From a macro-theoretical perspective, it is not surprising that panel and cross-sectional analyses produce such different results. Panel specifications such as (1) capture the impact of cyclone *strikes* on realized growth, whereas cross-sectional regressions intend to capture the effect of cyclone *risk* on average long-run growth, although omitted variable bias is of course a major concern. Conceptually, cyclone strikes should have a direct negative impact on GDP growth if they destroy productive assets or disrupt production processes. As households and firms respond to the risk of such strikes, however, several indirect mechanisms may lead to a different relationship between cyclone risk and long-run growth. For example, an increase in economic risk may induce households to save more, that is, to undertake precautionary savings (e.g., Bewley, 1977). Ceteris paribus, an increase in savings rates can increase average growth rates across a range of macroeconomic models.[17] As another example, to the extent that cyclone risk alters the relative attractiveness of different investment options (e.g., physical versus human capital), it may also alter long-run growth indirectly by changing the *composition* of an economy's assets. Importantly, these considerations suggest that neither panel nor cross-sectional growth regressions are sufficient to quantify the full impacts of future changes in cyclone risks. On the one hand, while panel approaches are clearly attractive in terms of econometric identification, they fail to account for the indirect effects of cyclone risk on long-run growth.[18] Cross-sectional

between average cyclone-induced capital depreciation and growth.

[17] For example, an increasing in savings rates could increase growth (i) in a Solow growth model during the transition to a long-run balanced growth path, (ii) in an endogenous growth model with aggregate capital externalities (see, e.g., Devereux and Smith, 1993), (iii) in an AK-type endogenous growth model (see, e.g., Krebs, 2006), and (iv) in a Lucas (1988)-style model of human capital-driven growth (see, e.g., Ikefuji and Horii, 2012).

[18] Formally, the fixed effects related to countries' average growth rates in (1), γ_j and θ_j, are endogenous to cyclone *risk*. This endogeneity becomes important if one wishes to use panel estimates to predict climate change impacts. That is, while some empirical studies have analyzed climate change impacts by evaluating (1) at alternative potential future storm *realizations* (e.g., Hsiang and Jina, 2014), this approach does not account for climate change impacts on average growth rates due to changes in expected cyclone risk. A prior version of this paper explored a two-step estimator to evaluate cyclone impacts through both channels

approaches, on the other hand, are vulnerable to omitted variable bias (see, e.g., discussion in Auffhammer, 2018). More fundamentally, growth impacts also need not be informative about welfare. It is long known that changes in economic risk can affect growth and welfare in opposite ways (see, e.g., Devereux and Smith, 1993). For example, if higher cyclone risk increases growth by increasing precautionary savings, this change is clearly welfare-reducing. Consequently, even a perfectly identified cross-sectional growth regression would not be sufficient to quantify welfare impacts of cyclone risk changes. In sum, these results thus highlight the need for a structural approach to capture both the welfare and general equilibrium effects of climate-induced changes in future cyclone risks. The next section describes our framework.

Before proceeding, we note that panel output growth regressions do provide essential insights that can inform the design of environment-economy models. For example, limited financial markets are clearly an empirically relevant contributor to vulnerability, but not accounted for in many IAMs. Another common empirical finding is that negative cyclone strike impacts on output *levels* appear *persistent* (e.g., Raddatz, 2007; Strobl, 2011; Hsiang and Jina, 2014; Elliott et al., 2015). This stylized fact is at odds with a standard Ramsey model, which would imply a growth rebound after the initial negative impact, motivating our exploration of an alternative framework.

3 Stochastic Endogenous Growth Cyclone-Economy Model

This section presents our stochastic endogenous growth cyclone-economy model. The goal of the model is to both incorporate empirical estimates of the direct impacts of storms and to account for indirect impacts of cyclones on growth and welfare. Our framework builds closely on Krebs (2003ab, 2006; see also Krebs et al., 2015).[19] We model each country as a closed economy where agents can invest in human and physical capital. Cyclone strikes can damage both types of capital as well as total factor productivity (TFP). Intuitively, human capital damages may represent mortality, other physical or mental health impacts, and disruptions to education. TFP impacts could likewise result from a variety of channels such as electricity outages (Alcott et al., 2016), labor displacement (Tierney, 1997), or complementarities among heterogeneous types of capital (Hallegatte and Vogt-Schilb, 2019), as discussed further in Section 4. Households respond to the risk of cyclones through their savings and investment decisions. Importantly for our purposes, the model thus enables us to represent both direct and indirect cyclone impact

(Bakkensen and Barrage, 2016).

[19] Krebs develops a heterogeneous agent version of this class of model to study the implications of idiosyncratic human capital and business cycle risks for household savings, investment, growth, and welfare. We consider a representative agent economy but allow for (i) correlated shocks to both human and physical capital, and (ii) an application and damage specification to natural disaster risk, specifically tropical cyclones.

channels and to reproduce some key results of the empirical literature. For example, the model predicts both negative and partly persistent output impacts from cyclone *strikes* (e.g., Raddatz, 2007; Strobl, 2011; Hsiang and Jina, 2014; Elliott et al., 2015) and ambiguous growth impacts of cyclone *risk*, mediated through channels such as relatively higher human capital accumulation (e.g., Skidmore and Toya, 2002). This section first presents the model and then proceeds to describe some of its key features below.

3.1 Model Setup

Each country j is inhabited by a representative household who can invest in human capital ($h_{j,t}$) and physical capital ($k_{j,t}$). Each period t, the economy faces a cyclone shock $\varepsilon_{j,t}$ which is independent and identically distributed $\varepsilon_{j,t} \sim f_j(\varepsilon_j)$. The variable $\varepsilon_{j,t}$ here denotes cyclone intensity, and is later quantified to represent maximum sustained wind speeds per unit of land area in a given year. The dependence of its distribution on the climate is suppressed at this stage for notational simplicity. Cyclones can destroy both physical and human capital. Formally, the fractions of physical and human capital destroyed by a storm of intensity $\varepsilon_{j,t}$ are denoted by $\eta_j^k(\varepsilon_{j,t})$ and $\eta_j^h(\varepsilon_{j,t})$, respectively. The relationship between storm intensity and damages also varies across countries j.[20] The representative agent in country j chooses state-contingent plans for consumption $c_{j,t}$ and investments in human and physical capital ($x_{j,t}^h, x_{j,t}^k$) to maximize:[21]

$$\max E_{j,0} \sum_{t=0}^{\infty} \beta^t u(c_{j,t}) \tag{2}$$

$$\begin{aligned} \text{s.t.} \quad &: \quad c_{j,t} + x_{j,t}^k + x_{j,t}^h = k_{j,t} R_{j,t}^k + h_{j,t} R_{j,t}^h \\ k_{j,t+1} \quad &= \quad (1 - \delta_k - \eta_j^k(\varepsilon_{j,t})) k_{j,t} + x_{j,t}^k \\ h_{j,t+1} \quad &= \quad (1 - \delta_h - \eta_j^h(\varepsilon_{j,t})) h_{j,t} + x_{j,t}^h \\ & \quad\quad k_{j,0}, h_{j,0} \text{ given and } k_{j,t} \geqslant 0, h_{j,t} \geqslant 0 \end{aligned} \tag{3}$$

Here, $R_{j,t}^k$ and $R_{j,t}^h$ denote returns to physical and human capital and δ_m denotes baseline de-

[20] For now we suppress the time subscripts on the damage functions $\eta_j^h(.)$, $\eta_j^k(.)$ as the model treats these as constant within the current steady-state. In comparing present and future steady-states, however, we later allow for the possibility that damage functions change along with cyclone risks.

[21] As is standard in this type of model, there is no non-negativity constraint on human capital investment (see, e.g., Krebs et al., 2015; Krebs, 2003). In theory, such disinvestment could represent, for example, agents taking on more physically demanding labor which diminishes their health (e.g., mining). In practice, we do not find disinvestment in our quantitative analysis. That is, a non-negativity constraint would likely not be binding in our quantitative model. Even after a simulated category 5 hurricane, human capital investment remains nonnegative for all countries.

preciation of asset m. Conceptually, baseline human capital depreciation reflects factors such as skill depreciation (due to, e.g., unmodeled unemployment as in Dinerstein et al., 2020) and baseline mortality (which necessitates new investment in human capital of the young even with steady population levels). Specification (3) assumes that both physical and human capital can be quickly rebuilt after a storm event. Though necessary for tractability, this assumption is likely to bias our estimates of disaster impacts downwards, as discussed below.

Aggregate production by the representative firm rents households' factors $K_{j,t} \equiv k_{j,t}L_j$ and $H_{j,t} \equiv h_{j,t}L_j$ in competitive national markets, where L_j denotes the country's population. The representative firm maximizes intratemporal profits:

$$\max_{K_{j,t},H_{j,t}} A_{j,t}(\varepsilon_{j,t})K_{j,t}^{\alpha}H_{j,t}^{1-\alpha} - R_{j,t}^{k}K_{j,t} - R_{j,t}^{h}H_{j,t} \tag{4}$$

where $A_{j,t}(\varepsilon_{j,t})$ denotes TFP, which is also a function of storm realizations $\varepsilon_{j,t}$.

3.1.1 Equilibrium Growth and Welfare

We can now derive expressions for both expected long-run growth and realized annual growth in country j. First, let $\widetilde{k}_{j,t} \equiv \frac{k_{j,t}}{h_{j,t}}$ denote the household's ratio of physical to human capital. In equilibrium, by market clearing, the household's and the aggregate physical-human capital ratios are equal, $\widetilde{k}_{j,t} = \widetilde{K}_{j,t} \equiv \frac{K_{j,t}}{H_{j,t}}$, implying that factor returns consistent with profit-maximization are:

$$\begin{aligned} R_{j,t}^{k} &= (\alpha)A_{j,t}(\varepsilon_{j,t}) \cdot (\widetilde{k}_{j,t})^{\alpha-1} \\ R_{j,t}^{h} &= (1-\alpha)A_{j,t}(\varepsilon_{j,t}) \cdot (\widetilde{k}_{j,t})^{\alpha} \end{aligned} \tag{5}$$

Next, let the household's wealth at time t be defined by the sum of its physical and human capital: $w_{j,t} \equiv k_{j,t} + h_{j,t}$. The household's realized rate of return on this wealth in period t is given by the weighted sum of the net returns on physical and human capital:

$$\begin{aligned} r_j(\widetilde{k_{j,t}}, \varepsilon_{j,t}) \equiv\ & \omega_k(\widetilde{k_{j,t}})\left[R_{j,t}^{k}(\widetilde{k}_{j,t}, \varepsilon_{j,t}) - \delta_k - \eta_j^k(\varepsilon_{j,t})\right] \\ & + \left(1 - \omega_k(\widetilde{k_{j,t}})\right)\left[R_{j,t}^{h}(\widetilde{k}_{j,t}, \varepsilon_{j,t}) - \delta_h - \eta_j^h(\varepsilon_{j,t})\right] \end{aligned} \tag{6}$$

where $\omega_k(\widetilde{k_{j,t}}) \equiv \left(\frac{\widetilde{k}_{j,t}}{1+\widetilde{k}_{j,t}}\right)$ denotes the share of the household's wealth invested in physical capital. Intuitively, equation (6) already showcases multiple channels through which cyclones may affect household incomes. On the one one hand, we see that the immediate destruction of both physical and human capital (via $\eta_j^k(\varepsilon_{j,t})$ and $\eta_j^h(\varepsilon_{j,t})$) directly leads to a decline in the household's returns on its assets, ceteris paribus. Negative impacts of storm realizations on TFP (via $A_{j,t}(\varepsilon_{j,t})$ in 5) further reduce factor incomes, ceteris paribus. On the other hand, the potential for indirect or long-term impacts is also apparent. If households respond to cyclone risk by shifting their investments, then this change in the physical-human capital ratio $\widetilde{k}_{j,t}$ could alter both the equilibrium factor returns (via 5) and the relative importance of the asset destruction impacts (via $\omega_k(\widetilde{k_{j,t}})$). For example, if storms pose a bigger risk to physical than human capital, households may respond to storm risk by shifting their investments towards human capital, lowering their direct vulnerability but also decreasing the returns to human capital on the margin. Our quantitative model predicts this adjustment to occur (see Online Appendix).

A final channel through which cyclone risk can affect growth in the model is through savings rates. Let $\widetilde{s}_{j,t} \equiv 1 - \frac{c_{j,t}}{w_{j,t}(1+r_j(\widetilde{k}_{j,t},\varepsilon_{j,t}))}$ denote the household's savings-out-of-wealth ratio. From now on we assume that preferences follow a constant elasticity of substitution form:

$$u(c_{j,t}) = \frac{c_{j,t}^{1-\gamma}}{1-\gamma} \text{ if } \gamma \neq 1, \; = \log(c_{j,t}) \text{ if } \gamma = 1 \tag{7}$$

Following Krebs (2003b), it is straightforward to show (see Online Appendix) that the capital ratio $\widetilde{k}_j$ and the savings rate $\widetilde{s}_j$ that solve the household's problem in stationary equilibrium (where $\widetilde{k}_{j,t} = \widetilde{k}_j$ and $\widetilde{s}_{j,t} = \widetilde{s}_j$) are determined by the following two equations:

$$\widetilde{s}_j = \left(\beta E_j[(1 + r_j(\widetilde{k}'_j, \varepsilon'_j))^{1-\gamma}]\right)^{\frac{1}{\gamma}} \tag{8}$$

$$0 = \beta E_j \left[\frac{\left[R^k_j(\widetilde{k}_j, \varepsilon'_j) - \delta^k_j - \eta^k_j(\varepsilon'_j)\right] - \left[R^h_j(\widetilde{k}_j, \varepsilon'_j) - \delta^h_j - \eta^h_j(\varepsilon'_j)\right])}{(1 + r_j(\widetilde{k}'_j, \varepsilon'_j))^{\gamma}} \right] \tag{9}$$

Intuitively, optimal savings $\widetilde{s}_j$ follows from the household's Euler Equation, whereas (9) expresses an optimality condition for $\widetilde{k}_j$ based on the risk-adjusted expected returns to human and physical capital. Intuitively, households face an optimal portfolio choice problem with two risky assets, so that their optimal investment allocation depends on expected returns as well as the variances and co-variances of the returns on each type of capital (see, e.g., Campbell and Viceira, 2002). Importantly, (9) does not imply that the expected returns to physical and human capital will be equated in equilibrium but allows for the riskier asset to command a risk premium.

We can now characterize long-run or *average growth* as equal to: (see Online Appendix):

$$\bar{g}_j \equiv E\left[\frac{c'_j}{c_j}\right] = (\widetilde{s}_j)(1 + E_j[r_j(\widetilde{k}'_j, \varepsilon'_j)]) \tag{10}$$

Realized year-to-year growth $g_{j,t}$, in turn, is given by:

$$g_{j,t} = \frac{c_{j,t}}{c_{j,t-1}} = (\widetilde{s}_j)[1 + r_j(\widetilde{k}_{j,t}, \varepsilon_{j,t})] \tag{11}$$

Equations (8)-(11) illustrate how cyclone risk can alter growth through its potential impact on savings rates. For example, if households respond to higher cyclone risk with increased (precautionary) savings $\widetilde{s}_j$, average growth (10) may increase, ceteris paribus. Our quantitative model predicts such increases in savings rates with increasing cyclone risk (see Online Appendix). Cyclone strikes, however, unambiguously reduce returns and thus year-to-year growth (11). The structure of the model also implies that some of these losses will remain over time. This persistence is due to the fact that the model features constant returns to scale in reproducible factors, and as neither the optimal capital ratio nor the household's savings rate (8)-(9) depend on wealth levels (see also Online Appendix Figures A5 and A6 for a quantitative illustration). Though common in stochastic growth models of disasters and climate risk (e.g., Pindyck and Wang, 2013; Bretschger and Vinogradova, 2016; van den Bremer and van der Ploeg, 2018), there are well-known caveats associated with this modeling approach, such as its shortcomings in matching empirical moments such as on cross-country growth convergence (Mankiw, Romer, Weil, 1994). While alternative models may thus better explain other aspects of cross-country growth, for our objective of capturing the marginal effects of cyclone risk changes, our model arguably provides a natural starting point in line with related literature. Another limitation of our approach is that we do not account for frictions and delays that may prevent economies from quickly rebuilding their physical and human capital stocks after disasters. Other scholars have developed models that capture these frictions in detail, most prominently Hallegatte et al. (2007). Importantly, we note that the primary focus of our analysis is on the long-run impacts of cyclone risk changes. In order to quantify the costs of individual cyclone strikes to the economy accurately, our analysis also considers a specification based on cumulative TFP impacts over a 5-year period as described in Section 4.1. To the extent that these cumulative impacts account for the costs imposed by some of the omitted frictions, they are thus still indirectly included in our analysis. To the extent that delays in the rebuilding of human capital stocks in particular are still not captured, however, we ultimately consider our estimates a likely lower bound on cyclone costs.[22]

Finally, we highlight our measure of welfare. Following the same approach as Krebs (2003b),

[22] Several empirical studies have documented very long-run and even intergenerational impacts of disasters (e.g., Caruso and Miller, 2015; Kousky, 2016).

one can express the representative agent's expected lifetime utility $U_{0,j}$ as:

$$\begin{aligned} U_{0,j} &\equiv E_{0,j}\sum_{t=0}^{\infty}\beta^t\frac{c_{j,t}^{1-\gamma}}{1-\gamma} \\ &= \sum_{t=0}^{\infty}\beta^t\frac{E_{0,j}[\{c_{0,j}g_{j,t}(\widetilde{k}_{j,t},\varepsilon_{j,t})^t\}^{1-\gamma}]}{1-\gamma} \\ &= \frac{c_{0,j}^{1-\gamma}}{(1-\gamma)(1-\beta E_{0,j}[\overline{g}_j(\widetilde{k}_j,\varepsilon_j)^{1-\gamma}])} \end{aligned} \tag{12}$$

Here the second line follows from (11) and from the assumption that cyclone strikes are independently distributed. The third line follows from the fact that initial consumption $c_0 = (1-\widetilde{s})(1+r(\widetilde{k}_0,\varepsilon_0))w_0$ is pre-determined as initial assets h_0, k_0, and initial storm realization ε_0 are given and as the savings rate (8) is constant in stationary equilibrium. We use (12) to evaluate the welfare impacts of cyclone risk in each country, specifically by computing the balanced growth path consumption equivalent, that is, the percentage by which consumption each period would have to be increased in order to make households indifferent to a cyclone risk change.

4 Model Quantification

This sections describes the quantification of our stochastic endogenous growth model for each country in the data. Sections 4.1 and 4.2 present the empirical estimation of direct cyclone impacts on TFP and the destruction of physical and human capital, respectively. Section 4.3 describes our quantification of the cyclone intensity probability distribution for each country under current and future climates. Finally, Section 4.4 presents the remaining calibration.

4.1 Total Factor Productivity Impacts

Though the empirical literature frequently focuses on GDP per capita growth as an outcome variable, these impact estimates are difficult to incorporate directly into macroeconomic models as GDP growth is typically endogenized. In contrast, climate impacts upon structural model *parameters* are straightforward to interpret and utilize. We thus begin by conducting a standard growth accounting exercise that decomposes cyclone output growth impacts into productivity versus factor input changes. The appropriate empirical specification will generally depend on the structure of the climate-economy model for which the estimates are intended. For the aggregate production structure in our framework (4), taking logs on both sides yields:

$$\ln(A_{j,t}) = \ln(Y_{j,t}) - \alpha_{j,t}\ln(K_{j,t}) - (1-\alpha_{j,t})\left[\ln(hc_{j,t}) + \ln(L^{Pop}_{j,t})\right] \tag{13}$$

We use Penn World Tables data on GDP, capital stocks, populations, and human capital per worker to back out TFP $A_{j,t}$ for each country-year. The human capital variable maps (13) into the data following standard approaches (e.g., Hall and Jones, 1999) that specify human capital-augmented labor $H_{j,t}$ as the product of the number of workers $L_{j,t}$ and human capital per worker $hc_{j,t}$. The latter, in turn, is provided by PWT based on schooling data and returns to education estimates (Inklaar and Timmer, 2013). As our model features inelastic labor supply, we also use $L^{Pop}_{j,t}$ as a measure of workers. Following Gollin (2002) we assume common labor shares across countries and set $1-\alpha_{jt} = 0.67\ \forall j,t$.

Our preferred specification de-trends each TFP series log-linearly through the inclusion of country-specific time trends $(\gamma_j \cdot t)$ and year fixed-effects δ_t in an estimating equation which follows the standard panel approach (analogous to (1) but for TFP):

$$\ln(A_{j,t}) = \gamma_j + \delta_t + (\theta_j \cdot t) + \sum_{l=0}^{L}\beta^A_{1+l}\varepsilon_{j,t-l} + \epsilon_{j,t} \tag{14}$$

where γ_j denotes country fixed-effects and $\varepsilon_{j,t-l}$ are cyclone intensity measures up to lag L. Standard errors $\epsilon_{j,t}$ are heteroskedasticity-robust and clustered at the country level. We consider a range of values of L. Table 2 presents results for cyclone intensity measured by maximum wind speed per square kilometer.

Table 2: TFP Impacts

	(1)	(2)	(3)	(4)	(5)
Max. Wind/sqkm$_{j,t}$	-1.485*	-1.661*	-1.951*	-2.069*	-2.061*
	(0.859)	(0.948)	(1.111)	(1.201)	(1.171)
Max. Wind/sqkm$_{j,t-1}$		-1.569**	-1.856**	-1.995*	-2.095*
		(0.734)	(0.892)	(1.013)	(1.082)
Max. Wind/sqkm$_{j,t-2}$			-1.899*	-2.035*	-2.129*
			(1.009)	(1.132)	(1.207)
Max. Wind/sqkm$_{j,t-3}$				-1.704	-1.821
				(1.156)	(1.241)
Max. Wind/sqkm$_{j,t-4}$					-1.497*
					(0.889)
Obs.	6,161	6,033	5,905	5,777	5,649
Clusters	144	144	144	144	144
Adj. R^2	0.642	0.639	0.635	0.631	0.625
AIC	-8447	-8386	-8327	-8255	-8160
BIC(n=#Clusters)	-8316	-8255	-8197	-8124	-8029

Table presents regression of natural log of countries' TFP on a constant, country- and year-fixed effects, country-specific linear time trends, and max. wind speed per sqkm. Standard errors are heteroskedasticity-robust and clustered at the country level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The results indicate significant negative impacts of cyclone strikes on TFP. While the Bayesian and Akaike information criteria are minimized for the contemporaneous impacts specifications, we also find negative and at least marginally precisely estimated TFP impacts persisting up to around 5 years. The Online Appendix shows results for additional lags, which reduce the estimates' precision, but leave the magnitudes similar. The Online Appendix also presents results for specifications that (i) de-trend TFP through HP-filtering, which leads to broadly similar results, and (ii) use dissipated energy as cyclone intensity measure, which yields somewhat noisier estimates. Overall, the empirical results thus confirm that one of the channels through which cyclone strikes affect realized growth is by lowering TFP.[23]

The broader literature reveals a number of mechanisms through which TFP effects may occur. First, cyclones can cause extensive power outages; Alcott et al. (2016) show how power outages map into reductions in measured productivity in a standard production framework. Second, our framework assumes homogeneous capital stocks. In reality, production requires the combination of heterogeneous and often complementary capital inputs which cannot readily be substituted for each other, such as a road leading to a factory. Hallegatte and Vogt-Schilb (2019) showcase several mechanisms through which capital heterogeneity can lead to output losses conditional

[23] Loayza et al. (2012) consider a productivity impact channel for disasters by including capital investment rates in several output impact regressions, but do not estimate a structural damage function for TFP impacts.

on capital levels in the aftermath of a disaster. Intuitively, storms cause not only a reduction in capital levels but also a misallocation of capital across categories (e.g., cars versus roads). General production input-output linkages and complementarities have also been linked to reductions in output after disasters even for firms not damaged by storms (that is, conditional on capital and labor), see, e.g., Boehm et al. (2019). Finally, disasters may displace labor through, e.g., evacuations or transportation disruptions. Such labor displacement can force temporary closures of businesses that were physically unaffected by an event (e.g., Tierney, 1997). In our production framework, a loss of output conditional on capital, labor, and human capital would show up as a reduction in TFP. One implications of each of these mechanisms is that TFP should recover as repair and reconstruction activities restore critical infrastructure. In line with this prediction, our results do indeed suggest that TFP impacts dissipate over time, as we fail to detect significant effects after four to five years (see Online Appendix).

We formally map the Table 2 results into the model (4) via the following damage function:

$$\begin{aligned} A_{j,t}(\varepsilon_{j,t}) &= \overline{A}_{j,t}(1 - \eta^A \cdot \varepsilon_{j,t}) \\ \eta^A &= \widehat{\beta_1^A} \end{aligned} \tag{15}$$

where we use $\widehat{\beta_1^A}$ from Column 5 in Table 2 as benchmark estimate. For robustness we also consider a cumulative 5-year impact specification ($\eta^A(\varepsilon_{j,t}) = (\widehat{\beta_1^A} + \widehat{\beta_2^A} + ... + \widehat{\beta_5^A})\varepsilon_{j,t}$) based on Column 5 in Table 2.

4.2 Physical and Human Capital Losses

While there is limited literature guidance for the estimation of cyclone TFP impacts, numerous studies have quantified cyclone destruction of property and human life as a function of storm characteristics. Following these studies (e.g., Kahn, 2005; Nordhaus, 2010b; Schumacher and Strobl, 2011; Hsiang and Narita, 2012), we specify damages as polynomial function of cyclone intensity $\varepsilon_{j,t}$ (measured by maximum wind speed per square kilometer country area):

$$\begin{aligned} \eta^k_{j,t}(\varepsilon_{j,t}) &\equiv \frac{\text{PropertyDamages}_{j,t}}{K_{j,t}} = \xi^k_{1j,t}(\varepsilon_{j,t})^{\xi^k_{2j,t}} \\ \eta^h_{j,t}(\varepsilon_{j,t}) &\equiv \frac{\text{Fatalities}_{j,t}}{L_{j,t}} = \xi^h_{1j,t}(\varepsilon_{j,t})^{\xi^h_{2,j,t}} \end{aligned} \tag{16}$$

We note that the focus on fatalities as the only measure of human capital impacts is due to data limitations and expected to bias our cyclone impact estimates downward as it misses disruptions in education, morbidity, and mental health effects of storms.

Our estimation allow the damage functions (16) to vary across countries and time, in line with prior literature. That is, letting $\mathbf{x}'_{j,t}$ denote a vector of country covariates (e.g., population share in low-lying coastal areas), we allow both the multipliers and exponents in (16) to vary with $\mathbf{x}'_{j,t}$ by estimating:[24]

$$\ln(\eta^m_{j,t}) = \mathbf{x}'_{j,t}\boldsymbol{\beta}^{\mathbf{m}} + \beta^m_\varepsilon \ln \varepsilon_{j,t} + (\ln \varepsilon_{j,t} \cdot \mathbf{x_{j,t}})'\boldsymbol{\gamma}^{\mathbf{m}} + \epsilon_{j,t},\ m \in \{k, h\} \tag{17}$$

Specification (17) implies that the direct losses in, e.g., physical capital that a country experiences from a cyclone of a given intensity $\varepsilon_{j,t}$ depend on its characteristics. Given (17) one can infer the coefficients in (16) via:

$$\begin{aligned} \widehat{\xi^m_{1,j,t}} &= e^{\mathbf{x}'_{j,t}\widehat{\boldsymbol{\beta}^{\mathbf{m}}}} \\ \widehat{\xi^m_{2,j,t}} &= \widehat{\beta}_\varepsilon + \mathbf{x_{j,t}}'\boldsymbol{\gamma}^{\mathbf{m}} \end{aligned} \tag{18}$$

We consider three variables as potential covariates $\mathbf{x}'_{j,t}$: Country fixed effects, lagged GDP per capita, and the share of the population living below 5 meters elevation in coastal areas.[25] Table 3 displays the results for our preferred cyclone intensity measure of $\varepsilon_{j,t}$ as maximum wind speed per square kilometer of country area. As expected, capital losses are increasing in wind speeds, albeit with heterogeneous steepness across countries. Column (1) adopts country fixed effects as damage covariates $\mathbf{x}'_{j,t}$. This specification allows countries to differ in baseline damages conditional on experiencing a cyclone, but with common curvature in wind speed. Given the empirical literature's finding that damage curves are considerably steeper in the United States (e.g., Nordhaus, 2010b; Strobl, 2011) than globally (Hsiang and Narita, 2012; Bakkensen and Mendelsohn, 2016), Column (2) presents a U.S.-only specification, which confirms this pattern.[26] Finally, Columns (4) and (6) allow damages to vary with countries' levels of economic development and the low-lying coastal area population share. As expected, the results indicate that both physical and human capital losses are significantly larger in countries with larger population shares in low-lying coastal areas, and significantly mitigated in countries with higher economic development. Importantly, these results also indicate that countries' future vulnerability to cyclones may decrease as they develop economically. The calibrated model thus uses the results of Column (4) to quantify capital damages for all countries except the United States, for which we use the results from Column (2). For fatalities, the calibration uses the results from Column (6).

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24 Since we use the same explanatory variables for physical capital and fatality regressions, a seemingly unrelated regression (SUR) approach would not change the results.

25 While there are many other potential determinants of countries' cyclone vulnerability, these are the covariates we would expect to have first-order relevance and for which one can obtain projections of future levels, as is required for us to consider changes in countries' future vulnerabilities.

26 Quantitatively, the results may differ from studies normalizing damages by GDP as we study damages as a fraction of countries' capital stocks, which are not equiproportional to GDP across countries.

Table 3: Physical and Human Capital Losses

Dependent Variable:	$\ln(\text{PropertyDamages}_{j,t}/K_{j,t})$				$\ln(Fatalities_{j,t}/L_{j,t})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(\frac{MaxWind_{j,t}}{sqkm_j})$	1.112**	4.704***	2.034***	2.209***	0.771***	1.967***
	(0.530)	(0.959)	(0.564)	(0.559)	(0.226)	(0.339)
$\ln(\frac{MaxWind_{j,t}}{sqkm_j})\cdot \ln(\text{GDP pc})_{j,t-1}$			-0.164**	-0.201***		-0.150***
			(0.064)	(0.064)		(0.037)
$\ln(\frac{MaxWind_{j,t}}{sqkm_j})\cdot(\text{Pct. Below 5m})_{j,t}$				0.023***		0.011**
				(0.007)		(0.005)
$\ln(\text{GDP pc})_{j,t-1}$			-1.940***	-2.352***		-2.088***
			(0.644)	(0.645)		(0.370)
Pct. Below $5\text{m}_{j,t}$				0.198***		0.081**
				(0.062)		(0.038)
Constant	1.456	45.304***	13.797**	16.045***	-6.891***	10.373***
	(4.784)	(10.957)	(5.574)	(5.520)	(2.042)	(3.357)
Country Fixed Effects?	Yes	U.S. Only	No	No	Yes	No
Observations	356	29	356	356	472	471
Adj. R-Squared	0.0350	0.401	0.218	0.236	0.0316	0.489

Table presents regression of natural log of fractions of capital stock destroyed (Cols. 1-4) or population killed (Cols. 5-6) on natural log of max. wind speed normalized by country area, lagged GDP per capita levels and max. wind interactions (Cols. 3, 4, 6), the percentage of population living below 5 meters elevation in levels and max. wind interactions (Cols. 4, 6), and country fixed-effects (Cols. 1, 5). Col. 2 restricts sample to U.S. storms only. Damage data source is EMDAT. Heteroskedasticity-robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 3 is estimated using EMDAT data on cyclone damages. For robustness, we repeat the specification using MunichRe data (see Online Appendix Table A6). On the one hand, the MunichRe data yield steeper wind speed curvature estimates in the fixed effects specifications (e.g., U.S. damage elasticity of 5.9 instead of 4.7). On the other hand, the specifications with interaction terms are comparatively attenuated.

4.3 Cyclone Risk Changes

The empirical estimates presented thus far quantify the impacts of weather shocks $\varepsilon_{j,t}$. Linking these estimates to climate change requires a quantification of how the probability distribution of these shocks will change with global warming. That is, letting T_τ denote global mean surface temperature in period τ, the quantification of our model requires estimates of cyclone probability density functions (*pdfs*) $f_j(\varepsilon|T_\tau)$. The availability of atmospheric science data to estimate such *pdfs* was previously limited, forcing some earlier literature to evaluate damage functions at the projected future *means* of cyclone intensity, effectively computing damages at expected intensity rather than expected damages (e.g., Narita, Tol, Anthoff, 2009; see also review by Ranson et al., 2014). Of course, if damage functions (16) are convex, this approach risks underestimating expected future impacts. In this paper we gratefully take advantage of advances in climatological research from Kerry Emanuel and co-authors (Emanuel, 2008; Emanuel, Sundararajan, and Williams, 2008; and as utilized by Mendelsohn et al., 2012) to construct estimates of cyclone *pdf*s. Their work generates 68,000 simulated synthetic tropical cyclone tracks under each of the current (1980-2000) and future climate, specifically 2080-2100 under the IPCC's A1B emissions scenario and processed through four different general circulation models. Our benchmark analysis focuses on results using NOAA's Geophysical Fluid Dynamics Laboratory (GFDL) model (Manabe et al., 1991) yielding 17,000 simulated tracks. We also consider alternatives in the sensitivity analysis below. The synthetic cyclone tracks contain parallel information to the historical record, such as storm latitude, longitude, and wind speeds at points along the track life. Recent literature that has used synthetic tracks to inform both current cyclone risk assessments (Hallegatte, 2007; Elliott, Strobl, Sun, 2015) and projections of direct cyclone damages from climate change (Hallegatte, 2009; Mendelsohn et al., 2012).

In order to estimate cyclone *pdfs* at the country-year level, we conduct Monte Carlo simulations based on current and future landfall frequencies and sampling from either the historical cyclone record (to estimate current risk) or from synthetic tracks (to estimate future risk), as described in the Online Appendix. Importantly, this process captures changes in expected future intensity driven both by changes in the *number* and *characteristics* of storms. For landfall frequencies, we adopt a Poisson distribution (Emanuel, 2013). For our preferred cyclone measure of maximum wind speeds, the literature has found Weibull distributions to provide the best fit (Johnson and Watson 2007), which we consequently use to estimate cyclone *pdfs* for each country.[27] To validate this approach, we compare the expected annual maximum wind speeds from the Weibull model against empirically observed means in the data. The Weibull model reproduces the data extremely well, with a correlation coefficient of 0.9982 (plotted in Online Appendix Figure A1).

In order to illustrate the potential impacts of climate change on cyclone risks, Figure 1 next compares the current (from data) and projected future maximum wind speed distribution for four example countries. The simulations indicate highly heterogeneous impacts, with cyclone risk increases in some regions (e.g., the United States), but decreases in others (e.g., Australia). Countries are also predicted to experience heterogeneous changes in the variability of cyclone

[27] While 'fat tails' have been noted as a concern for some climate risks, cyclone wind speeds face a physical upper bound (Holland and Emanuel, 2011), and fitting even a log-normal distribution can imply "meteorologically unrealistic" upper tail behavior of excessive wind speeds (Johnson and Watson, 2007). Relatedly, Conte and Kelly (2016) find that cyclone damages in the United States follow a fat tailed distribution due to the spatial distribution of properties, but that household-level damages and the wind speed distribution are thin tailed. We account for uniquely high U.S. damages by utilizing a separate capital depreciation elasticity.

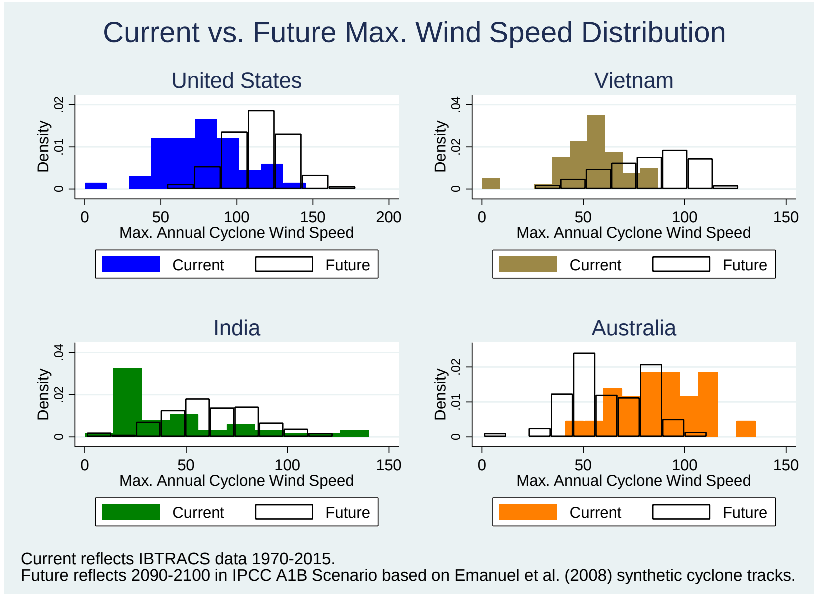

Figure 1: Example comparisons of current versus future cyclone risk distributions in 2100 under the IPCC A1B scenario.

intensity, with tightening distributions in some (e.g., India), but increasing variability in others. Figure 2 presents results for a broader set of countries, specifically by comparing current annual maximum wind speeds (x-axis) against expected future annual maximum wind speeds (y-axis). By comparing the location of each point (country) against the plotted 45° line, we see again some countries are predicted to experience substantial increases in average risk, whereas others are predicted to see declines in average cyclone activity. The Online Appendix also presents analog versions to Figure 2 for maximum wind speed per square kilometer of country area, in line with the intensity measure used in the quantitative model.

4.4 Remaining Model Elements

We quantify the remainder of the model for each country using a combination of data, estimation, matching of moments, and external calibration. Table 4 summarizes the calibration strategy. Initial capital stock levels ($K_{2014,j}$) are taken directly from the data (Penn World Tables), with a model base year of 2014. Human capital stocks are backed out via $H_{2014,j} = \frac{K_{2014,j}}{\widetilde{k}_{2014,j}}$ after solving the model for initial asset allocation ratios ($\widetilde{k}_{2014,j}$) via (9). Baseline (i.e., non-cyclone) depreciation rates (δ_k, δ_h) are calibrated in line with the literature,[28] as are the capital share

[28] For human capital, literature estimates vary. For example, Krebs et al. (2015) set δ_h equal to 0.0429 per year based on a target value for the ratio of human capital investment to gross domestic product. Manuelli

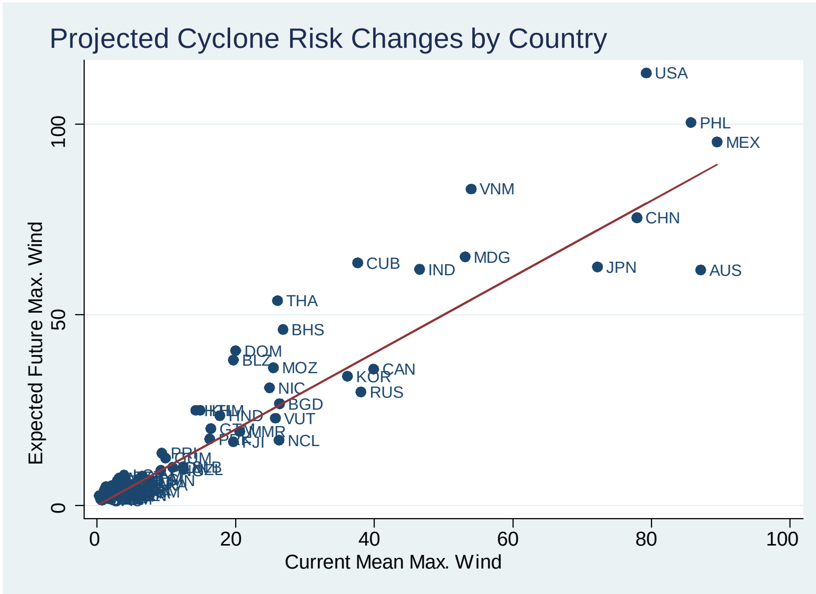

Figure 2: Current average maximum sustained wind speed (x-axis) versus expected future mean maximum wind speed (y-axis) around 2100 in IPCC A1B scenario based on estimates from Emanuel (2008). Country names are provided in Online Appendix Table A7.

(α), utility discount factor (β), and coefficient of relative risk aversion (γ). Initial productivity levels $\overline{A}_{2014,j}$ are chosen to match observed base year GDP per capita growth $g_{2014,j}$ (from Penn World Tables) at base year cyclone realizations $\varepsilon_{2014,j}$ (from IBTrACS) in each country.[29] Our counterfactual analysis considers the impacts of changes in cyclone risk both in today's economy and at the end of the century. We set future productivity $\overline{A}_{2095,j}$ and baseline wealth levels $W_{2095,j}$ to match projected year 2095 GDP per capita levels and growth rates (sans cyclone risk changes) based on projections from the RICE model (Nordhaus, 2011).[30] The corresponding physical and human capital stocks then follow after solving for the optimal asset allocation $\widetilde{k}_{2095}$ via (9). Finally, for scenarios which evaluate damage functions (18) at future covariate levels, we use projections of low-lying coastal population shares in 2100 from CIESIN (2013).

4.5 Model Assessment

Before proceeding to counterfactual simulations, we compare some of the model's predictions to empirical counterparts that were not targeted in the calibration. First we compare the model's

and Seshadri (2014) jointly match a set of moments with δ_h equal 0.027. Some older literature adopts higher values: Jones et al. (1999) assume δ_h equal to 0.075 and Krebs (2003b) adopts a value of 0.06. We thus select 0.04 as an intermediate value across this range.

29 At this step we drop some countries from the sample that experienced negative growth in 2014, in some cases severely so due to warfare or other non-modeled crises (e.g., Venezuela).

30 That is, as the RICE model does not account directly for cyclone impacts, we calibrate our model so that it matches the RICE predictions in a scenario without cyclone risk changes.

Table 4: Model Calibration

Item	Description	Source or Value
Country-Specific from Data, Estimation, Matched Moments		
Item	Description	Source or Value
$K_{2014,j}$	Capital stock	PWT Data
$H_{2014,j}$	Human capital	Back out via $H_{2014,j} = \frac{K_{2014,j}}{\widetilde{k}_{2014,j}}$
$f_j(\varepsilon\|T_\tau)$	Cyclone risk pdf	Estimated from IBTrACS cyclone records, Emanuel et al. (2008) synthetic tracks, see Section 4
$\eta_j^k(\varepsilon), \eta_j^h(\varepsilon)$ $\underline{\eta}_j^A(\varepsilon)$	Damage functions	Estimated from global macro panel, damage data; see Section 4
$\overline{A}_{2014,j}$	TFP	Match initial GDP growth (PWT)
$\overline{A}_{2095,j}$	TFP	Match projected 2095 GDP per capita levels, subsequent
$W_{2095,j}$	Wealth	growth rates absent cyclone risk changes from Nordhaus (2011)
$K_{2095,j}$	Capital stock	Back out via $K_{2095,j}$= $W_{2095,j}(\widetilde{k}_{2095,j}/(1+\widetilde{k}_{2095,j}))$
$H_{2095,j}$	Human capital	Back out via $H_{2095,j}$= $W_{2095,j}(1/(1+\widetilde{k}_{2095,j}))$
Globally Standard from Literature		
α	Capital share	0.33
δ_k	Baseline depr.	$10\%/yr$
δ_h	Baseline depr.	$4\%/yr$
γ	Risk Aversion	2
β	Utility discount	0.975

projected output growth impacts of cyclone strikes with the reduced-form empirical evidence presented in Section 2. That is, we use the structural model to predict the contemporaneous output growth impacts of a hypothetical Category 5 hurricane striking each country in the base year. We then derive an analogous prediction from the reduced-form empirical evidence in Table 1.[31] Figures 3 and 4 show scatter plots of the resulting structural versus empirical predictions among the full sample of countries and zoomed in among countries with predicted growth impacts of less than 5 percentage points, respectively. Both figures show that the structural model predictions align well with the empirical reduced-form results.

[31] We specifically use Table 1 results in Column 6 for maximum wind speed per square kilometer and evaluate the predicted impacts at each country's size and base year GDP. Results using the more precisely estimated coefficients in Table 1 Column 2 instead are extremely similar and shown in the Online Appendix.

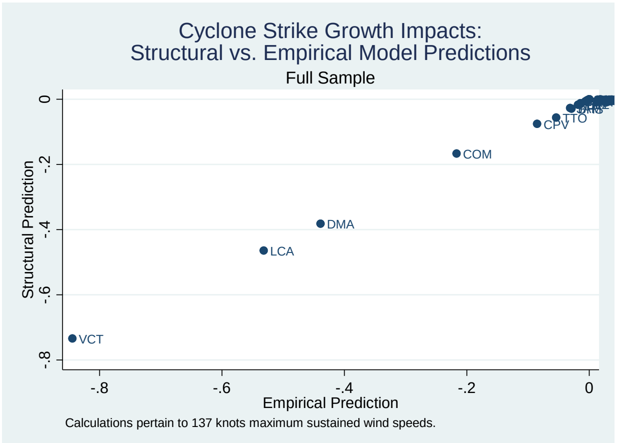

Figure 3: Comparison of empirical vs. structural model predictions of output growth impacts from a category 5 cyclone.

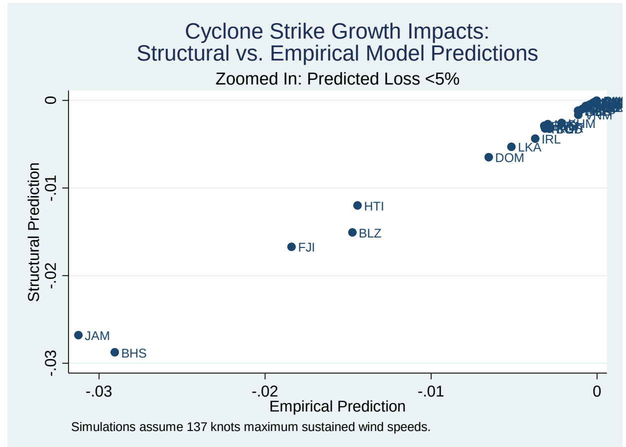

Figure 4: Zoomed in comparison of empirical vs. structural model predictions of output growth impacts from a category 5 cyclone.

As a second assessment we compare the model's predictions for investment in physical capital to data on gross fixed capital formation in the model base year. While the model's predictions are quantitatively reasonable, ranging from 20.2% to 26.9%, they do not correlate well with variation across countries in the data. This is arguably not surprising as our model is designed to capture marginal changes in investment rates due to variation in storm risks and thus abstracts from broader determinants of savings and investment such as age dependency ratios, pension systems, fiscal policy, capital controls, etc. In order to ensure the robustness of our results to this potential shortcoming, we implement an alternative calibration that allows utility discount factors β_j to vary across countries in order to match observed base year capital investment rates. The Online Appendix details this exercise. Importantly, the results are broadly similar to the benchmark model for welfare and virtually identical for the predicted growth impacts of cyclone risk.

As a final assessment, we also verify that the model predicts persistence in output losses from storms. While this is a qualitative feature of the model, we also showcase the quantitative predicted output dynamics following a hypothetical storm for several example countries in the Online Appendix. The results confirm that, while the contemporaneous negative growth impact is mitigated after the storm, some output losses are persistent, in line with the empirical evidence (e.g., Raddatz, 2007; Strobl, 2011; Hsiang and Jina, 2014; Elliott et al., 2015).

5 Model Results

Our main results consider the following four scenarios as summarized in Table 4. First, we evaluate the effects of present-day cyclone risk by comparing each country's observed baseline economy to a counterfactual one with cyclone risk set to zero.[32] Second, we consider the ceteris paribus effect of changing cyclone risks to future levels (2095-2105) consistent with our benchmark warming scenario.[33] The predicted changes in cyclone risk for each country are displayed in Figure 2 in terms of maximum wind speed, and in Online Appendix Figures A2 and A3 in terms of maximum wind speed per square kilometer. This scenario leaves both the economy and cyclone vulnerability - specifically damage functions (16, 18) - at baseline levels. Third, we consider the impacts of cyclone risk *changes* in each country's projected future economy. That is, we adjust technology levels and capital stocks to be consistent with future GDP projections (2095) and evaluate the impacts of warming-induced cyclone risk changes in this setting. One comparison assumes that countries' vulnerabilities remain at baseline levels (specifically by maintaining damage functions (16, 18) at their 2015 levels). The other assumes that cyclone vulnerability will continue to decline with growing income levels as suggested in Table 3 (specifically by evaluating damage functions at 2095 GDP levels and low-lying population shares). Table 4 summarizes the four different comparison scenarios we consider.

Table 4: Model Scenario Summary

Scenario	Benchmark			Comparison		
	Economy	Vulnerability	Cyclone Risk	Economy	Vulnerability	Cyclone Risk
#1	Baseline	Baseline	Baseline	Baseline	Baseline	Zero
#2	Baseline	Baseline	Baseline	Baseline	Baseline	Future
#3	Future	Baseline	Baseline	Future	Baseline	Future
#4	Future	Future	Baseline	Future	Future	Future

Figure 5 shows the estimated welfare impacts of both current and future cyclone risk on each country's baseline economy (Scenarios 1 and 2). First, the results show that many countries are already suffering large welfare losses from present-day cyclone risk, with welfare losses of over 5% in some small island states. Second, global warming is projected to dramatically increase these effects in many countries. Some of the most severe increases are projected to occur in countries that are already among the most vulnerable, such as Caribbean island states. Strikingly, the United States also stands out as having an almost three-fold projected increase in welfare costs from cyclones due to warming. While some countries are also projected to see declines in welfare costs, consistent with Figure 2, these generally appear smaller in magnitude (e.g., Australia). Figure 6 displays the corresponding growth rate impacts of current and future cyclone risk in each country's baseline economy (Scenarios 1 and 2). Growth impacts broadly mirror projected

[32] For comparability we keep observed 2014 cyclone realizations, but set future risk expectations to zero.

[33] In line with Emanuel's (2008) estimates we focus on IPCC's A1B emissions scenario which different climate models estimate to result (on average) in 2.8C warming over 1980-99 temperatures by 2100 (IPCC, 2007).

welfare losses, but are smaller in magnitude. Interestingly, we also find that cyclone risk decreases growth in all countries, despite leading to increases in savings rates. This result is at odds with the cross-sectional empirical findings of Skidmore and Toya (2002) suggesting a positive correlation between cyclone risks and growth. This difference could be indicative of omitted variable bias in the cross-country regression, although we of course cannot rule out model misspecification.[34]

Our model enables us to distinguish growth impacts from the direct effects (via capital destruction, fatalities, and lower TFP) and indirect effects (via changes in savings rates and investment allocation) of cyclone risk. Figure 7 presents a comparison of the direct and total (direct + indirect) impacts of future cyclone risks on growth, relative to a baseline economy with zero cyclone risk as in Scenario 2. The results indicate that total impacts are usually smaller than direct impacts. That is, behavioral responses can counteract the negative direct growth impacts of increasing cyclone risk by up to 30-40% (e.g., in Belize, Vietnam, United States).

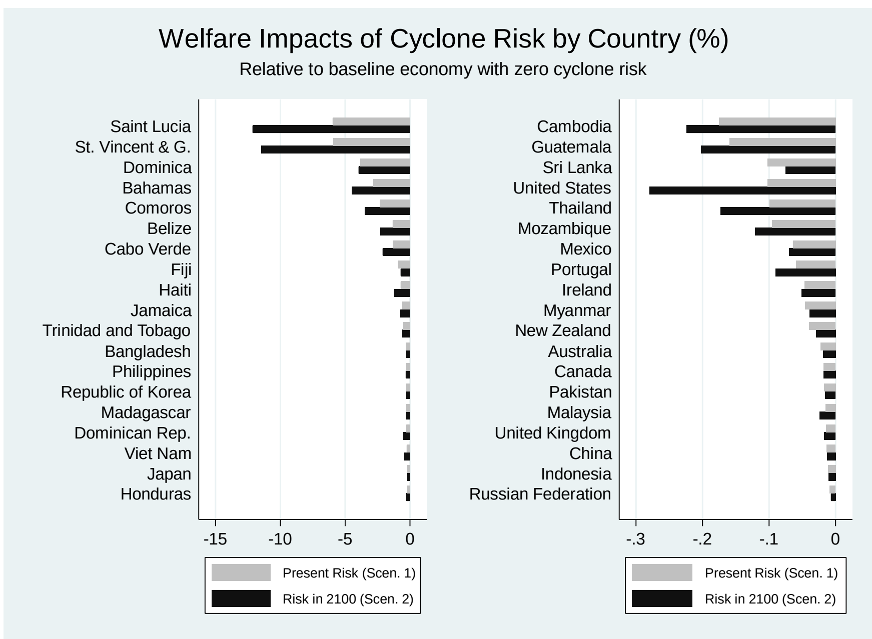

Figure 5: Welfare impacts of present-day (Scen. 1) and year 2100 (Scen. 2) cyclone risk on each country's baseline economy.

[34] One could also argue that our model omits some potentially growth-enhancing consequences of cyclone risk, such as positive externalities from increased human capital accumulation as in Lucas (1988).

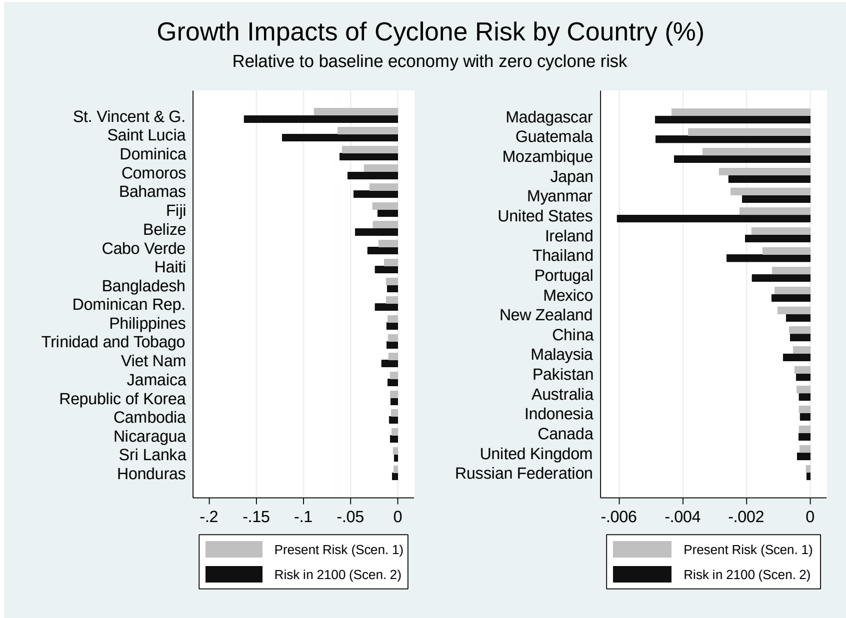

Figure 6: Growth impacts of present-day (Scen. 1) and year 2100 (Scen. 2) cyclone risk on each country's baseline economy.

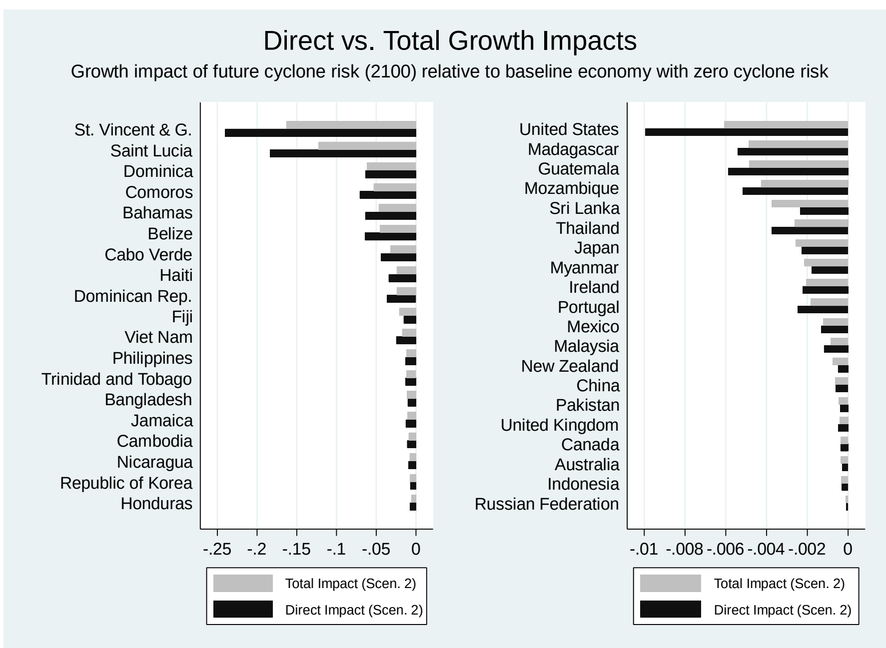

Figure 7: Direct versus total (direct + indirect) impacts of future cyclone risk (2100) relative to baseline economy with zero cyclone risk.

Next, Figures 8 and 9 display projected welfare and growth impacts, respectively, of increasing cyclone risk from 2015 levels to 2100 levels in the projected future economy of each country (Scenarios 3 and 4). Climate change is projected to have substantial negative welfare impacts through cyclone risk changes even in the wealthier economies of the future. Interestingly, the United States stands out among the 'top 10' of most negatively impacted countries, which are otherwise mostly poor and/or small island states. This result is in line with empirical evidence that the United States appears uniquely vulnerable to hurricanes in spite of its levels of income and exposure (see, e.g., Bakkensen and Mendelsohn, 2016). The results also suggest that some countries may benefit from future cyclone risk changes, in line with Figure 2 showing that some countries may see cyclone activity reductions as the climate warms. However, these benefits are quantitatively small, not consistent across climate models, and subject to major caveats. Most importantly, our analysis does not account for sea level rise, which poses a major threat to some of the projected "beneficiary" countries such as Fiji and Myanmar. Higher sea levels increase cyclone damages conditional on storm intensity. Whether the projected reductions in cyclone intensity would still translate into reductions in damages once higher sea levels were accounted for is thus highly questionable.

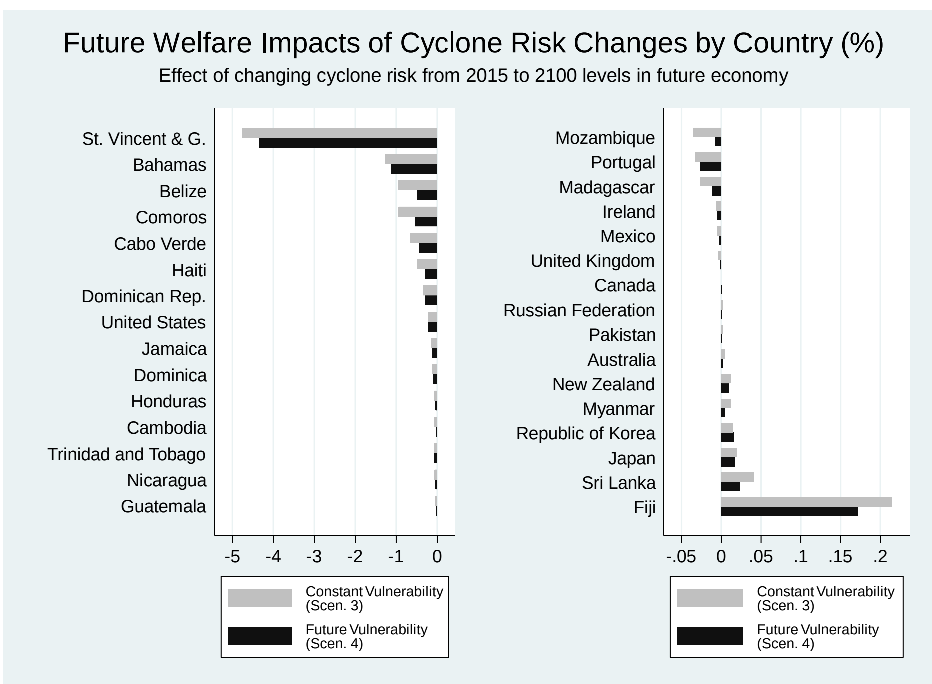

Figure 8: Welfare impacts of future cyclone risk changes in 2100 with constant (Scenario 3) or future (Scenario 4) damage functions.

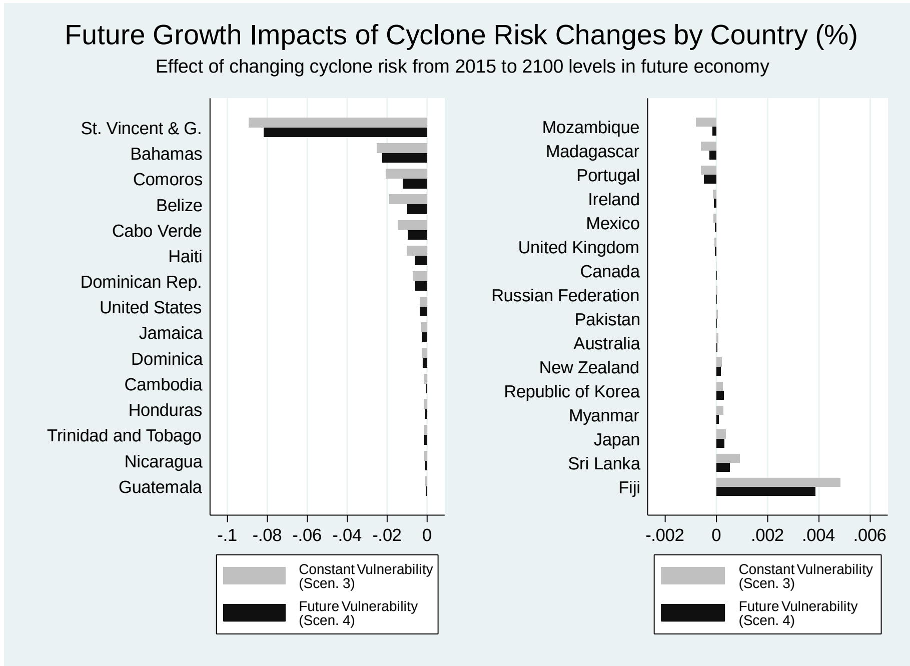

Figure 9: Growth impacts of future cyclone risk changes in 2100 with constant (Scenario 3) or future (Scenario 4) damage functions.

The results presented thus far incorporate only the contemporaneous one year impact of cyclones on TFP. The empirical results in Section 4 suggest that TFP losses persist for several years, however. Figure 10 presents results from an alternative model based on the cumulative 5-year TFP impacts of storms. The estimated welfare impacts are considerably larger than in the benchmark. For example, the welfare loss of future cyclone risk in Jamaica (Scenario 2) rises from 0.75% to more than 2%.[35]

[35] Some of the most vulnerable countries no longer have valid impact estimates in this specification. They end up as 'dismal cases' in that their expected damages can no longer be properly computed over the full integral of their Weibull wind distributions. We note that the 5-year specification likely exaggerates expected damages as cumulative impacts are aggregated to occur within one model period.

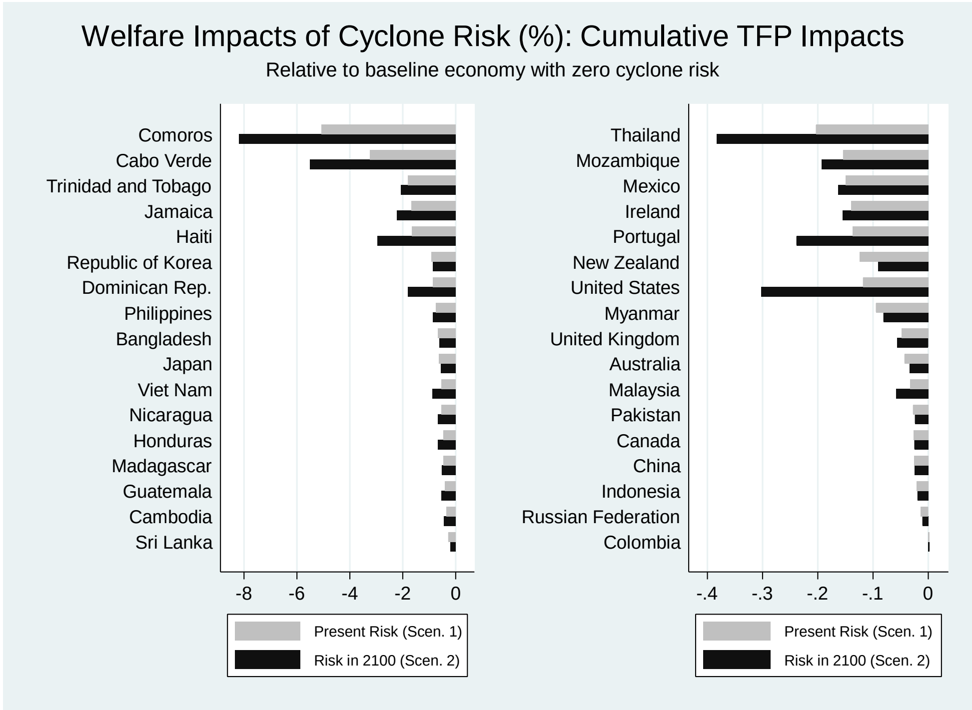

Figure 10: Welfare impacts of present-day (Scen. 1) and year 2100 (Scen. 2) cyclone risk on each country's baseline economy with cumulative (5-Year) TFP effects.

The Online Appendix presents additional model results for cyclone risk projections based on three alternative climate models (MIROC, CNRM, and ECHAM). The results are mostly similar, although some differences arise. For example, some of the welfare benefits from cyclone risk reductions predicted by the benchmark model are not robust to consideration of other climate models. On the other hand, the other climate models also predict smaller future welfare costs in the United States.

The results presented thus far are disaggregated by country. Given that several cyclone-vulnerable countries are excluded from our analysis (due to, e.g., data limitations), we can only produce a *lower bound* on global impacts by computing the GDP-weighted global aggregate effects. The results indicate that the global aggregate costs of present-day cyclone risk (Scenario 1) are equivalent to at least a 0.044% permanent consumption change.[36] The total costs of future cyclone risks (Scenario 2) are at least 0.074% in balanced growth path consumption equivalent. To put these numbers in context, Barrage (2020) estimates total global welfare gains from optimized climate policy in the 21st century of 0.95% in balanced growth consumption equivalent.

[36] Aggregating with population instead of GDP weights yields a slightly lower estimate of 0.037%.

Finally, we must caution that there are important drivers of future cyclone impacts which our model omits. For example, learning from increased cyclone exposure and investments in protective infrastructure will likely lower future vulnerability to storms below what our model predicts, ceteris paribus (see, e.g., Schumacher and Strobl, 2011; Hsiang and Narita, 2012; and Fried, 2021). On the other hand, however, our model also does not account for sea level rise, which will certainly increase future damages from storms (conditional on intensity). We also do not consider fiscal responses and impacts of storms, which can affect welfare costs through multiple channels (e.g,. Deryugina, 2017; Barrage, 2021; Phan and Schwartzman, 2021). Finally, the future locations of populations and economic activity has been shown to be critically important in determining climate change impacts (e.g., Desmet et al., 2021). While our framework attempts to capture some of these dynamics based on exogenous predictions of future population shares in low-lying coastal areas, recent work has also demonstrated the potential for endogenous feedbacks between population locations, economic growth, and exposure to storm damages (Hallegatte, 2017). Joint consideration of these dynamics in quantitative models of climatic risks is thus clearly an important area for future work.

6 Conclusion

This paper proposes a novel empirical-structural approach to analyze the macroeconomic consequences of climate change with a focus on tropical cyclones. We first empirically and conceptually review competing approaches to quantifying cyclone impacts on growth. We highlight that differences in reduced-form findings, driven in part by empirical choices, are maintained using a comprehensive dataset. Importantly, theory also tells us that even perfectly identified reduced-form regressions of growth on cyclone shocks or risk are individually insufficient to characterize the full welfare effects of future changes in cyclone risks given broader general equilibrium changes.

Second, we present our approach to estimating and modeling cyclone impacts designed to combine empirical evidence with the structure of a model to deliver such welfare cost estimates. We propose that empirical research focus on quantifying cyclone impacts on the *structural determinants of growth*, and not just growth itself, as the latter is typically endogenous in macroeconomic models. We then present a stochastic endogenous growth cyclone-climate-economy model that we quantify separately for 40 cyclone-vulnerable nations. Important for policy, we find significant heterogeneity of projected climate change impacts, including large negative welfare costs of up to -5% in balanced growth consumption equivalent in some of the most vulnerable locations. The United States stands out among the most negatively impacted countries. The model results also demonstrate the importance of accounting for macroeconomic adjustments to cyclone risk, which are projected to lower average growth impacts by up to 30-40%.

A broader implication of our approach is to showcase the potential benefits of making the weather versus climate distinction explicit in a climate-economy model. This distinction permits (i) direct incorporation of plausibly causally identified cyclone impact estimates, (ii) accounting for macroeconomic adaptation through endogenous adjustments in savings and investments, and (iii) computing welfare costs of future changes in climatic risks. As frontier advancements in stochastic climate-economy models are now able to account for multiple sources of uncertainty at high frequency (e.g., Cai and Lontzek, 2019), extending a truly integrated assessment models to explicit consideration of weather impacts may thus be an interesting area for future work and facilitate linkages to the empirical literature. Similarly, while our quantitative results are subject to numerous limitations ranging from our abstractions of advancements in wind-field modeling (Strobl, 2011; Hsiang and Narita, 2012) to distinguishing productive and adaptation capital (e.g., Fried, 2021), our proposed method seeks to complement these empirical and modeling advancements so as to facilitate the integration of both frontiers and to improve our understanding of the social costs of climate change.

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