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

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Abstract

Empirical analyses of the impacts of climatic shocks on growth, while critical for policy, have found seemingly disparate results and are seldom incorporated into macroeconomic climate-economy models. This paper seeks to bridge this micro-macro gap through the case of tropical cyclones. First, we present a stochastic endogenous growth model that can reconcile key divergent empirical studies' findings as capturing different components of the overall impact of disasters on growth. Second, we empirically estimate cyclone impacts on the structural determinants of growth (total factor productivity, depreciation, fatalities), instead of growth itself, facilitating direct inclusion into climate-economy models. Third, we illustrate a mapping of these estimates into both the seminal global DICE climate-economy model and our country-specific stochastic endogenous growth framework. While future changes in cyclone risks are projected to have mixed effects on output growth, we estimate a benchmark increase in the social cost of carbon of up to 15%.

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1 Introduction

How do environmental shocks affect macroeconomic outcomes? A growing body of empirical work has documented significant negative economic growth impacts from climatic events such as temperature shocks (e.g., Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015; Bansal and Ochoa, 2011) and tropical storms (e.g., Noy, 2009; Hsiang and Jina, 2014). Though widely influential (Obama, 2017), these empirical studies' findings have been slow to be incorporated in macroeconomic climate-economy models. For example, while the seminal DICE model's (Nordhaus, e.g., 2008, 2010a) climate change damage function remains the most widely used quantification of climate impacts informing both the macroeconomic literature (e.g., Golosov et al., 2014) and policy applications (e.g., U.S. Interagency Working Group, 2010), DICE and other integrated assessment models (IAMs) have been criticized for being slow to incorporate these and other new empirical damage estimates (Burke et al., 2016). While several studies have worked to introduce explicit growth effects into IAMs, the corresponding policy implications depend on the underlying mechanisms (e.g., productivity versus capital stock impacts), which remain unclear (Fankhauser and Tol, 2005; Dietz and Stern, 2015; Moore and Diaz, 2015). Despite their potential importance, the inherent difficulty in mapping reduced-form growth impact estimates into the structure of climate-economy models thus remains as a critical challenge for the literature.

This paper seeks to bridge this micro-macro gap through a detailed analysis of a climate risk of special academic and policy interest: tropical cyclones (e.g., hurricanes, typhoons). Cyclones are among the costliest sources of environmental risk, and their direct impacts are predicted to increase significantly with climate change (Mendelsohn et al., 2012). While a rich empirical literature has found significant impacts of cyclones on growth (for reviews see, e.g., Cavallo and Noy, 2011; Klomp and Valckz, 2014; Kousky, 2014), it faces three fundamental gaps. First, different studies have found a range of seemingly contradictory results, ranging from positive (e.g., Skidmore and Toya, 2002) to large negative impacts (e.g., Hsiang and Jina, 2014). These results have yet to be reconciled. Second, the empirical literature has remained largely disconnected from theoretical models of natural disasters and economic growth (e.g., Ikefuji and Hoori, 2012), making it difficult to compare results across approaches. Third, despite their potentially large implications, these studies' findings have generally not been incorporated into climate-economy models.[1] Cyclones and growth are thus not only of independent interest, but exemplify the challenges of the broader micro-macro climate gap.

[1] One important study by Narita, Tol, and Anthoff (2009) uses the FUND model to estimate climate change impacts on direct damages from tropical cyclones. Our study builds on their insights but differs in fundamental ways, including by (i) presenting a stochastic endogenous growth model to review empirical literature, (ii) empirically estimating cyclone impacts, (iii) considering total factor productivity impacts, and (iv) estimating future cyclone probability density functions to compute expected damages.

The paper confronts these gaps in three steps. First, we present a simple stochastic endogenous growth model (building on Krebs, 2003ab, 2006) as a lens to review the empirical evidence. We find that several of the literature's seemingly disparate results can be reconciled as measuring different components of the overall impact of extreme weather on growth. For example, cross-sectional regressions capture the effect of cyclone *risk*, whereas panel fixed-effects models isolate the effects of cyclone *strikes.* Theory predicts that the effect of cyclone *risk* on average growth can be positive or negative, whereas cyclone *strikes* decrease contemporaneous growth (in incomplete financial markets). Intuitively, higher risk may induce higher precautionary savings (and, empirically, higher investment in human over physical capital), which may increase growth, ceteris paribus. In contrast, cyclone strikes destroy productive assets, thus depressing output growth. In line with these predictions, the empirical literature has found both positive and negative impacts of cyclone *risk* on average growth (Skidmore and Toya, 2002; Hsiang and Jina, 2015), but negative *strike* impacts in panel regressions. We also find similar results in an empirical analysis utilizing a harmonized global dataset. The model further illustrates both lessons and limitations of reduced-form growth impact estimates for IAMs. On the one hand, the empirical literature provides qualitative guidance for structural features that models seeking to capture cyclones' full growth and welfare impacts ought to have, such as financial market incompleteness (e.g., Kahn, 2005; McDermott et al., 2014) and limits to growth rebounding after disasters (e.g., Raddatz, 2007; Hsiang and Jina, 2014; Elliott et al., 2015). On the other hand, however, the model demonstrates the limitations of reduced-form growth estimates for the quantification of IAMs. For example, an increase in cyclone risk can affect growth and *welfare* in opposite ways. We also find that panel regressions estimating the effect of storm realizations are insufficient to project climate change impacts if they hold the effects of baseline risk constant in country fixed-effects, as risk will change along with the climate. Through the lens of the model, the output growth impacts of climatic risks are thus multi-dimensional, potentially countervailing, and may differ from welfare effects.

Second, we thus present and implement a modified estimation approach designed to facilitate the inclusion of empirical results in IAMs. This idea is to quantify cyclone impacts on the *structural determinants of growth*, rather than the (typically endogenous) outcome of growth itself. We focus on cyclone strike impacts on total factor productivity, capital destruction, and fatalities for each country from a comprehensive global database of historical cyclones (1970-2015). Importantly, existing empirical studies may require only minor additions to implement this approach. For example, with the addition of publicly available capital stock data, one can conduct a growth decomposition exercise to determine whether output growth impacts are driven by changes in productivity or factor inputs, and calibrate the model accordingly.

Third, we present mapping from these empirical estimates into the structure of both the seminal DICE climate-econmy model and a country-specific version of our stochastic endogenous growth framework. We compute probability density functions of future cyclone realizations in each country based on synthetic cyclone track simulations from Emanuel et al. (2008). In the stochastic model, changes in cyclone risk distributions are projected to have heterogeneous welfare impacts across countries and ambiguous effects on output growth. Incorporating our empirically estimated cyclone damage functions in the DICE-2010 model increases the global social cost of carbon by up to around 15%.[2]

The paper proceeds as follows. Since our theoretical analysis also showcases corroborating empirical results, Section 2 first describes the data. Section 3 then describes the theoretical background, model, and the results. Section 4 presents out main empirical analysis of cyclone strike impacts on the determinants of growth. Section 5 presents the mapping of these estimates into climate-economy models and the associated results. Section 6 concludes.

2 Data

The first step in our analysis is to compile a comprehensive, harmonized global panel of cyclones and relevant economic indicators at the country-year level. Building on best practices in the literature, we gather historical global tropical cyclone tracks from the International Best Track Archive for Climate Stewardship (IBTrACS; Knapp et al., 2010). IBTrACS provides extensive historical cyclone records of positions and intensity characteristics collected from meteorological agencies across the world. We process the tracks in ArcGIS to capture the cyclone characteristics at landfall and aggregate data up to the country-year level.[3] We calculate cyclone intensity metrics including annual maximum wind speed (in knots) and annual energy (the sum of the cube of wind speed at landfall, a metric based on the power dissipation index developed by Emanuel (2005).[4] We focus on 1970-2015, the post-satellite era for which cyclones have been most reliably tracked. Next, in order to estimate future changes in cyclone risks, we incorporate 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 5.

[2] Hallegatte (2009) presents a roadmap from data and both direct and indirect damage estimation to climate change cost calculations for U.S. hurricanes, but does not produce a global cyclones climate damage function.

[3] We process the data without a dedicated wind-field model to capture broader geographic impacts of these storms. For recent advancements on such modeling, see, e.g., Strobl (2011), Hsiang and Narita (2012), Hsiang and Jina (2014).

[4] 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 or 25 for tropical depressions. Lastly, we convert 1 minute sustained wind speeds to 10 minute sustained wind speeds for unit constency.

We collect annual national-level macroeconomic indicators including real GDP (2011 $US), capital stocks, and population from the Penn World Tables 9.0 ("PWT", Feenstra et al., 2015). Educational attainment data are based on Barro and Lee (2012). In line with the literature (e.g., Noy, 2009; McDermott et al., 2014), we use the World Bank's measure of *domestic credit provided by the financial sector* (as a percentage of GDP) as main proxy for financial market development. As an alternative, we also consider the estimated share of the adult population with an account at a financial institution, obtained from the World Bank's Findex database. A central challenge in correlating cyclone *risk* with economic growth is that the climate is not randomly distributed across space, and likely correlated with other factors that may influence growth, such as geography (Sachs and Warner, 1997; Hall and Jones, 1996) and institutions (Acemoglu, Johnson, Robinson, 2001). In an effort to control for some of these well-known confounders, we obtain geographical data from the Harvard World Map (e.g., average distance to coast or river), and institutional quality indicators from Transparency International's Corruption Perception Index (2015) as proxy for institutional quality.

Finally, estimates of cyclone property damages and fatalities are gathered from EMDAT, the International Disaster Database (Guha-Sapir et al., 2016). While EMDAT data are subject to well-known data quality caveats (Skidmore and Toya, 2002; Gall et al., 2009; Hsiang and Narita, 2012; Cavallo et al., 2013), they are standard in the literature (e.g., Skidmore and Toya, 2002; Raddatz, 2007; Noy, 2009; Hsiang and Narita, 2012; etc.). We also note that these data are not central to our contribution, which is present a novel *approach* to climate risk change impact estimation and modeling. Indeed, repeating this exercise with alternative damage data (such as proprietary information from insurers) would be a fruitful topic for future work.

3 Theoretical Perspective

3.1 Model Motivation

This section presents a simple stochastic endogenous growth model where cyclones threaten both physical and human capital. The model builds closely on Krebs (2003ab, 2006; see also Krebs et al., 2015), who 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. While our application adds some elements (e.g., a cyclone damage specification with correlated shocks to both types of capital, partial insurance) and studies different comparative statics, the model follows Krebs' insights and approach closely, and is not intended as a theoretical innovation. Several studies also present detailed theoretical analyses of the growth impacts of natural disasters in alternative endogenous growth models (e.g., Ikefuji and Horii, 2012; Akao and Sakamoto, 2013). The central innovation of our study is to connect such a model to the data.

3.2 Model Setup

Each country j is inhabited by a representative household who can invest in human capital ($h_{j,t}$) and physical capital ($k_{j,t}$). Both assets are at risk for cyclone depreciation shocks $\eta_j^h(\varepsilon_{j,t})$, $\eta_j^k(\varepsilon_{j,t})$ that depend on the realized disaster intensity $\varepsilon_{j,t}$ (e.g., dissipated cyclone energy). For tractability, we capture market incompleteness by assuming that fraction π_j of damages can be insured at actuarially fair rates, so that $(1-\pi_j)$ denotes the fraction of uninsured damages.[5,6,7] The representative agent in country j chooses state-contingent plans for consumption $c_{j,t}$ and investments $(x_{j,t}^h, x_{j,t}^k)$ to maximize:

$$\max E_{j,0}\sum_{t=0}^{\infty}\beta^t u(c_{j,t}) \tag{1}$$

subject to constraints:

$$\begin{aligned} c_{j,t}+x_{j,t}^k+x_{j,t}^h &= k_{j,t}R_{j,t}^k+h_{j,t}R_{j,t}^h \\ k_{j,t+1} &= (1-\delta_k-\pi_j\mu_j^k-(1-\pi_j)\eta_j^k(\varepsilon_{j,t}))k_{j,t}+x_{j,t}^k \\ h_{j,t+1} &= (1-\delta_h-\pi_j\mu_j^h-(1-\pi_j)\eta_j^h(\varepsilon_{j,t}))h_{j,t}+x_{j,t}^h \\ & \quad k_{j,0}, h_{j,0} \text{ given} \end{aligned} \tag{2}$$

Here, $R_{j,t}^k$ and $R_{j,t}^h$ denote returns to physical and human capital, δ_m denotes baseline depreciation of asset m, and $\mu_j^m \equiv E_j[\eta_j^m(\varepsilon)]$ denotes the expected cyclone damages to asset m. (Insurance premia $\pi_j\mu_j^m$ can be written in the capital evolution equations without loss of generality as both assets are produced linearly from the final consumption good.) Disaster intensity follows some *iid* distribution $\varepsilon_{j,t}\sim f_j(\varepsilon_j)$ with mean $\mu_{j,\varepsilon}\equiv E_j[\varepsilon_{j,t}]$.

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 firm maximizes:

$$\max_{K_{j,t},H_{j,t}} A_{j,t}K_{j,t}^{\alpha}H_{j,t}^{1-\alpha}-R_{j,t}^kK_{j,t}-R_{j,t}^hH_{j,t} \tag{3}$$

5 Properly microfounding this parameter would require a specification of international asset markets.

6 For example, according to Swiss Re, only 8% of the $50 billion in cyclone and flood damages in Asia in 2014 were covered by insurance (*The Economist*, 09/02/2017).

7 Assuming equal insurability across capital types simplifies the derivations, but does not drive the results.

where $A_{j,t} = A_j(\varepsilon_{j,t})$ denotes total factor productivity (TFP), which may also vary with storm realizations. Common factor shares α are not important for the analytic results and motivated in Section 4.

Together, (3) and (2) imply that there are constant returns to scale in reproducible factors, allowing endogenous growth. It is important to note that this effective AK structure of the model implies well-known shortcomings for matching certain moments in cross-country growth data (see, e.g., Mankiw, Romer, and Weil, 1994; Klenow and Rodriguez, 2005). On the other hand, however, the same feature of AK models that is a liability in matching convergence data actually becomes an asset in matching the empirical literature's findings on the common dynamics of disaster growth impacts, specifically the lack of a rebounding recovery and the persistence of output losses (Raddatz, 2007; Strobl, 2011; Hsiang and Jina, 2014). We also stress that the qualitative findings from this study are also *not* contingent upon the details of the model,[8] and that we present quantitative results for both the present framework and the seminal DICE model (Nordhaus, 2008), which follows a Solow growth structure.[9]

Next, letting $\widetilde{k}_{j,t} \equiv \frac{k_{j,t}}{h_{j,t}}$ denote the physical-human capital ratio in country j at time t, and noting that, in equilibrium, by market clearing, $\widetilde{k}_{j,t} = \widetilde{K}_{j,t} \equiv \frac{K_{j,t}}{H_{j,t}}$, factor returns are given by:

$$\begin{aligned} R^k_{j,t} &= (\alpha) A_j(\varepsilon_{j,t}) \cdot (\widetilde{k}_{j,t})^{\alpha-1} \\ R^h_{j,t} &= (1-\alpha) A_j(\varepsilon_{j,t}) \cdot (\widetilde{k}_{j,t})^{\alpha} \end{aligned} \tag{4}$$

Let the household's wealth at time t be defined by $w_{j,t} \equiv k_{j,t} + h_{j,t}$, 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 savings-out-of-wealth ratio, $\omega_k(\widetilde{k_{j,t}}) \equiv \left(\frac{\widetilde{k}_{j,t}}{1+\widetilde{k}_{j,t}}\right)$ the share of the household's wealth invested in physical capital, and $\overline{\delta}^m_j \equiv \delta_m + \pi_j \mu^m_j$ the known losses of asset m (baseline depreciation plus insurance premia). The household's realized return on his portfolio at time t is then given by the weighted sum of net returns:

$$\begin{aligned} r_j(\widetilde{k_{j,t}}, \varepsilon_{j,t}) \equiv\; & \omega_k(\widetilde{k_{j,t}}) \left[R^k_{j,t}(\widetilde{k}_{j,t}, \varepsilon_{j,t}) - \overline{\delta}^k_j - (1-\pi_j)\eta^k_j(\varepsilon_{j,t}) \right] \\ & + \left(1 - \omega_k(\widetilde{k_{j,t}})\right) \left[R^h_{j,t}(\widetilde{k}_{j,t}, \varepsilon_{j,t}) - \overline{\delta}^h_j - (1-\pi_j)\eta^h_j(\varepsilon_{j,t}) \right] \end{aligned} \tag{5}$$

Finally, we assume that preferences are of the form:

$$u(c_{j,t}) = \frac{c_{j,t}^{1-\gamma}}{1-\gamma}$$

[8] For example, cyclone risk (cross-sectional methods) and strikes (panel methods) would also be predicted to induce different effects in a Solow growth model.

[9] That being said, of course we hope that future work will extend our approach to build alternative and structurally richer empirically-based stochastic endogenous growth weather-climate-economy models.

Equilibrium Growth

Following the same approach as in 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 jointly determined by:

$$\widetilde{s}_j = \left(\beta E_j[(1 + r_j(\widetilde{k}'_j, \varepsilon'_j))^{1-\gamma}]\right)^{\frac{1}{\gamma}} \tag{6}$$

$$0 = \beta E\left[\frac{\left[R^k_j(\widetilde{k}_j, \varepsilon'_j) - \overline{\delta^k_j} - (1-\pi_j)\eta^k_j(\varepsilon'_j)\right] - \left[R^h_j(\widetilde{k}_j, \varepsilon'_j) - \overline{\delta^h_j} - (1-\pi_j)\eta^h_j(\varepsilon'_j)\right])}{(1+\widetilde{k}'_j)^2 \cdot (1 + r_j(\widetilde{k}'_j, \varepsilon'_j))^{\gamma}}\right] \tag{7}$$

Intuitively, optimal savings $\widetilde{s}_j$ follows from the household's Euler Equation, whereas (7) expresses a no-arbitrage condition for human and physical capital. Equations (6)-(7) thus implicitly characterize how cyclone risk affects equilibrium savings and investments which, in turn, alter growth. Long-run or *average growth* can then easily be shown (see Online Appendix) to equal:

$$\overline{g}_j \equiv E\left[\frac{c'_j}{c_j}\right] = (\widetilde{s}_j)(1 + E_j[r_j(\widetilde{k}'_j, \varepsilon'_j)]) \tag{8}$$

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

$$g_{j,t} = \frac{c_{j,t}}{c_{j,t-1}} = (\widetilde{s}_j)[1 + r_j(\widetilde{k}_{j,t}, \varepsilon_{j,t})] \tag{9}$$

3.3 Results: Empirical-Theory Mapping

Empirical estimates of cyclones and growth broadly differ on (i) whether they use cross-sectional or temporal (panel) variation, (ii) what variable they use to measure disasters (e.g., maximum wind speed, fatalities, etc.), and (iii) the empirical setting (e.g., global, OECD countries, etc.). We consider these below. Note that, for analytic tractability, this section assumes $A_{j,t} = A_j$, but we return to cyclone impacts on TFP impacts in the quantitative analysis.

3.3.1 Cross-Sectional Estimates

First, we note that cross-sectional regressions capture the impact of *average storm risk* on *average growth*. For example, Skidmore and Toya (2002) regress countries' average 1960-90 growth rates on average disaster metrics $\mu_{\varepsilon,j}$ (e.g., average number of cyclone landfalls per year), which can be mapped into the model as:

$$\begin{aligned}\overline{g}_{1960-1990,j} &= \beta_0 + \beta_1 \mu_{\varepsilon,j} + \mathbf{X}'\boldsymbol{\beta} + \epsilon_j \\ \widehat{\beta_1} &\Rightarrow \frac{d\overline{g}}{d\mu_\varepsilon}\end{aligned}$$

Skidmore and Toya (2002) find a positive association between cyclones and growth ($\widehat{\beta_1} > 0$), and between cyclone risk and human capital investment. It may be noted that the disaster risk indicators used in their study are more coarse than in new work utilizing detailed cyclone data, such as Hsiang and Jina (2014). We thus first repeat a cross-sectional specification in the spirit of Skidmore and Toya (2002) on our harmonized global dataset, which permits us to compute cyclone risk indicators based on the detailed IBTrACS cyclone records. Table 1 presents the results, which confirm a significant positive correlation between cyclone risk and average economic growth. This correlation remains after controlling for key measures of geography, a proxy for institutional quality, and initial income levels. While such cross-sectional estimates always remain subject to the caveat of omitted variable bias, a positive causal effect of risk on growth can be rationalized through the lens of the model.

Proposition 1 *An increase in average cyclone risk has a theoretically ambiguous effect on average growth:*

$$\frac{d\overline{g}}{d\mu_\varepsilon} \lesseqqgtr 0$$

Proof: See Online Appendix. Intuitively, cyclone risk μ_ε may affect average growth $\overline{g}$ through three channels: (1) *Precautionary Savings Effect:* If households are sufficiently risk averse, an increase in storm risk may increase the equilibrium savings rate $\widetilde{s}$, increasing average growth, ceteris paribus. (2) *Portfolio Effect*: If human and physical capital have different vulnerability to storms ($\eta_j^h(\varepsilon_{j,t}) \neq \eta_j^k(\varepsilon_{j,t})$), an increase in cyclone risk may change the household's optimal portfolio allocation $\widetilde{k_j}$. In particular, if physical capital is more susceptible to storms, higher cyclone risk may induce households to invest relatively more in human capital.[10] We find empirical evidence consistent with both of these mechanisms. In Table 1, we see that the association between cyclone risk and growth is attenuated once savings rates and education are controlled for. In addition, Table 2 presents direct evidence from a regression of gross savings rates and schooling attainment on cyclone risk and standard controls. We find a positive and significant association between both savings rates and human capital investment (proxied by schooling) and cyclone risk. These results are in line with the findings of Skidmore and Toya (2002), but we

[10] Though absent in our model, human capital externalities as in Lucas (1988) could further account for the positive relationship between cyclone risk and average growth (as modeled by Akao and Sakamoto, 2013).

present them to highlight that they survive in the same harmonized global dataset which will yield negative cyclone strike impact estimates below.

The third impact channel is the (3) *Direct Depreciation Effect*: Higher storm risk increases average depreciation, decreasing average growth, ceteris paribus. There is also empirical evidence supporting this channel: Hsiang and Jina (2015) estimate a negative relationship between average cyclone-induced capital depreciation ($\frac{d\overline{g}}{d\overline{\eta^k}}$) and growth (among 34 cyclone-affected countries).

Table 1: Cross-Sectional Cyclone Risk and Growth Association

Dependent Variable:	Avg. Real GDP/Capita Growth $\overline{g}_{1970-2015,,j}$						
$\overline{\text{Cyclones}_j}$ Measure:	#Landfalls/Year			Max. Wind		Max. Wind/km2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\overline{\text{Cyclones}_j}$	0.0021**	0.0022***	0.0014*	0.00014**	0.00011*	13.5550	-3.6062
	(0.0010)	(0.0008)	(0.0008)	(0.0001)	(0.0001)	(11.3916)	(11.0104)
Tropics (%Land Area)		-0.0114*	-0.0006	-0.0120**	-0.0008	-0.0134**	0.0010
		(0.0058)	(0.0059)	(0.0058)	(0.0059)	(0.0061)	(0.0064)
Abs. Latitude		-0.0002	0.0000	-0.0002	0.0000	-0.0003	0.0000
		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Dist. to coast or river		-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Institutions (CPI_{2015})		0.0002**	0.0001	0.0002**	0.0001	0.0003**	0.0001
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Initial GDP/Cap._{1970}		-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\overline{\text{SavingsRate}_j}$			0.0008***		0.0008***		0.0009***
			(0.0002)		(0.0002)		(0.0002)
$\overline{\text{YearsSchooling}_j}$			0.0002		0.0001		0.0005
			(0.0008)		(0.0008)		(0.0008)
Constant	0.0169***	0.0207***	0.0005	0.0213***	0.0002	0.0221***	-0.0022
	(0.0013)	(0.0072)	(0.0085)	(0.0072)	(0.0085)	(0.0074)	(0.0087)
Observations	182	122	107	122	107	122	107
Adj. R-Squared	0.0170	0.263	0.310	0.252	0.313	0.228	0.291

Table presents OLS regression of countries' avg. real GDP per capita growth rate (1970-2015) on averages of number of cyclone landfalls per year (Cols. 1-3), max. wind speed (Cols. 4-5), or max. wind speed/km2 (cols. 6-7), controls for the share of countries' land areas in the geographical tropics (Cols. 2-7), absolute value of latitude (Cols. 2-7), average distance to coast or river (Cols. 2-7), the Transparency International Corruption Perceptions Index (Cols. 2-7), initial (1970) GDP per capita (Cols. 2-7), average savings rates (Cols. 3,5,7), average years of schooling (Cols. 3, 5,7), and a constant. (*** p$<$0.01, ** p$<$0.05, * p$<$0.1).

Table 2: Cyclone Risk Impact Mechanisms

$\overline{\text{Cyclones}_j}$ Measure:	#Landfalls/Year		Max. Wind		Max. Wind/km2	
Dependent Variable:	$\overline{\text{SavingsRate}_j}$	$\overline{\text{YearsSchooling}_j}$	$\overline{\text{SavingsRate}_j}$	$\overline{\text{YearsSchooling}_j}$	$\overline{\text{SavingsRate}_j}$	$\overline{\text{YearsSchooling}_j}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\text{Cyclones}_j}$	1.2405***	0.2026**	0.0604*	0.0187**	12,422.2**	3,326.0**
	(0.4560)	(0.1009)	(0.0351)	(0.0076)	(6,106.8)	(1,331.0)
Tropics (%Land Area)	-10.1436***	-0.4082	-10.4411***	-0.4782	-11.9842***	-0.9659
	(3.1596)	(0.7230)	(3.2215)	(0.7165)	(3.3162)	(0.7470)
Abs. Latitude	-0.2411**	0.0276	-0.2490**	0.0256	-0.2827***	0.0144
	(0.1005)	(0.0229)	(0.1025)	(0.0227)	(0.1038)	(0.0232)
Dist. to coast or river	0.0000	-0.0013***	0.0001	-0.0013***	0.0015	-0.0009*
	(0.0021)	(0.0005)	(0.0021)	(0.0005)	(0.0022)	(0.0005)
Institutions (CPI_{2015})	0.1010*	0.0827***	0.1016*	0.0823***	0.1183**	0.0881***
	(0.0514)	(0.0118)	(0.0524)	(0.0116)	(0.0525)	(0.0118)
Initial GDP/Cap.$_{1970}$	0.0001***	-0.0000	0.0001***	-0.0000	0.0001***	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	25.9942***	1.6083*	26.4397***	1.6477*	26.9957***	1.8243**
	(3.9312)	(0.8837)	(4.0004)	(0.8743)	(3.9839)	(0.8738)
Observations	120	109	120	109	120	109
Adj. R-Squared	0.348	0.665	0.323	0.671	0.329	0.672

Table presents OLS regression of countries' average (1970-2015) savings rates (Cols. 1,3,5) or years of schooling (Cols. 2,4,6) on avg. number of cyclone landfalls/year (Cols. 1-3), max. wind speed (Cols. 4-5), or max. wind speed/km2 (Cols. 6-7), plus controls for the share of countries' land areas in the geographical tropics, absolute value of latitude, avg. distance to coast or river, the Transparency International Corruption Perceptions Index, initial (1970) GDP/capita, and a constant. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

These mechanisms underlying Proposition 1 have an additional important implication.

Corollary 1 *An increase in cyclone risk may affect average growth and welfare in opposite ways.*

Proof: See Online Appendix. Intuitively, while higher cyclone risk may increase growth, this effect is driven by an increase in precautionary savings and thus clearly welfare-reducing. While such tensions between risk, growth, and welfare are well-established by related theoretical models (e.g., Devereux and Smith, 1994), this result is important to highlight as it highlights the potential limitations of reduced-form growth impact estimates to inform the welfare costs of climate change (without further structure and analysis).

3.3.2 Panel Estimates

Arguably the most common empirical approach to studying climate shocks' impacts on growth is through panel fixed-effects models. This approach captures the impact of cyclone *strikes* on realized growth (9), e.g.:

$$g_{j,t} = \underbrace{\gamma_j}_{\text{Fixed effects}} + \underbrace{\beta_1 \varepsilon_{j,t}}_{\text{Estimated cyclone impact}} + ... + \epsilon_{j,t} \tag{10}$$

Through the lens of the model, realized growth can be written (after taking logarithms and combining (8)-(9)) as:

$$g_{j,t} \approx \underbrace{\bar{g}_j}_{\text{Avg. growth}} + \underbrace{\left\{ r_j(\widetilde{k}_{j,t}, \varepsilon_{j,t}) - E_j[r_j(\widetilde{k}'_j, \varepsilon'_j)] \right\}}_{\text{Year } t \text{ deviation of returns from their mean}} \tag{11}$$

The empirical literature's common findings on $\widehat{\beta_1}$ can be summarized as follows: (1) Cyclones are generally found to have negative impacts on contemporaneous growth (e.g., Noy, 2009; Strobl, 2011; Strobl 2012; Hsiang and Jina, 2014; see also reviews by Cavallo and Noy, 2011; Kousky, 2014). (2) Many studies find negative impacts to be concentrated in countries that are poor and/or have worse (financial) institutions (e.g., Kahn, 2005; Loayza et al., 2009; Noy, 2009; Raddatz 2009; Strobl 2012; Fomby, Ikeda, and Loayza, 2013; McDermott et al., 2014), whereas (3) growth impacts in OECD economies appear small or negligible (e.g., Noy 2009; Strobl, 2011). (4) Negative impacts on output levels have also been found to be persistent in the sense that they are not made up through a positive growth rebound (e.g., Raddatz, 2007; Strobl, 2011; Hsiang and Jina, 2014; Elliott et al., 2015). The theoretical model can again reconcile these results, yielding the following predictions:

Proposition 2 *If financial markets are incomplete ($\pi_j < 1$), then:*

1) Cyclone realizations have a negative effect on contemporaneous growth ($\frac{dg_{j,t}}{d\varepsilon_{j,t}} < 0$).

2) Cyclone realizations have a persistently negative effect on output levels in the sense that there is no compensating positive growth rebound after the storm ($\sum_{j=0}^{L} \frac{dg_{t+j}}{d\varepsilon_{j,t}} < 0$).

3) If financial markets are complete ($\pi_j = 1$), cyclone realizations do not affect contemporaneous growth ($\frac{dg_{j,t}}{d\varepsilon_{j,t}}|_{\pi_j=1} = 0$).

Proof: See Online Appendix. On the one hand, these empirical results can be used to inform the structure of IAMs. For example, limited financial markets are clearly an empirically relevant contributor to vulnerability, but not accounted for in many IAMs. Similarly, the persistence of output losses is at odds with the predictions of a standard Solow model. Matching this finding may require a different growth model (as in the present setting), or the introduction of frictions that inhibit recoveries. For example, Hallegatte et al. (2007) develop a 'non-equilibrium dynamic model' of disasters where goods markets may not clear in the short-run to capture frictions delaying disaster recovery. As neither our AK model nor a non-equilibrium approach may be fully satisfactory from a modern macroeconomic perspective, however, the development of climate-economy models that can match a broader set of empirical facts is thus arguably an important area of future research.

On the other hand, the model again highlights some of the challenges in using reduced-form growth impact estimates to quantify IAMs. Comparing (11) and (10), the estimated coefficients on cyclone realizations $\widehat{\beta_1}$ capture the ceteris paribus effect of *strikes,* whereas average growth (net of strike damages) - and thus the impact of cyclone *risk* - is captured in the fixed effects $\widehat{\gamma_j}$. That is, the model predicts that the country fixed-effects $\widehat{\gamma_j}$ in (10) depend on cyclone risk. The broader climate literature has long recognized the endogeneity of weather shock impact coefficients such as $\widehat{\beta_1}$ to baseline risk due to adaptation, and has developed sophisticated methods to address this concern (see, e.g., Carleton et al. (2018) on temperature and mortality, or Auffhammer (2018) on temperature and energy consumption). In the present setting, however, there may additionally be general equilibrium 'adaptation' via changes in savings and investment, rendering $\widehat{\gamma_j}$ endogenous to risk as well. Though not a concern econometrically, this association is important for projecting future effects of climate change, which will alter cyclone realizations precisely through changes in risk (i.e., the moments of the cyclone distribution). Consequently, empirical estimates of the effects of cyclone strikes $\widehat{\beta_1}$ may not be sufficient to project the growth rate impacts of climate change.

While Tables 1 and 2 already provide suggestive empirical support for such general equilibrium effects, we conclude by presenting a direct illustration of the potential empirical relevance of this theoretical concern through a two-step estimation on our global harmonized dataset. First, we estimate a standard panel fixed-effects specification to capture the effects of storm strikes on growth. Second, we cross-sectionally regress the resulting fixed effects on countries' cyclone risk, along with the benchmark controls from Tables 1 and 2. Our panel specification builds on the basic model in Hsiang and Jina (2014):

$$g_{j,t} = \gamma_j + \delta_t + (\theta_j \cdot t) + \sum_{l=0}^{L} \beta_{1+l} \varepsilon_{j,t-l} + \beta_{Int}(q_j \cdot \varepsilon_{j,t}) + \epsilon_{j,t} \tag{12}$$

Here, $g_{j,t}$ is a country's annual real GDP per capita growth rate, γ_j are country fixed-effects, $(\theta_j \cdot t)$ are country-specific linear time trends, and $\varepsilon_{j,t-l}$ are cyclone realization measures up to lag L. For the present purposes of exploring the association of γ_j with cyclone risk, we focus on contemporaneous strike impacts only ($L = 0$). The main empirical analysis in Section 4 considers richer lag structures as well.[11] Next, we also consider interactions of cyclone realizations with proxies for countries' financial market development q_j, specifically indicator variables for countries being in the top quartile of either domestic credit or financial account holdings.[12] Standard errors $\epsilon_{j,t}$ are heteroskedasticity-robust and generally clustered at the country level.

Table 3 presents the results for Step 1 using dissipated cyclone energy (sum of maximum wind speeds cubed) as intensity metric.[13] As expected, the estimated effect of cyclone strikes on contemporaneous growth appears negative. While the global average impact is initially estimated with limited precision (Columns 1 and 2), allowing for heterogeneous impacts reveals a significant negative effect in countries in the bottom quartiles of our financial development proxy, and a negligible impact on countries in the top quartile (Column 3). These results are firmly in line with the literature's panel impact estimation studies, as noted above. Importantly, these results (together with Table 1) thus also illustrate that some of the literature's most notable qualitative differences of finding positive or negative cyclone impacts on growth remain even when revisited on a harmonized dataset, and are thus more plausibly due to differences in the structural interpretation of the estimated parameters, as suggested by the model.

Finally, Table 4 presents the results from Step 2, which regresses the estimated fixed effects $\widehat{\gamma}_j$ plus each country's estimated linear growth trend $\widehat{\theta}_j\bar{t}$ (evaluated at its average time in the sample) on countries' average cyclone risk and benchmark controls.[14] As expected, the results indicate a positive (albeit only marginally significant) association between cyclone risk and predicted average growth. This association is also again attenuated by adding controls for the predicted underlying mechanisms, namely controls for savings and education.

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[11] The association between the $\gamma_j' s$ and cyclone risk also occurs with long lags included in (12) as documented in an earlier version of this paper (Bakkensen and Barrage, 2016).

[12] We also experimented with richer specifications including multiple quartile indicators. While the point estimates are as expected (with larger negative impacts in lower quartiles), these estimates were imprecise.

[13] We note that the results in Table 3 are sensitive to this choice and that we obtain noisy estimates using maximum wind speeds as impact measure. Reassuringly, however, a rich prior literature has documented such negative effects using a wide array of sophisticated specifications and robustness checks (e.g., Hsiang and Jina, 2014). Importantly, we also obtain more robustly precise estimates in our main empirical analysis in Section 4, which focuses on total factor productivity rather than GDP growth as outcome metric.

[14] The estimated dependent variable may lead to inefficiency and larger standard errors (Hausman, 2001).

Table 3: Panel Regression: Cyclone Strikes

Dependent Variable:	Real GDP/Capita Growth$_t$			
	(1)	(2)	(3)	(4)
Energy$_t$	-9.37e-10*	-9.37e-10	-1.95e-09**	-1.24e-09*
	(5.13e-10)	(5.74e-10)	(7.87e-10)	(7.09e-10)
Q4 $\overline{\text{Credit}}$*Energy$_t$			1.87e-09**	
			(8.73e-10)	
Q4 $\overline{\text{Fin.Accts}}$*Energy$_t$				1.30e-09*
				(7.69e-10)
Constant	0.0200	0.0200***	0.0192***	0.0122***
	(0.0581)	(0.00291)	(0.00293)	(0.00301)
S.E. Cluster:	-	Country	Country	Country
Observations	7,573	7,573	7,198	6,180
Adj. R-Squared	0.148	0.148	0.145	0.146

Table presents regression of countries' annual real GDP per capita growth rates (1970-2015) on cyclone energy (sum of max. wind speeds cubed), plus energy interacted with dummy for countries in the top quartile of mean domestic credit provided by financial sector (%GDP) (Col 2.), or energy interacted with dummy for top quartile of fraction of current population with an account at a financial institution (Col 3.), plus a constant. Standard errors are heteroskedasticity-robust and clustered as indicated. (*** p$<$0.01, ** p$<$0.05, * p$<$0.1).

Table 4: Fixed Effects Association with Cyclone Risk

Dependent Variable:	Avg. Predicted GDP/Capita Growth	
	without cyclone strikes: $\widehat{\gamma_{0,j}}+(\widehat{\theta_j}\cdot\bar{t})$	
	(1)	(2)
$\overline{\text{Energy}_j}$	2.65e-09*	1.69e-09
	(1.49e-09)	(1.42e-09)
Tropics (%Land Area)	-0.0108*	0.000872
	(0.00599)	(0.00609)
Abs. Latitude	-0.000185	8.25e-05
	(0.000192)	(0.000188)
Dist. to coast or river	-3.31e-06	-4.86e-06
	(4.03e-06)	(4.01e-06)
Institutions (CPI_{2015})	0.000195**	2.79e-05
	(9.83e-05)	(0.000114)
Initial GDP/Cap._{1970}	-2.31e-07***	-3.53e-07***
	(4.53e-08)	(6.33e-08)
$\overline{\text{SavingsRate}_j}$		0.000836***
		(0.000195)
$\overline{\text{YearsSchooling}_j}$		0.000410
		(0.000798)
Constant	0.0323***	0.00919
	(0.00746)	(0.00871)
Observations	122	107
Adj. R-Squared	0.213	0.284

Table presents OLS regression of estimated country fixed effects plus country-specific time trends times average time in sample from panel regression (Table ZA, Col. 1, of annual GDP/capita growth on these terms plus cyclone strike intensity) on indicated controls plus a constant. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

4 Modified Empirical Approach

The results presented thus far illustrate some of the challenges in mapping existing empirical evidence on cyclones and growth into the structure and quantification of standard macroeconomic climate-economy models, and thus also into estimates of the social cost of carbon. In the remainder of the paper, we thus propose modifications to both empirics and modeling and showcase how these approaches can help bridge this gap.

On the empirical side, we present an estimation of climate shock impacts on the *structural determinants of growth*. While the precise nature of these determinants is generally model-specific, we illustrate impact estimates for total factor productivity (TFP) and depreciation rates of capital and the labor force and showcase how they can be adjusted for inclusion in both the seminal DICE framework (Nordhaus, e.g., 2008, 2010a) and our stochastic endogenous growth cyclones-climate economy model.

One important point to note is that our empirical estimation abstracts from several active debates in the cyclones literature (e.g., advances in wind-field modeling (Strobl, 2011; Hsiang and Narita, 2012; Hsiang and Jina, 2014), competing adaptation specifications (Kahn, 2005; Kellenberg and Mobarak, 2008; Schumacher and Strobl, 2011; Hsiang and Narita, 2012; Fankhauser and McDermott, 2014; Bakkensen and Mendelsohn, 2016; etc.)). As our analysis seeks to illustrate how empirical results can be structured for inclusion in climate-economy models, we stress that it is intended to serve as a complement to - not a substitute for - the rich empirical cyclones literature.

4.1 Total Factor Productivity

First we conduct a standard growth accounting exercise to decompose output growth impacts into productivity versus factor input changes. The appropriate specification depends on the macroeconomic model. For example, in the DICE framework countries produce GDP $Y_{j,t}$ with capital $K_{j,t}$ and labor $L_{j,t}^{Pop}$ (measured by population) inputs via Cobb-Douglas technology:

$$Y_{j,t} = A_{j,t}^{DICE} K_{j,t}^{\alpha_D} (L_{j,t}^{Pop})^{1-\alpha_D}$$

Taking logs and rearranging yields:

$$\ln(A_{jt}^{DICE}) = \ln(Y_{j,t}) - \alpha_D \ln(K_{j,t}) - (1-\alpha_D) \left[\ln(L_{j,t}^{Pop})\right] \tag{13}$$

Using Penn World Tables (PWT) data on GDP, capital stocks, and populations, one can thus back out ‘DICE TFP’ from (13) given an assumed capital share ($\alpha_{DICE} = 0.67$). For DICE, climate change impacts on human capital factors such as educational attainment should thus be counted in TFP. In contrast, our benchmark model specifies production as a Cobb-Douglas aggregate of physical and human capital stocks:

$$Y_{j,t} = A_{j,t} K_{j,t}^{\alpha_{j,t}} H_{j,t}^{1-\alpha_{j,t}} \tag{14}$$

We map (14) into the data following standard approaches (e.g., Hall and Chones, 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 measured by $hc_{j,t} = e^{\phi(E_{j,t})}$ where $E_{j,t}$ is average years of schooling (based on data from Barro and Lee, 2012) and $\phi(.)$ is a piecewise linear function based on cross-sectional estimates of returns to education for different amounts of schooling from Psacharopoulos (1994). Indeed, this measure of $hc_{j,t}$ is also computed as such and provided directly by PWT (Inklaar and Timmer, 2013). As our model features inelastic labor supply, we use $L^{Pop}_{j,t}$ as a measure of workers in the benchmark. However, given recent efforts to study labor supply impacts of climate change both empirically (e.g., Zivin and Neidell, 2014) and as a structural feature in climate-economy models (Barrage, 2018), we also showcase TFP impact estimates as would be appropriate in such an extended model by using PWT estimates of the number of workers (including both employees and estimates of self-employment), $L^{Empl}_{j,t}$. These considerations lead to the following TFP estimates:

$$\ln(A_{jt}) = \ln(Y_{j,t}) - \alpha_{j,t}\ln(K_{j,t}) - (1-\alpha_{j,t})\left[\ln(hc_{j,t}) + \ln(L^{Pop}_{j,t})\right] \tag{15}$$

$$\ln(A^{Empl.}_{jt}) = \ln(Y_{j,t}) - \alpha_{j,t}\ln(K_{j,t}) - (1-\alpha_{j,t})\left[\ln(hc_{j,t}) + \ln(L^{Empl}_{j,t})\right] \tag{16}$$

While the PWT provide some labor share estimates, for emerging economies these are often substantially below the standard U.S. value of 0.67. Gollin (2002) finds that these differences are largely eliminated once the data are adjusted for self-employment income, which the literature has taken to support common labor shares across countries. We consequently take a common labor share of $1 - \alpha_{jt} = 0.67\ \forall j, t$ also for our benchmark model.

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 a specification which follows the standard panel approach (similar to Hsiang and Jina, 2014, but for TFP):

$$\ln(A_{j,t}) = \gamma_j + \delta_t + (\theta_j \cdot t) + \sum_{l=0}^{L} \beta^A_{1+l}\varepsilon_{j,t-l} + \epsilon_{j,t} \tag{17}$$

where γ_j denotes country fixed-effects and $\varepsilon_{j,t-l}$ are cyclone realization 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 and find negative (marginally) precisely estimated TFP impacts persisting up to around 6 years. Inclusion of further lags reduces the estimates' precision, but leaves the magnitudes similar (see Online Appendix for comparison across lag lengths and relevant information criteria). Table 5 presents results for maximum wind speed as cyclone intensity measure. The Online Appendix shows alternative specifications that (i) de-trend through HPfiltering, which leads to broadly similar results, and (ii) use energy as cyclone intensity measure, which yields noisier estimates but shows some precisely estimated negative TFP impacts as well.

Table 5: TFP Impacts

	(1)	(2)	(3)	(4)
Dep. Variable:	$\ln(A_{jt}^{DICE})$	$\ln(A_{jt})$	$\ln(A_{jt}^{Empl.})$	$\ln(A_{jt}^{DICE})$
Labor Measure:	Pop.	hc·Pop	hc·Empl.	Pop.
MaxWind_t	-1.089*	-0.964*	-0.795*	0.0777
	(0.560)	(0.554)	(0.425)	(0.130)
MaxWind_{t-1}	-1.106**	-0.971*	-0.798**	0.135
	(0.498)	(0.494)	(0.379)	(0.0953)
MaxWind_{t-2}	-1.065**	-0.918*	-0.729*	0.140*
	(0.495)	(0.488)	(0.416)	(0.0836)
MaxWind_{t-3}	-0.815	-0.758	-0.823*	0.101
	(0.514)	(0.508)	(0.440)	(0.0731)
MaxWind_{t-4}	-0.756*	-0.678*	-0.719**	-0.00657
	(0.402)	(0.397)	(0.331)	(0.0726)
MaxWind_{t-5}	-0.801**	-0.701*	-0.628*	-0.0604
	(0.397)	(0.392)	(0.338)	(0.0611)
MaxWind_{t-6}	-0.821**	-0.710**	-0.490*	-0.0535
	(0.315)	(0.316)	(0.286)	(0.0653)
Obs.	5,281	5,281	5,281	6,685
Clusters	144	144	144	180
Adj. R^2	0.981	0.972	0.972	0.975

Table presents regression of natural log of countries' TFP on a constant, country fixed-effects, year fixed-effects, country-specific linear time trends, and cyclones (max. wind speed/km^2). Cols. 1 and 4 use DICE Model TFP (labor measured by population). Col. 2 uses benchmark model (labor measured by population times human capital); Col. 3 extended model (labor measured by workers times human capital). Cols. 1-3 use consistent sample of country-years with available Penn World Table data on human capital and workers. Col. 4 uses extended sample incl. countries without education, labor data. 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. Columns (1)-(3) present estimates for our different TFP measures (15)-(17) on a consistent sample of countries. First, the DICE TFP measure in Column (1) yields the largest cyclone impact estimates. Moving to Column (2) effectively takes human capital (schooling attainment) out of the TFP residual, and yields a smaller impact estimate, consistent with empirical evidence that cyclone strikes lead to disinvestment in health and human capital (Anttila-Hughes and Hsiang, 2013). Next, moving to Column (3) effectively takes changes in employment out of the TFP residual. This change again yields lower impact estimates, consistent with the notion that some TFP impacts in Columns (1) and (2) were driven by changes in employment, as may be expected from dislocation, morbidity, but also labor demand changes due to disruptions in input-output networks, etc. Finally, for completeness, Column (4) presents estimates of the DICE TFP impacts on the full sample of available country-years for this indicator. That is, compared to Column (1), Column (4) add 36 countries that lack PWT data on education and/or employment, which renders the cyclone impact estimates noisy. We speculate that this difference may be due to lower data quality among this extended sample.

4.2 Depreciation

While there is limited literature guidance for the estimation of cyclone TFP impacts,[15] 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; Bakkensen and Mendelsohn, 2016), we specify depreciation damage functions as follows:

$$\begin{aligned} \delta^k_{j,t}(\varepsilon_{j,t}) &\equiv \frac{\text{PropertyDamages}_{j,t}}{K_{j,t}} = \xi^k_{1j,t}(\varepsilon_{j,t})^{\xi^k_{2j,t}} \\ \delta^h_{j,t}(\varepsilon_{j,t}) &\equiv \frac{\text{Fatalities}_{j,t}}{L_{j,t}} = \xi^h_{1j,t}(\varepsilon_{j,t})^{\xi^h_{2,j,t}} \end{aligned} \tag{18}$$

This setup allows the damage function coefficients to vary across countries and time, in line with both the model and empirical studies. We estimate (18) in logs:[16]

$$\ln(\delta^m_{j,t}) = \mathbf{x}'_{j,t}\boldsymbol{\beta}^{\mathbf{m}} + \beta^m_\varepsilon \ln \varepsilon_{j,t} + (\ln\varepsilon_{j,t} \cdot \mathbf{x_{j,t}})'\boldsymbol{\gamma}^{\mathbf{m}} + \epsilon_{j,t},\ m \in \{k, h\} \tag{19}$$

Given (19) one can infer each country's vulnerability coefficients as a function of its development covariates via:

$$\begin{aligned} \widehat{\xi^m_{1,j,t}} &= e^{\mathbf{x}'_{j,t}\widehat{\boldsymbol{\beta}^{\mathbf{m}}}} \\ \widehat{\xi^m_{2j,t}} &= \widehat{\beta}_\varepsilon + \mathbf{x_{j,t}}'\boldsymbol{\gamma}^{\mathbf{m}} \end{aligned} \tag{20}$$

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

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

Table 7 displays the results for our preferred cyclone measure of maximum wind speed (per square kilometer). Potential covariates include domestic credit, GDP per capita, and country fixed-effects. We lag GDP to avoid endogeneity to the year t disaster realization, but consider contemporaneous credit as it reduces vulnerability precisely through its response to disasters. Column (4) also presents a U.S.-only specification.

Table 7: Depreciation Impacts

Dependent Variable:	$\ln(\text{PropertyDamages}_{j,t}/K_{j,t})$				$\ln(Fatalities_{j,t}/L_{j,t})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(\text{MaxWind}_{j,t})$	0.627***	2.773***	1.125**	4.817***	2.218***	0.932***
	(0.161)	(0.615)	(0.545)	(1.058)	(0.382)	(0.223)
$\ln(\text{MaxWind}_{j,t})\cdot\text{Credit}_{j,t}$	-0.00320**					
	(0.00139)					
$\ln(\text{MaxWind}_{j,t})\cdot\ln(\text{GDP pc})_{j,t-1}$		-0.272***			-0.173***	
		(0.0712)			(0.0422)	
$\text{Credit}_{j,t}$	-0.0336***					
	(0.0124)					
$\ln(\text{GDP pc})_{j,t-1}$		-3.083***			-2.252***	
		(0.721)			(0.418)	
Constant	-2.793**	21.74***	1.629	46.71***	12.05***	-5.394**
	(1.417)	(6.157)	(5.062)	(12.10)	(3.758)	(2.065)
Country Fixed Effects?	No	No	Yes	U.S. Only	No	Yes
Observations	320	324	329	28	440	446
R-Squared	0.107	0.145	0.032	0.415	0.458	0.042
Adj. R-Squared	0.0981	0.137	0.0293	0.393	0.455	0.0401

Table presents regression of natural log of fractions of capital stock destroyed (Cols. 1-4) or population killed (Cols. 5-6) on $\text{MaxWind}_{j,t}$ (max. wind speed normalized by country area), $\text{Credit}_{j,t}$ (domestic credit provided by the financial sector), lagged GDP per capita, and country fixed-effects (Cols. 3,6). Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

As expected, depreciation losses are increasing in wind speeds. In line with the empirical literature, we find considerably less curvature in this damage function for the global sample (Hsiang and Narita, 2012; Bakkensen and Mendelsohn, 2016) compared to the United States (Column 4; Nordhaus, 2010b; Strobl, 2011).[17] The results also indicate that both credit markets and economic development are associated with lower cyclone strike vulnerability, again in line

[17] Quantitatively, the estimates may also differ from other studies which almost universally normalize damages by GDP, whereas we study damages as a fraction of countries' capital stocks, which are not equiproportional to GDP across countries.

with prior empirical studies. In order to construct a cyclone damage function based on Table 7, we account for these protective effects by evaluating the coefficients $\widehat{\xi^{m}_{j,t}}$ variably at countries' GDP levels in 2015 or projected GDP in 2095.[18]

5 Climate Change Cyclone Impact Analysis

5.1 Cyclone Risk Changes

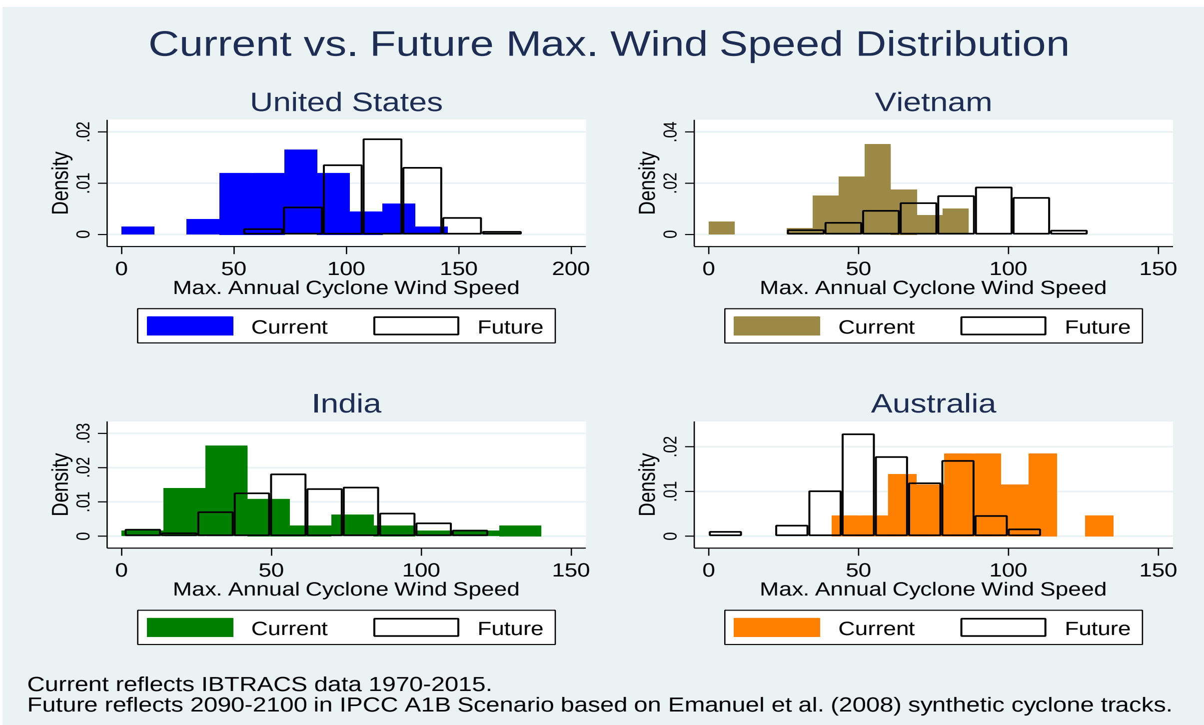
The empirical estimates presented thus far quantify the impacts of *weather* shocks (cyclone strikes). Linking these estimates to climate-economy models requires a quantification of how the probability distribution of these shocks will change along with the global climate. For example, in the DICE model, damages are specified as deterministic losses due to changes in the climate, represented by mean global atmospheric temperature change T_τ in decade τ. The first step in mapping our estimates of, e.g., capital losses $\widehat{\delta^k_{j,t}}(\varepsilon_{j,t})$ into DICE tis thus to compute expected annual losses as a function of the climate:

$$\delta^k_\tau(T_\tau) \sim E_j[\widehat{\delta^k_{j,\tau}}(\varepsilon)|T_\tau] = \int_0^\infty \widehat{\delta^k_{j,\tau}}(\varepsilon) \cdot f_j(\varepsilon|T_\tau)d\varepsilon \tag{21}$$

were $f_j(\varepsilon_j|T_\tau)$ thus denotes country $j's$ cyclone intensity probability density function (*pdf*) conditional on T_τ. The availability of atmospheric science data to estimate $f_j(.)'s$ was previously limited, forcing some earlier literature on direct cyclone damages from climate change to approximate (21) based on projected changes in the *means* of cyclone intensity, effectively computing $\widehat{\delta^k}(E[\varepsilon|T_\tau])$ (e.g., Narita, Tol, Anthoff, 2009; see also literature review by Ranson et al., 2014). Of course, if damage functions $\delta^k(\varepsilon_{j,t})$ are convex (as argued for the U.S. by, e.g., Emanuel, 2005; Nordhaus, 2010; etc.), this approach would underestimate expected future damages, and vice versa for concave damage functions. 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 these *pdf*s for each country. They generate 34,000 simulated *synthetic tropical cyclone tracks* under the current (1980-2000) and future climate (2080-2100 under the IPCC's A1B emissions scenario through NOAA's GFDL general circulation model by Manabe et al., 1991; as also utilized in Mendelsohn et al., 2012). These tracks contain parallel information to the historical cyclone 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

[18] Projections are based on regionally differentiated business-as-usual per capita GDP growth projections from the RICE model (Nordhaus, 2011), applied to each country's GDP per capita levels in 2015.

climate change (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 the synthetic tracks for each country (see Online Appendix for details). Importantly, this process captures changes in expected future intensity driven both by changes in the *number* and *characteristics* of storms. For our preferred cyclone measure of maximum wind speeds, the literature has found Weibull distributions to provide the best fit (Johnson and Watson 2007; Tye et al. 2014), which we consequently use to estimate $f_j(\widehat{\varepsilon|T_{2090}})$ for each country.[19] Figure 1 presents simulation results for four example countries to illustrate the heterogeneity in projected climate change impacts, with increases in some regions (e.g., United States), but decreases in others (e.g., Australia).



Finally, in order to estimate current cyclone *pdfs* $f_j(\widehat{\varepsilon|T_{2000}})$, we repeat the simulation-Weibull fit procedure for current landfall frequencies and sampling historical cyclone tracks from IBTrACS.

[19] 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 across the coastal United States, but that household-level damages and the wind speed distribution are thin tailed. We nonetheless account for uniquely high U.S. damages by utilizing a separate capital depreciation elasticity.

5.2 DICE Damage Function

The seminal DICE climate-economy model (Nordhaus, e.g., 2008) is a central benchmark across the literature, and one of three models used by the U.S. government to value the social cost of carbon. Given its status, we thus first seek to incorporate our empirical estimates into the DICE model. First, given the estimated cyclone damage functions (18)-(19) and probability distributions, one can readily compute expected capital depreciation and fatality rates under the current and future climate for each country via (21). For TFP impacts, taking the results in Table 5 at face value further yields the following general damage function for annual time t losses in TFP due to cyclone realizations:

$$\delta^A(\varepsilon_{j,t}, ...\varepsilon_{j,t-6}) = \widehat{\beta_1^A}\varepsilon_{j,t} + \widehat{\beta_2^A}\varepsilon_{j,t-1} + ... + \widehat{\beta_7^A}\varepsilon_{j,t-6} \tag{22}$$

Assuming independence in year-to-year cyclone fluctuations, expected annual cyclone TFP impacts in country j can then be approximated by an analogous specification to (21). Currently, we further compute *cumulative* losses in TFP at time $t \geq 1$ due to the history of cyclones since $t = 0$ as follows:

$$D_t^A(\varepsilon_{j,t}, \varepsilon_{j,t-1}, ...\varepsilon_{j,0}) = 1 - \prod_{m=0}^{t-1}(1 - \delta^A(\varepsilon_{j,t-m}, ...\varepsilon_{j,t-m-6})) \tag{23}$$

The Online Appendix presents country-level results of these expected impacts. As DICE is a global model, we further aggregate these estimates based on current or future capital stocks, GDP, or population shares. Table 8 presents the results.

Table 8: Global Aggregate Annual Expected Cyclone Depreciation (%/year)

	Current Climate			Future Climate (T_{2090})		
TFP						
Aggregation Weights:	2015 GDP		2095 GDP	2015 GDP		2095 GDP
	.0355%		.0384%	.1048%		.1320%
Physical Capital						
Aggregation Weights:	2015 Capital		2095 GDP	2015 Capital		2095 GDP
Coefficients:						
2015 GDP, U.S. sep.	.0059%		.0063%	.0105%		.0101%
2095 GDP, U.S. sep.			.0023%			.0061%
2095 GDP, all			.0003%			.0003%
Historical Data:						
Avg. (1970-2014)	.0090%					
Year 2014	.0050%					
Fatalities						
Aggregation Weights:	2015 Pop.	2095 Pop.	2095 GDP	2015 Pop.	2095 Pop.	2095 GDP
Coefficients:						
2015 GDP	.000035%	.000043%	.000023%	.000042%	.000054%	.000026%
2095 GDP	.000007%	.000008%	.000006%	.000007%	.000009%	.000006%
Historical Data:						
Avg. (1970-2015)	.000380%					
Year 2014	.000008%					

While these estimates may appear small, their magnitude arguably matches historical data. While cyclones can be locally extremely destructive, their impacts are limited both geographically and physically. Even the $108 billion in damages caused by Hurricane Katrina - the costliest storm in U.S. history - account for only 0.24% of the U.S. capital stock at the time, ($44.4 trillion, $2011), or 0.042% of the global capital stock. Given the heterogeneity in projected cyclone changes, some expected losses are also cancelled out by other countries' gains from cyclone risk reductions.

The last step is to convert these results into damage functions, which ought to reflect the *additional* and *cumulative* cyclone impacts due to warming T_τ. Given that natural scientists generally project the global cyclone intensity-temperature relationship to be linear (Holland and Bruyere, 2014), and adopting NOAA's assessment that anthropogenic warming between pre-industrial and current times has not yet altered tropical cyclone patterns (GFDL, 2018), we arrive at the following damage functions (see Online Appendix for details). First, to capture the cumulative nature of TFP impacts resulting from (23), we specify an effective (i.e., net-of-cyclone-damages) decadal TFP term $Z_A(T_\tau)$:

$$Z_A(T_\tau) = \prod_{j=0}^{\tau}(1 - \widehat{\alpha_A} T_{\tau-j})^{10} \tag{24}$$
$$\widehat{\alpha_A} \in \{0.000182, 0.000295\}$$

We proceed analogously for fatality impacts. In particular, as the DICE model's welfare weighting of future generations depend on their population size, we do not model mortality impacts as changes in the population, and introduce an effective labor parameter $Z_H(T_\tau)$ instead, where the cumulative loss in the effective work force is given by:

$$Z_H(T_\tau) = \prod_{j=0}^{\tau}(1 - \widehat{\alpha_h} T_{\tau-j})^{10} \tag{25}$$
$$\widehat{\alpha_h} \in \{2.98e^{-08}, 8.09e^{-08}\}$$

Aggregate production in the cyclone-extended DICE model is thus:

$$Y_\tau = A_\tau(1 - D(T_\tau)) \cdot Z_A(T_\tau) \cdot [K_\tau]^\alpha [L_\tau Z_H(T_\tau)]^{1-\alpha}$$

where $D(T_\tau)$ denotes other climate damages (from agriculture, malaria, etc., see Nordhaus and Boyer, 2002). Finally, capital impacts are modeled as an addition to the annual depreciation rate $\delta^k_{yr}(T_\tau) = \overline{\delta} + \widehat{\alpha_k} T_\tau$, implying decadal depreciation:

$$\delta^k_{10yr}(T_\tau) = 1 - [(1 - \overline{\delta} - \widehat{\alpha_k} T_\tau)^{10}] \tag{26}$$
$$\widehat{\alpha_k} \in \{0.000001, 0.00002\}$$

Table 9 summarizes the welfare costs of incorporating damage functions (24)-(26) into the DICE-2010 model. The results are stated in terms of the percentage increase in the (optimal) social cost of carbon in 2015 (ΔSCC_{2015}), and on average over the 21st century ($\overline{\Delta SCC_{2015-2115}}$). The benchmark coefficients imply an increase in the optimal carbon price of 10%, driven overwhelmingly by the TFP impacts due to their accumulation over time.

Table 9: Cyclone Impacts on the Social Cost of Carbon (SCC)

Impacts Case	$\widehat{\alpha_A}$	$\widehat{\alpha_h}$	$\widehat{\alpha_k}$	ΔSCC_{2015}	$\overline{\Delta SCC_{2015-2115}}$
Benchmark	.000295	$8.09e^{-08}$	0.00002	+12.6%	+10.3%
Lower Depreciation	0.000182	$2.98e^{-08}$	0.000001	+12.5%	+10.2%
No TFP	0	$8.09e^{-08}$	0.00002	+0.2%	+0.1%
Higher TFP	.000402	$8.09e^{-08}$	0.00002	+17.2%	+14.1%

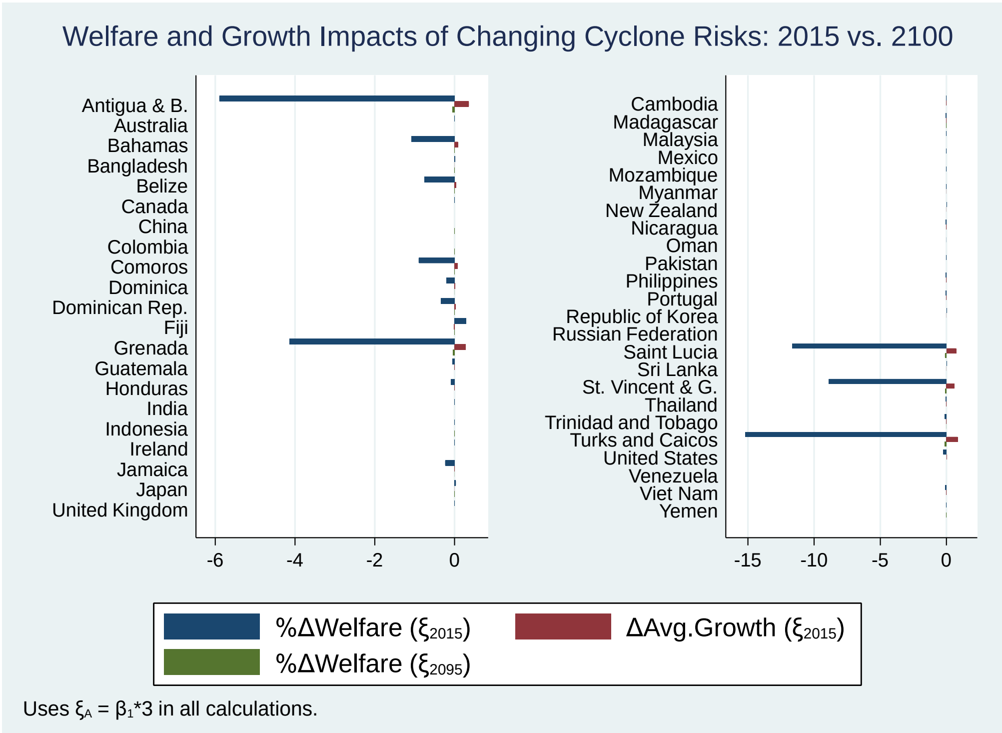
5.3 Stochastic Endogenous Growth Cyclone-Economy Model

While the DICE model is a central benchmark in the literature, it is not designed to capture the types of investment, growth, and welfare impacts of changes in (partly uninsurable) cyclone risks as described in Section 3. This is because DICE is both deterministic and based on a Solow growth model. We thus conclude by presenting results from a quantitative version of our stochastic endogenous cyclone-climate growth model from 3. This first step towards a *weather*-climate economy model has the important advantage that we can adopt the empirically estimated weather impact functions directly to quantify the corresponding model elements $\eta_j^h(\varepsilon_{j,t})$, $\eta_j^k(\varepsilon_{j,t})$, $A_{j,t}(\varepsilon_{j,t})$. Changes in the climate are then represented explicitly by changes in the distribution of these shocks (implicit in the expectations operator in Section 3), and general equilibrium adaptation to these changing risks is explicitly represented in the model.

We generate a separate calibrated version of the model for each country, data-permitting. The calibration matches initial (2014) real GDP growth rates for each country. One important remaining unknown parameter is insurance availability π_j. While global re-insurers such as MunichRe produce estimates of 'insurance penetration,' these are based on averaged premiums and thus confound take-up, risk, and availability. Prior empirical work also suggests that general fiscal transfers may constitute an important source of implicit insurance (Deryugina, 2011). We thus begin by setting π_j by assumption, but are exploring method of moments options to infer $\pi_j's$ from each country's estimated output growth response to cyclone strikes.

Figure 2 presents the current results.[20] Welfare changes are presently measured as percent change in stationary equilibrium welfare under the current versus future climate. The blue bars represent welfare changes for damage functions evaluated at *current* GDP levels ($\widehat{\xi_{j,2015}}$), thus assuming no reductions in cyclone vulnerability over the next century. The green bars represent welfare changes for damage functions evaluated at projected *future* GDP levels ($\widehat{\xi_{j,2095}}$), thus assuming that the protective effect of development on cyclone vulnerability will extend into the future. Finally, the red bars showcase projected changes in output growth in the 'current damage functions' scenario. Several insights stand out. First, there is significant heterogeneity in the projected welfare impacts of cyclone risk changes, as may be expected given Figure 1. Small island states such as Antigua and Barbuda may face significant losses, whereas countries whose cyclone risks are projected to decline are also estimated to receive small welfare gains (e.g., Australia). Second, these welfare losses may be accompanied by *increases* in average output growth, in line with the theoretical results. Finally, reductions in future cyclone vulnerability due to continued economic development may vastly mitigate the potential losess from future cyclone risk changes.

[20] This benchmark calibration further sets $\beta = 0.975$, $\gamma = 2$, $\overline{\delta^h} = \overline{\delta^k} = .1$, and $\pi_j = 0 \ \forall j$.



6 Conclusion

Do climatic shocks pose a threat to economic growth? While empirical studies have found a range of results suggesting the potential for large effects, macroeconomic climate-economy models used to value the social cost of carbon (SCC) have been slow to incorporate these results. This paper seeks to help bridge this micro-macro gap through the case of tropical cyclones. First, we review the empirical evidence through the lens of a stochastic endogenous growth model, finding that: (i) seemingly disparate empirical results can potentially be reconciled as measuring different components of the impact of cyclones on growth; (ii) the empirical evidence has important implications for the structure of models seeking to capture the full impacts of changes in cyclone risks, but that (iii) reduced-form output growth impact estimates are difficult to use directly in the *quantification* of standard climate-economy models. Second, we suggest a modified empirical approach that estimates cyclone impacts on structural determinants of growth, namely total factor productivity, depreciation, and fatalities. We implement this approach and present a complete mapping from the data to an empirically estimated cyclones damage function for the seminal DICE model. The estimates imply that cyclones increase the SCC by 10-15%. These results are strikingly driven by the TFP channel, a heretofore greatly underexplored mechanism in the empirical literature that warrants future work.

Third, we present country-specific quantitative estimates from our stochastic endogenous growth cyclones-climate-economy model. This first step towards a *weather*-climate economy model allows for the direct integration of empirically estimated weather shock (cyclone strike) impacts into the model, and deals with adaptation to changing cyclone risks by making it explicit and endogenous in the model.

Though informative, these results are subject to numerous caveats. On the empirical side, these include active debates surrounding variable selection, functional forms, adaptation, data accuracy, the physical interplay between climate and cyclones. On the modeling side, our framework currently does not address important issues such as transitional impacts, cross-country trade and financial flows, technology spillovers, and growth convergence, to name a few. Far from claiming to provide final estimates of cyclone costs and climate change, this paper thus presents a basic approach to bridging the micro-macro gap that would be easy to incorporate as a complement to empirical work to increase its usability for structural modelers. Indeed, this call to bridge the micro-macro gap is not new (Burke et al., 2016) and is being carefully and scientifically addressed across other climate-relevant outcomes in ongoing work by groups such as the Climate Impacts Lab (e.g., Hsiang et al., 2017; Carleton et al., 2018). With greater synergy and understanding between the ever-improving empirical evidence, and increasingly sophisticated macroeconomic climate-economy models, the literature can make great progress towards understanding the impacts of environmental risks and the true social cost of carbon.

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