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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. We first present a stochastic endogenous growth model that can reconcile previous empirical findings. We then empirically estimate the impacts of cyclones on the structural determinants of growth (total factor productivity, depreciation, fatalities), instead of growth itself, facilitating direct inclusion into the seminal DICE climate-economy model. Cyclone damages are estimated to increase the social cost of carbon by 10-15%.

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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 failing 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 many 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. 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 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. 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 implement this approach and present a complete mapping from the data to a cyclones damage function for inclusion in the seminal DICE climate-economy model. We first estimate cyclone damage functions for total factor productivity, depreciation, and fatalities for each country from a comprehensive global database of all historical cyclones (1970-2015). Second, we compute probability density functions of future cyclone realizations in each country based on state-of-the-art synthetic cyclone track simulations from Emanuel et al. (2008). Third, we compute expected future impacts and extrapolate global damage functions. Incorporating our empirically estimated cyclone damage function in the DICE-2010 model increases the social cost of carbon by +10-15%.[2]

The paper proceeds as follows. Section 2 describes the theoretical background and model, and reviews competing empirical approaches. Section 3 presents our modified empirical specifications, data, and results. Section 4 maps the estimated coefficients into climate damage functions and computes their contribution to the social cost of carbon in DICE. Section 5 concludes.

2 Theoretical Perspective

2.1 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. Instead, the contribution lies in the application of this type of framework to review and inform empirical estimates of cyclones' macroeconomic impacts. Several theoretical studies present detailed analyses of the growth impacts of natural disasters (e.g., Ikefuji and Horii, 2012; Akao and Sakamoto, 2013). While there are again modeling differences across these and the present setting, the meaningful innovation of our study is the connection of the model to the empirics.

We also acknowledge that the AK structure of the model has well-known shortcomings for matching certain moments in cross-country growth data (see, e.g., Mankiw, Romer, and Weil, 1994; Klenow and Rodriguez, 2005). The motivation to nonetheless use this type of model is twofold. First, the same feature of AK models that is a liability in matching convergence data actually becomes an asset in matching the 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). The second advantage is that AK models provide a highly transparent

[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.

illustration of why and how different empirical estimation methods may map into different structural interpretations. This general point is not contingent upon the model. For example, cyclone risk (cross-sectional methods) and strikes (panel methods) would also be predicted to induce different effects in a Solow growth model. In this broad sense, the focus on an AK-type model is without loss of generality, whilst matching the empirical disasters literature and providing transparent analytic insights even in the rich settings developed by Krebs (2003ab, 2006, 2015).

2.2 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.[3,4,5] 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

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

4 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).

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

firm maximizes:

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

where $A_{j,t}$ denotes total factor productivity (TFP). Common factor shares α are not important for the results and motivated in Section 3. There we also allow storms to affect TFP $A_{j,t}(\varepsilon_{j,t})$. For the analytic results, we assume that $A_{j,t} = A_j$. 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:

$$\begin{aligned} R_{j,t}^{k} &= (\alpha)A_j(\widetilde{k}_{j,t})^{\alpha-1} \\ R_{j,t}^{h} &= (1-\alpha)A_j(\widetilde{k}_{j,t})^{\alpha} \end{aligned} \tag{4}$$

Next, 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 $\overline{\delta}_j^m \equiv \delta_m + \pi_j\mu_j^m$ 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:

$$\begin{aligned} r_j(\widetilde{k_{j,t}},\varepsilon_{j,t}) \equiv\ & \omega_k(\widetilde{k_{j,t}})\left[R_{j,t}^{k}(\widetilde{k}_{j,t}) - \overline{\delta_j^k} - (1-\pi_j)\eta_j^k(\varepsilon_{j,t})\right] \\ & + \left(1-\omega_k(\widetilde{k_{j,t}})\right)\left[R_{j,t}^{h}(\widetilde{k}_{j,t}) - \overline{\delta_j^h} - (1-\pi_j)\eta_j^h(\varepsilon_{j,t})\right] \end{aligned} \tag{5}$$

Finally, we assume that preferences are of the form:

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

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:

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

$$0 = \beta E\left[\frac{\left[R_j^k(\widetilde{k}_j) - \overline{\delta_j^k} - (1-\pi_j)\eta_j^k(\varepsilon'_j)\right] - \left[R_j^h(\widetilde{k}_j) - \overline{\delta_j^h} - (1-\pi_j)\eta_j^h(\varepsilon'_j)\right])}{(1+\widetilde{k}'_j)^2\cdot(1+r_j(\widetilde{k}'_j,\varepsilon'_j))^{\gamma}}\right] \tag{7}$$

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:

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

2.3 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.

2.3.1 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. While cross-sectional estimates are always subject to the caveats of omitted variable bias, both results 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, in line with Skidmore and Toya's (2002) findings. Though absent in our model, positive human capital externalities as in Lucas (1988) could further account for the positive relationship between cyclone risk and average growth (see also Akao and Sakamoto, 2013). (3) *Direct Depreciation Effect*: Higher storm risk increases average depreciation, decreasing average growth, ceteris paribus.

The mechanisms underlying Proposition 1 have two noteworthy additional implications.

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; Krebs, 2003b; also discussed by Akao and Sakamoto, 2013), Corollary 1 retiterates this result for the present setting as it highlights potential limitations of reduced-form growth impact estimates for informing welfare costs of climate change.

Second, these mechanisms provide reasons why Skidmore and Toya (2002) find a positive association between cyclone risk and growth ($\frac{d\overline{g}}{d\mu_\varepsilon}$) (across 89 countries) whereas Hsiang and Jina (2015) estimate a negative relationship between average cyclone-induced capital depreciation ($\frac{d\overline{g}}{d\eta^k}$) and growth (among 34 cyclone-affected countries). One, since $\frac{d\overline{g}}{d\mu_\varepsilon}$ is theoretically predicted to vary in sign even across different levels of μ_ε within a given setting (see Online Appendix), it should not be surprising that studies estimating this relationship in different settings find qualitatively different results. Two, average cyclone intensity and capital destruction may affect growth differently. Consider, for illustrative purposes, the simplest possible case where physical and human capital are initially isomorphic including in storm vulnerability ($\eta_j^h(\varepsilon_{j,t}) = \eta_j^k(\varepsilon_{j,t})$). An increase in μ_ε would then affect growth only through the *Precautionary Savings Effect* and the *Direct Depreciation Effect* (as μ_ε does not affect the relative attractiveness of investing in physical versus human capital). In contrast, a ceteris paribus increase in physical capital risk would additionally shift the household's optimal portfolio toward human capital (*Portfolio Effect*). In reality, there may be numerous additional reasons for these studies' results to differ. Our core point, however, is that the theoretical prediction for (and interpretation of) $\frac{d\overline{g}}{d\mu_\varepsilon}$ may differ from that of $\frac{d\overline{g}}{d\eta^k}$ even though, from an empirical econometrician's perspective, average storm intensity and average storm destructiveness appear as reasonable proxies for the same core phenomenon (cyclone risk).

2.3.2 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.:

$$g_{j,t} = \underbrace{\beta_{0,j}}_{\text{Fixed effects}} + \underbrace{\beta_1 \varepsilon_{j,t}}_{\text{Estimated cyclone impact}} + ... + \epsilon_{j,t} \tag{10}$$

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

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

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 perspective of the model again highlights the limitations of reduced-form results for the *quantification* of IAMs. Comparing (11) and (10), the estimated coefficients on cyclone realizations $\widehat{\beta_1}$ capture the ceteris paribus effect of *strikes,* whereas average growth - and thus the impact of cyclone *risk* - is captured in the fixed effects $\widehat{\beta}_j$. Since global warming will alter future cyclone realizations precisely through its effects on cyclone risk (i.e., the moments of the cyclone distribution), evaluation of $\widehat{\beta_1}$ is insufficient to characterize climate change impacts. Even with a two-step adjustment for cyclone risk endogeneity of the fixed effects, the welfare interpretation of projected growth impacts remains unclear (see earlier version of this paper, Bakkensen and Barrage, 2016).

3 Modified Empirical Approach

In order to generate empirical estimates that (i) can be readily incorporated in climate-economy models, and (ii) provide welfare-relevant impact quantifications, we propose estimating climate shock impacts on the structural determinants of growth, rather than (only) growth itself. In the seminal DICE framework (Nordhaus, e.g., 2008, 2010a), the relevant cyclone-vulnerable parameters include total factor productivity (TFP) and depreciation rates of physical capital and the labor force. This section illustrates how *standard empirical approaches and datasets* can be used to construct a cyclone-damage function fit for inclusion in DICE.

First, we empirically estimate cyclone impact functions for depreciation $\eta^k_{j,t}(\varepsilon_{j,t})$, $\eta^h_{,j,t}(\varepsilon_{j,t})$ and TFP $\delta^A_j(\varepsilon_{j,t}, \varepsilon_{j,t-1}, ..)$. Second, we estimate country-specific probability distributions $f_j(\varepsilon_j|T_t)$ for cyclone realizations under both current and future climate T_t. Third, we integrate out to compute expected country-level impacts (which may vary with economic development), and back out aggregate global damage functions $\delta^k(T_t)$, $\delta^h(T_t)$, and $\delta^A(T_t)$, which we then add into DICE.

Before proceeding, three caveats deserve mention. The first is that parametric determinants of growth are generally model-specific. For example, what constitutes 'total factor productivity' depends on the underlying model. Educational attainment, for instance, should be contained in the TFP term in DICE, but is considered a factor input in other frameworks, such in the Penn World Tables' construction of TFP data. The empirical approach presented below may thus need to be modified to suit alternative macro models.

Second, 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), 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 empirical cyclones literature.

The third caveat is that the DICE model - while the undisputed benchmark across the literature, and one of three models used by the U.S. government to value carbon emissions - structurally cannot capture the growth impacts of climate risks described in Section 2. This is because DICE is deterministic and based on a Solow growth model. While we also quantify a heterogeneous-agent version of this paper's model in Bakkensen and Barrage (2017), the first order importance issue for the literature is clearly connecting to DICE, which we consequently focus on here.

3.1 Data

We utilize macroeconomic and cyclone data from 1970 to 2015, the post-satellite era for which cyclones have been most reliably tracked. 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). 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 proxy for financial market development. Country areas are from the Harvard World Map.

We gather historical global tropical cyclone tracks from the International Best Track Archive for Climate Stewardship (IBTrACS; Knapp et al., 2010). IBTrACS provides historical cyclone position 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. 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), normalizing by countries' land areas.[6]

[6] 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).

Global 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.) and also not central to our contribution, which is present an approach to damage estimation. Indeed, repeating this exercise with alternative damage data (such as proprietary information from insurers) would be a fruitful topic for future work.

3.2 Productivity

First we conduct a standard growth accounting exercise to decompose output growth impacts into productivity versus factor input changes. Adopting the DICE model's Cobb-Douglas specification, countries produce GDP $Y_{j,t}$ with capital $K_{j,t}$ and labor $L_{j,t}$ inputs:

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

Taking logs and rearranging yields:

$$\ln(A_{jt}) = \ln(Y_{j,t}) - \alpha_{j,t} \ln(K_{j,t}) - (1 - \alpha_{j,t}) \left[\ln(L_{j,t})\right] \tag{12}$$

Using PWT data on GDP, capital, and populations, one can thus back out TFP from (12) given factor shares $\alpha_{j,t}$. 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 labor share of $1 - \alpha_{jt} = 0.67\ \forall j, t$ in line with the global parameter in DICE.

Next, we de-trend the 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):

$$\ln(A_{j,t}) = \gamma_j + \delta_t + (\gamma_j \cdot t) + \sum_{l=0}^{L} \beta_{1+l}^{A} \varepsilon_{j,t-l} + \epsilon_{j,t} \tag{13}$$

where γ_j denotes country fixed-effects and $\varepsilon_{j,t-l}$ are cyclone realization measures up to lag L. De-trending through HP-filtering leads to similar results (see Online Appendix). Standard errors

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.

$\epsilon_{j,t}$ 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 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 1 presents results for the preferred specification using maximum wind speed (Col. 1) and energy (Col. 2) as cyclone intensity measures.

Table 1: TFP Impacts

	(1)		(2)
Dep. Variable:	$\ln(A_{j,t})$		$\ln(A_{j,t})$
MaxWind_t	-0.795*	Energy_t	-0.000323***
	(0.425)		(0.000122)
MaxWind_{t-1}	-0.798**	Energy_{t-1}	-0.000158
	(0.379)		(0.000134)
MaxWind_{t-2}	-0.729*	Energy_{t-2}	-0.000262
	(0.416)		(0.000165)
MaxWind_{t-3}	-0.823*	Energy_{t-3}	-0.000194
	(0.440)		(0.000164)
MaxWind_{t-4}	-0.719**	Energy_{t-4}	2.95e-05
	(0.331)		(0.000233)
MaxWind_{t-5}	-0.628*	Energy_{t-5}	5.81e-05
	(0.338)		(0.000258)
MaxWind_{t-6}	-0.490*	Energy_{t-6}	6.08e-05
	(0.286)		(0.000287)
Obs.	5,281		5,281
Clusters	144		144
Adj. R^2	0.972		0.972

Table presents results of regression of natural log of countries' TFP on a constant, country fixed-effects, year fixed-effects, country-specific linear time trends, and cyclone intensity for max. wind speed/km^2 (Col. 1) or energy/km^2 (sum of max. wind speeds cubed) (Col 2). Standard errors are heteroskedasticity-robust and clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1

The results indicate a significant negative impact of cyclone strikes on TFP. Intuitively, TFP impacts could reflect a number of mechanisms in line with the broader literature, such as reduced labor productivity from morbidity or dislocation, damages to public infrastructure, disruptions in input-output networks, etc. Taking the Column 1 results at face value, these estimates imply the following general damage function for *annual time t losses* in TFP due to cyclone realizations:

$$\delta^A(\varepsilon_{j,t}, ...\varepsilon_{j,t-6}) = \widehat{\beta_1^A}\varepsilon_{j,t} + \widehat{\beta_2^A}\varepsilon_{j,t-1} + ... + \widehat{\beta_7^A}\varepsilon_{j,t-6} \tag{14}$$

Cumulative losses in TFP at time $t \geq 1$ due to the history of cyclones since $t = 0$ are then:

$$D_t^A(\varepsilon_{j,t}, \varepsilon_{j,t-1}, ...\varepsilon_{j,0}) = 1 - \prod_{m=0}^{t-1}(1 - \delta^A(\varepsilon_{j,t-m}, ...\varepsilon_{j,t-m-6})) \tag{15}$$

3.3 Depreciation

While there is limited literature guidance for the specification of cyclone TFP impacts,[7] 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), depreciation damages are specified as:

$$\begin{aligned} \delta_{j,t}^k(\varepsilon_{j,t}) &\equiv \frac{\text{PropertyDamages}_{j,t}}{K_{j,t}} = \xi_{1j,t}^k(\varepsilon_{j,t})^{\xi_{2j,t}^k} \\ \delta_{j,t}^h(\varepsilon_{j,t}) &\equiv \frac{\text{Fatalities}_{j,t}}{L_{j,t}} = \xi_{1j,t}^h(\varepsilon_{j,t})^{\xi_{2,j,t}^h} \end{aligned} \tag{16}$$

This setup allows the damage function coefficients to vary across countries and time, in line with both the model and empirical studies. We estimate (16) in logs:[8]

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

Given (17) one can infer each country's vulnerability coefficients as a function of its development covariates via:

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

Table 2 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

[7] 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.

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

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 2: 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).[9] The results also indicate that both credit markets and economic development reduce countries' vulnerability, again in line with prior studies. In order to construct a cyclone damage function based on Table 2, we account for these protective effects by evaluating the coefficients $\widehat{\xi^m_{j,t}}$ variably at countries' GDP levels in 2015 or projected

[9] 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.

GDP in 2095.[10]

4 Climate Damage Estimates

The empirical results thus far relate cyclone *realizations* to impacts. In DICE, however, damages are specified as deterministic additional losses due to changes in the *climate*, represented by mean global atmospheric temperature change T_τ, which we now index by (and treat as constant within) decade τ. Given independence in year-to-year cyclone fluctuations, expected annual cyclone damages in country j can be computed via:

$$\delta_j^A(T_\tau) \sim E_j[\delta^A(\varepsilon_{j,t}, \varepsilon_{j,t-1})|T_\tau] = \int_0^\infty \delta^A(\varepsilon, \varepsilon) \cdot f_j(\varepsilon|T_\tau) d\varepsilon \tag{19}$$

$$\delta_j^k(T_\tau) \sim E_j[\delta_j^k(\varepsilon_{j,t})|T_\tau] = \int_0^\infty \delta_{j,\tau}^k(\varepsilon) \cdot f_j(\varepsilon|T_\tau) d\varepsilon \tag{20}$$

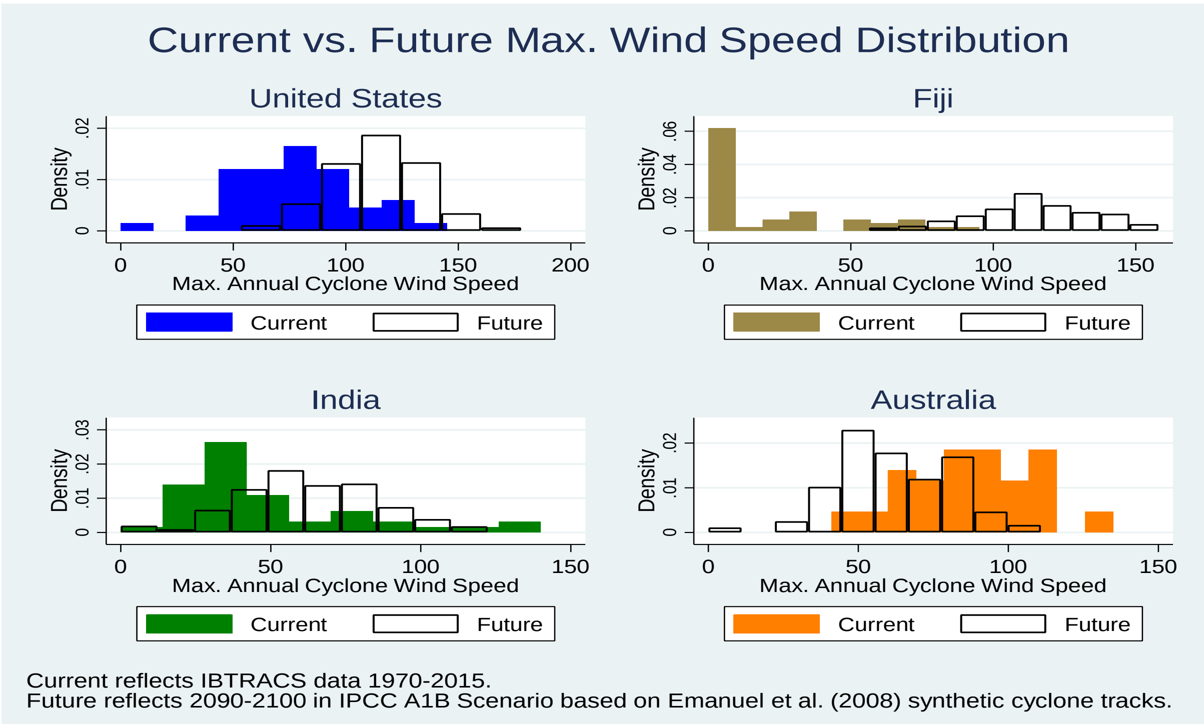
$$\delta_j^h(T_\tau) \sim E_j[\delta_j^h(\varepsilon_{j,t})|T_\tau] = \int_0^\infty \delta_{j,\tau}^h(\varepsilon) \cdot f_j(\varepsilon|T_\tau) d\varepsilon \tag{21}$$

Evaluating (19)-(21) requires estimates of countries' cyclone probability density functions (*pdf*) conditional on the climate. We gratefully take advantage of recent advances in climatological research from Kerry Emanuel and co-authors (Emanuel, 2008; Emanuel, Sundararajan, and Williams, 2008). 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 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.[11] Figure 1

[10] 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.

[11] 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

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 compute expected damages under the current climate (holding economic development constant), we repeat the simulation-Weibull fit procedure for current landfall frequencies and sampling historical cyclone tracks from IBTrACS.

Given the empirically estimated cyclone damage functions and probability distributions, we compute expected damages via (19)-(21). The Online Appendix presents country-level results. For integration in DICE - a global model - we aggregate these estimates based on current or future capital stocks, GDP, or population shares. Table 3 presents the results.

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.

Table 3: 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 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 (15), we specify an effective (i.e., net-of-cyclone-damages) decadal TFP term $Z_A(T_\tau)$:

$$\begin{aligned} Z_A(T_\tau) &= \prod_{j=0}^{\tau}(1-\widehat{\alpha_A}T_{\tau-j})^{10} \\ \widehat{\alpha_A} &\in \{0.000182, 0.000295\} \end{aligned} \tag{22}$$

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:

$$\begin{aligned} Z_H(T_\tau) &= \prod_{j=0}^{\tau}(1-\widehat{\alpha_h}T_{\tau-j})^{10} \\ \widehat{\alpha_h} &\in \{2.98e^{-08}, 8.09e^{-08}\} \end{aligned} \tag{23}$$

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:

$$\begin{aligned} \delta^k_{10yr}(T_\tau) &= 1-[(1-\overline{\delta}-\widehat{\alpha_k}T_\tau)^{10}] \\ \widehat{\alpha_k} &\in \{0.000001, 0.00002\} \end{aligned} \tag{24}$$

Table 4 summarizes the welfare costs of incorporating damage functions (22)-(24) 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 4: 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 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 *quantitatively* to inform 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 for the seminal DICE model and present a complete mapping from the data to an empirically estimated cyclones damage function for DICE. The estimates imply that cyclones increase the SCC by 10-15%. We note that these results are strikingly driven by the TFP channel, a heretofore greatly underexplored mechanism in the empirical literature that warrants future work.

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, while DICE is the central benchmark of both the academic literature and policy applications, as a deterministic Solow growth model it cannot capture the stochastic endogenous growth mechanisms considered by this and other papers. 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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