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

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Contents

1 Empirical Analysis

1.1 Panel Regressions

Table A1 presents output growth panel specification (2) using cyclone *energy* as intensity metric.

Table A1: Panel Analysis: Cyclone Strikes and Growth - Energy/sqkm

Dependent Variable:	Real GDP/Capita Growth$_{j,t}$					
Sample:	Unfiltered			Has Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
Energy/sqkm$_{j,t}$	-0.004	-0.208***	-0.583***	-0.074***	-0.241***	0.191
	(0.010)	(0.059)	(0.040)	(0.010)	(0.073)	(0.493)
Credit$_{j,t}\cdot$(Energy/sqkm$_{j,t}$)		0.002***			0.002***	
		(0.001)			(0.001)	
$\ln$ (GDP p.c.)$_{j,t-1}\cdot$(Energy/sqkm$_{j,t}$)			0.059***			-0.026
			(0.004)			(0.049)
Domestic Credit$_{j,t}$		-0.000			-0.000**	
		(0.000)			(0.000)	
$\ln$ (GDP p.c.)$_{j,t-1}$			-0.103***			-0.219***
			(0.013)			(0.033)
Country F.E.s:	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.s:	Yes	Yes	Yes	Yes	Yes	Yes
Country-Trends:	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Cluster	Country	Country	Country	Country	Country	Country
Observations	7,573	5,690	7,573	1,978	1,978	1,978
#Countries	182	171	182	116	116	116
Adj. R-Squared	0.110	0.102	0.167	0.178	0.201	0.278

Table presents regression of countries' real GDP per capita growth rate in year t on cyclone energy (sum of max. wind speeds cubed/1000 and normalized by land area) in year t plus controls for lagged natural log of real GDP per capita in level and interacted with energy (Cols. 3, 6) or domestic credit provided by financial sector (%GDP) in level and interacted with energy (Cols. 2, 5). All regressions include country fixed effects, year fixed effects, country-specific linear time trends, and a constant. Standard errors are heteroskedasticity-robust and clustered at the country level. (*** p$<$0.01, ** p$<$0.05, * p$<$0.1).

1.2 TFP Robustness

1.2.1 Varying Lag Lengths

Tables A2 and A3 present TFP impacts across varying cyclone lag lengths, along with Akaike/Bayesian Information Criteria (AIC/BIC). Table A2 focuses on the DICE TFP measure, whereas Table A3 focuses on our benchmark model measure. We restrict the sample to be the same across these specifications, so that Tables A2 and A3 extend main Table 1 Columns (1) and (2), respectively. The results are generally similar across lag lengths, but cease to be precisely estimated as more observations are excluded at higher lag lengths. The information criteria also imply that lower lag lengths are preferred.

1.2.2 HP-Filtering

Table A4 shows TFP results based on HP-filtering of each country's TFP series (using annual smoothing parameter $\lambda = 6.25$), and regressing the natural logarithm of the cyclical components, $\ln(\widetilde{TFP}_{j,t})$ on year fixed-effects and cyclone measures $\varepsilon_{j,t}$ (with robust errors $\epsilon_{j,t}$ clustered at the country-level):

$$\ln(\widetilde{TFP}_{j,t}) = \delta_t + \sum_{l=0}^{L} \beta^{A}_{1+l} \varepsilon_{j,t-l} + \epsilon_{j,t}$$

In line with the benchmark results, we find precisely estimated negative effects of cyclone strikes for our main model TFP measure (Column 2) and for the DICE model TFP measure in the consistent sample (Column 1). In the unfiltered sample which includes countries without capital stock or education information, the DICE results are again imprecise (Column 3).

1.2.3 Cyclone Energy

Table A5 presents results analogous to main paper Table 4 but using cyclone *energy* (maximum wind speeds cubed summed over the lifetime of a storm over a given country) per square kilometer - rather than maximum wind speeds per square kilometer - as cyclone intensity measure. While the point estimates continue to suggest negative TFP impacts that last for several periods, these estimates are generally imprecise (perhaps due to the additional weight given to outliers by the energy measure).

Table A2: DICE TFP Impacts at Varying Lag Lengths: Max. Wind / sqkm

MaxWind_t	-1.453*	-1.662*	-2.014*	-2.173*	-2.162*	-2.501*	-2.483*	-2.663*	-3.010*	-3.203
	(0.863)	(0.956)	(1.141)	(1.239)	(1.174)	(1.509)	(1.452)	(1.537)	(1.656)	(1.962)
MaxWind_{t-1}		-1.572**	-1.908**	-2.108**	-2.249**	-2.318**	-2.609*	-2.781*	-3.143*	-3.027*
		(0.739)	(0.905)	(1.048)	(1.118)	(1.158)	(1.433)	(1.521)	(1.667)	(1.717)
MaxWind_{t-2}			-1.965*	-2.148*	-2.303*	-2.490*	-2.518*	-2.824*	-3.191*	-3.068*
			(1.029)	(1.160)	(1.250)	(1.396)	(1.392)	(1.636)	(1.781)	(1.841)
MaxWind_{t-3}				-1.700	-1.852	-2.087	-2.231	-2.279	-2.890	-2.760
				(1.176)	(1.265)	(1.441)	(1.521)	(1.491)	(1.920)	(1.915)
MaxWind_{t-4}					-1.554*	-1.746	-1.950	-2.081	-2.353*	-2.629
					(0.903)	(1.056)	(1.204)	(1.266)	(1.344)	(1.721)
MaxWind_{t-5}						-2.015	-2.174	-2.388	-2.675	-2.612
						(1.246)	(1.385)	(1.526)	(1.647)	(1.740)
MaxWind_{t-6}							-1.786*	-1.966*	-2.371*	-2.201
							(0.998)	(1.154)	(1.375)	(1.443)
MaxWind_{t-7}								-1.850*	-2.207*	-2.139
								(1.009)	(1.247)	(1.363)
MaxWind_{t-8}									-2.349**	-2.180*
									(1.162)	(1.262)
MaxWind_{t-9}										0.687
										(1.382)
Obs.	6,161	6,033	5,905	5,777	5,649	5,521	5,393	5,265	5,137	5,009
Adj. R^2	0.714	0.710	0.707	0.704	0.700	0.696	0.691	0.688	0.685	0.683
AIC	-8551	-8490	-8433	-8363	-8263	-8167	-8066	-7991	-7906	-7813
BIC(n=#Clusters)	-8420	-8359	-8302	-8232	-8133	-8036	-7935	-7861	-7775	-7682

Regression of log DICE TFP $\ln(A_{jt}^{DICE})$ on a constant, country fixed-effects, year fixed-effects, country-specific linear time trends, and cyclones (max. wind speed/sqkm) for various lags. Standard errors are heterosk.-robust and clustered at the country level.

Table A3: Benchmark TFP Impacts at Varying Lag Lengths: Max Wind/sqkm

MaxWind_t	-1.485*	-1.661*	-1.951*	-2.069*	-2.061*	-2.345	-2.286	-2.406	-2.649	-2.922
	(0.859)	(0.948)	(1.111)	(1.201)	(1.171)	(1.500)	(1.460)	(1.558)	(1.696)	(1.946)
MaxWind_{t-1}		-1.569**	-1.856**	-1.995*	-2.095*	-2.158*	-2.382*	-2.496	-2.757	-2.601
		(0.734)	(0.892)	(1.013)	(1.082)	(1.157)	(1.429)	(1.539)	(1.710)	(1.749)
MaxWind_{t-2}			-1.899*	-2.035*	-2.129*	-2.263*	-2.280	-2.503	-2.770	-2.612
			(1.009)	(1.132)	(1.207)	(1.353)	(1.395)	(1.643)	(1.822)	(1.877)
MaxWind_{t-3}				-1.704	-1.821	-1.982	-2.080	-2.147	-2.648	-2.500
				(1.156)	(1.241)	(1.389)	(1.473)	(1.504)	(1.941)	(1.946)
MaxWind_{t-4}					-1.497*	-1.646	-1.771	-1.845	-2.095	-2.316
					(0.889)	(1.039)	(1.170)	(1.245)	(1.373)	(1.737)
MaxWind_{t-5}						-1.877	-1.988	-2.112	-2.306	-2.266
						(1.225)	(1.370)	(1.500)	(1.642)	(1.755)
MaxWind_{t-6}							-1.588	-1.704	-1.982	-1.778
							(1.002)	(1.163)	(1.379)	(1.439)
MaxWind_{t-7}								-1.584	-1.834	-1.705
								(0.999)	(1.240)	(1.341)
MaxWind_{t-8}									-1.927	-1.720
									(1.166)	(1.256)
MaxWind_{t-9}										0.955
										(1.288)
Obs.	6,161	6,033	5,905	5,777	5,649	5,521	5,393	5,265	5,137	5,009
Adj. R^2	0.642	0.639	0.635	0.631	0.625	0.618	0.610	0.602	0.594	0.588
AIC	-8447	-8386	-8327	-8255	-8160	-8067	-7968	-7898	-7813	-7722
BIC(n=#Clusters)	-8316	-8255	-8197	-8124	-8029	-7936	-7837	-7767	-7682	-7591

Regression of log benchmark TFP $\ln(A_{jt})$ on a constant, country fixed-effects, year fixed-effects, country-specific linear time trends, and cyclones (max. wind speed/sqkm) for various lags. Standard errors are heterosk.-robust and clustered at the country level.

Table A4: HP-Filtered TFP Impacts: Max Wind/sqkm			
	(1)	(2)	(3)
Dep. Variable:	$\ln(\widetilde{A}_{j,t}^{DICE})$	$\ln(\widetilde{A}_{j,t})$	$\ln(\overline{\widetilde{A}_{j,t}^{DICE}})$
Labor Measure:	Pop.	hc·Pop	Pop.
MaxWind_t	-59.357***	-52.971***	3.091***
	(8.051)	(8.380)	(0.656)
MaxWind_{t-1}	-29.702***	-27.829***	1.827
	(8.587)	(8.228)	(1.508)
MaxWind_{t-2}	-14.360*	-15.826*	3.027
	(7.770)	(8.696)	(2.202)
MaxWind_{t-3}	9.860	4.037	2.374
	(8.059)	(10.628)	(1.521)
MaxWind_{t-4}	1.362	-1.276	-0.182
	(6.551)	(7.161)	(1.783)
Obs.	2,812	2,812	3,462
Clusters	144	144	180
Adj. R^2	0.0496	0.0651	0.0507

Table presents regression of natural log of cyclical component of TFP (based on HP-filtering, with $\lambda = 6.25$) on a constant, year fixed-effects, and cyclone intensity (max. wind speed/km^2). Cols. 1 and 3 use DICE Model TFP (labor measured by population). Col. 2 uses benchmark model (labor measured by pop. times human capital). Cols. 1-2 use consistent sample with available Penn World Table data on human capital and workers. Col. 3 uses unfiltered sample incl. countries without education and labor data. Standard errors are heteroskedasticity-robust and clustered at country level. *** p$<$0.01, ** p$<$0.05, * p$<$0.1.

Table A5: TFP Impacts: Energy/sqkm			
	(1)	(2)	(3)
Dep. Variable:	$\ln\left(A_{jt}^{DICE}\right)$	$\ln\left(A_{jt}\right)$	$\ln\left(A_{jt}^{DICE}\right)$
Labor Measure:	Pop.	hc·Pop	Pop.
Energy$_t$	-0.217	-0.244*	-0.014
	(0.133)	(0.126)	(0.019)
Energy$_{t-1}$	-0.055	-0.074	0.035*
	(0.151)	(0.157)	(0.019)
Energy$_{t-2}$	-0.177	-0.190	0.025
	(0.186)	(0.187)	(0.016)
Energy$_{t-3}$	-0.047	-0.090	0.022
	(0.151)	(0.166)	(0.015)
Energy$_{t-4}$	0.186	0.153	0.011
	(0.211)	(0.228)	(0.009)
Obs.	5,649	5,649	6,997
Clusters	144	144	180
Adj. R^2	0.699	0.625	0.678

Table presents regression of natural log of countries' TFP on a constant, country fixed-effects, year fixed-effects, country-specific linear time trends, and cyclone energy/thousand km^2 (sum of max. wind speeds cubed). Cols. 1 and 4 use DICE TFP (labor measured by pop); Col. 2 uses benchmark (labor measured by population times human capital); Col. 3 extended (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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

1.3 Depreciation Robustness

Table A6 presents a robustness check for the depreciation impact estimation in paper Table 5 but using damage data from MunichRe instead of EMDAT (as aggregated to the country-year level for tropical cyclones and made available by Neumayer, Plumber, and Barthel (2014)).

Table A6: Depreciation Impacts Robustness: MunichRe (Neumayer et al., 2014) Damage Data

Dependent Variable:	$\ln(\text{PropertyDamages}_{j,t}/K_{j,t})$			
	(1)	(2)	(3)	(4)
$\ln(\text{MaxWind}_{j,t})$	3.568***	5.945***	0.976	1.053
	(0.412)	(1.062)	(0.765)	(0.758)
$\ln(\text{MaxWind}_{j,t})\cdot \ln(\text{GDP pc})_{j,t-1}$			-0.039	-0.067
			(0.085)	(0.085)
$\ln(\text{MaxWind}_{j,t})\cdot(\text{Pct. Below 5m})_{j,t}$				0.020**
				(0.008)
$\ln(\text{GDP pc})_{j,t-1}$			-0.627	-0.919
			(0.832)	(0.838)
Pct. Below $5\text{m}_{j,t}$				0.207***
				(0.068)
Constant	22.384***	59.324***	1.281	1.951
	(3.740)	(12.199)	(7.469)	(7.424)
Country Fixed Effects?	Yes	U.S. Only	No	No
Observations	320	27	320	320
Adj. R-Squared	0.196	0.602	0.169	0.190

Table presents regression of natural log of fractions of capital stock destroyed (Cols. 1-4) on natural log of $\text{MaxWind}_{j,t}$ (max. wind speed normalized by country area), lagged GDP per capita levels and max. wind interactions (Cols. 3, 4), the percentage of population living below 5 meters elevation in levels and max. wind interactions (Col. 4), and country fixed-effects (Col 1). Col. 2 restricts sample to U.S. storms only. Damages based on Neumayer et al. (2014) aggregates of MunichRe data. Heteroskedasticity-robust standard errors in parentheses (*** p$<$0.01, ** p$<$0.05, * p$<$0.1).

1.4 Cyclone Intensity Monte Carlo Simulation Details

First, we use the Emanuel et al.'s (2008) cyclone frequency data to estimate the projected mean number of storms making landfall in each country j under the future climate T_{2090}. Next we assume a Poisson distribution of cyclone counts (Emanuel, 2013) to randomly sample the *number* of storms making landfall in each country j per year under the future climate (taking $n = 5,000$ draws from the Poisson($\#landfalls_j|T_{2090}$) distribution for each country j). Third, for each draw of a *number* of storms making landfall in country j, we then randomly sample (with replacement) maximum wind speed from one of the 3,000 synthetic tracks per basin (5,000 tracks in the North Atlantic Ocean) in the Emanuel data. This process thus generates random draws over *annual* cyclone realizations, including years without storms. This process captures changes in expected future intensity driven both by changes in the number and characteristics of storms. Finally, we then fit Weibull distributions for each country.

In order to validate our approach, Figure A1 compares the estimated Weibull model's expected annual maximum wind speeds for each country under the current climate against their empirically observed mean maximum wind speeds in the data. The model appears to fit the data very well, with a correlation coefficient of 0.9982.

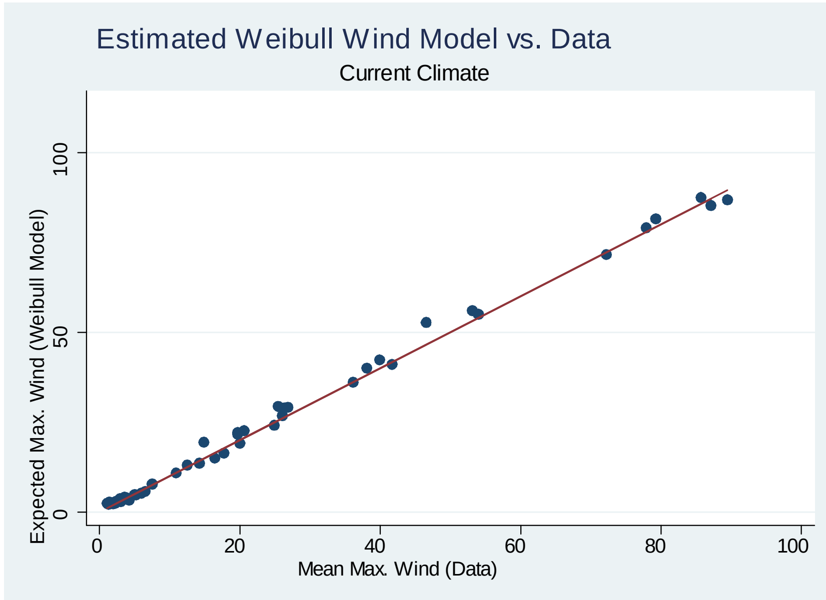

Figure A1: Estimated Weibull Expected Wind Speeds vs. Data

2 Quantitative Model

The benchmark model uses a TFP damage function based on the contemporaneous impacts specification (Table 4 Column 3). Figures A2 and A3 below showcase results for the case of a cumulative 5-year TFP impacts damage function instead (Table 4 Column 4). As expected, the estimated welfare impacts are generally larger in both directions. In comparing Figures A2 and A3 to their benchmark analogs (Figures 4 and 5), one further thing to note is that some countries no longer have valid impact estimates here. This is because some extremely vulnerable countries end up as 'dismal cases' in that their expected damages can no longer be properly computed over the full integral of their Weibull wind distributions. For example, in Turks and Caicos, the model with 5-period TFP impacts predicts negative overall returns $r_j(.)$ for wind speeds above 130 knots, at which point the model's optimality conditions can no longer be evaluated.[1]

Next we consider sensitivity of the results to future cyclone tracks simulated based on alternative climate model input, and to the MunichRe data-based damage function (specifically based on Table A6 Columns 1 and 2). The results are presented in Figures A4 and A5, and suggest variable sensitivity of countries' results to these modeling choices.

[1] Such highly destructive scenarios arguably have parallels in the historical record. For example, in 2017, Hurricane Irma reportedly destroyed 90% of buildings on the small Caribbean island of Barbuda. See: Philipps, Claire, "Irma's Destruction: Island by Island" The Guardian, September 10, 2017. URL (accessed 11/12/2019): https://www.theguardian.com/world/2017/sep/07/irma-destruction-island-by-island-hurricane

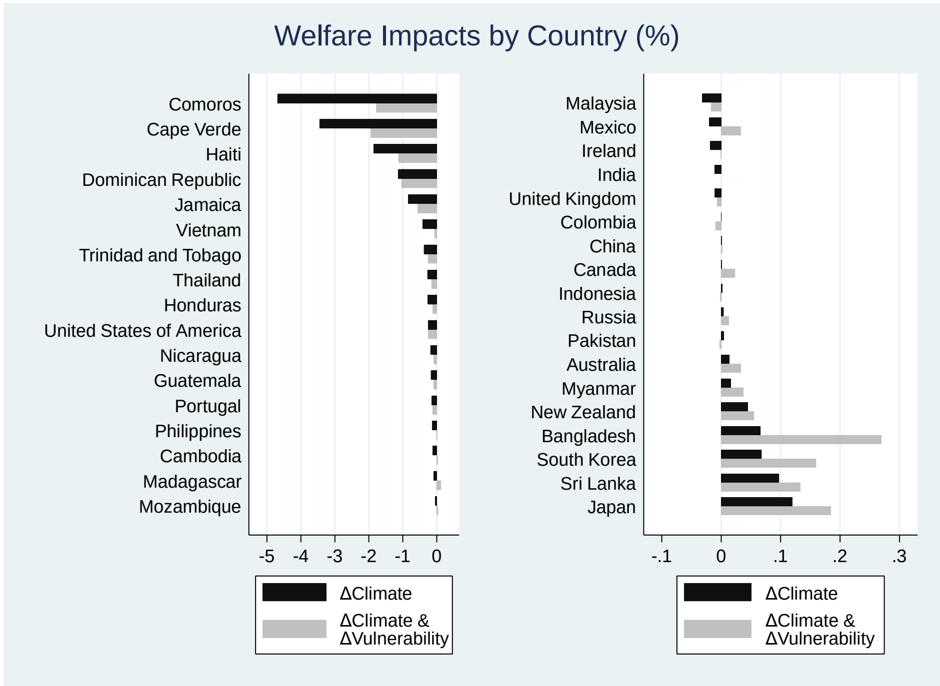

Figure A2: Welfare Impacts with Cumulative (5-Year) TFP Effects

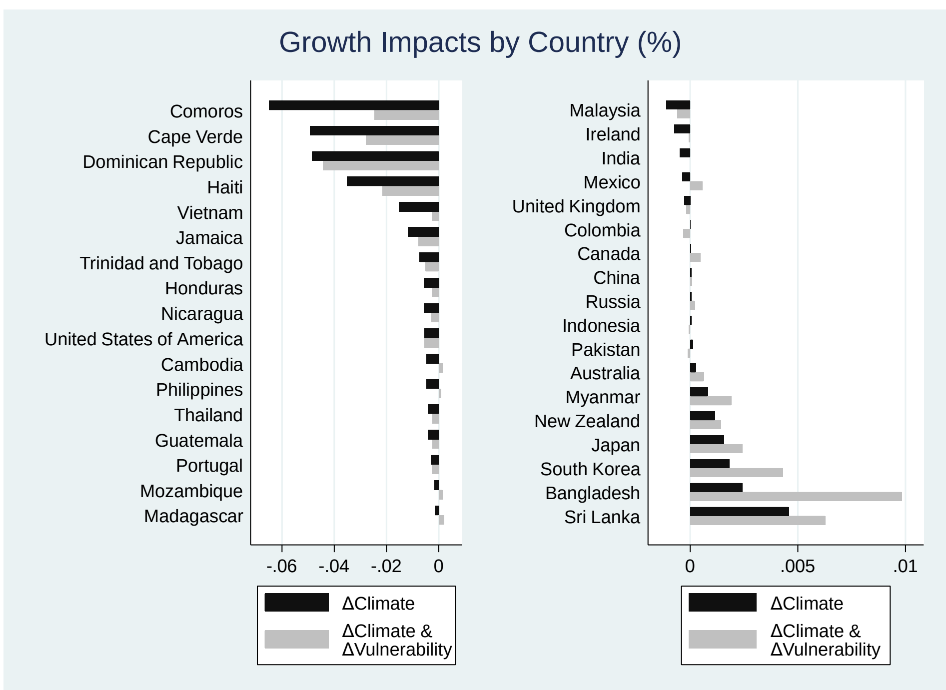

Figure A3: Growth Impacts with Cumulative (5-Year) TFP Effects

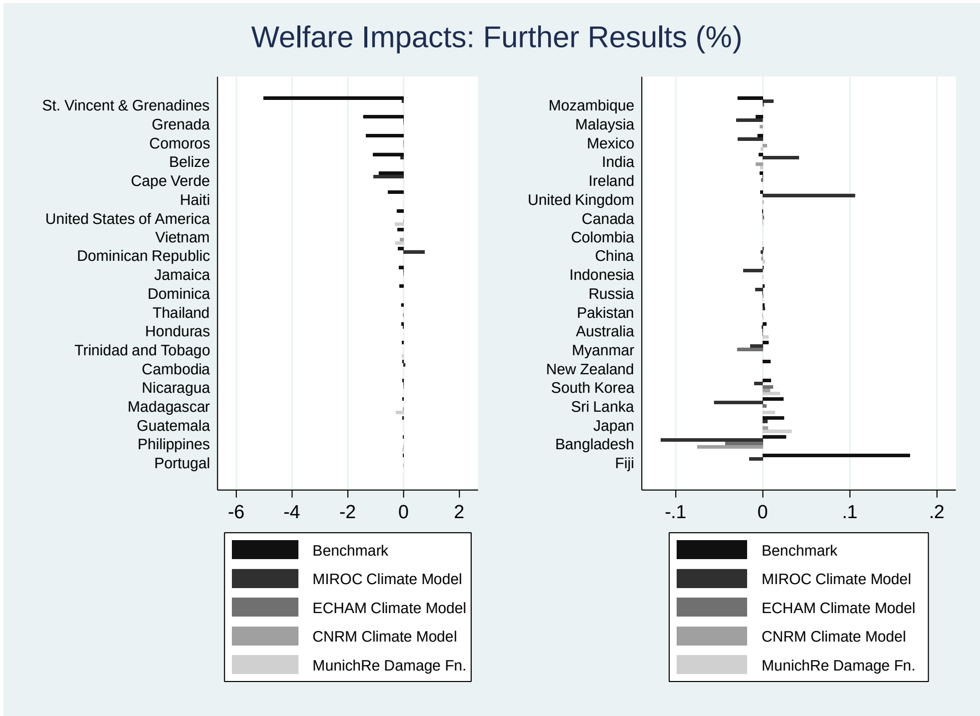

Figure A4: Welfare Impacts with Alt. Climate Models, Damage Data

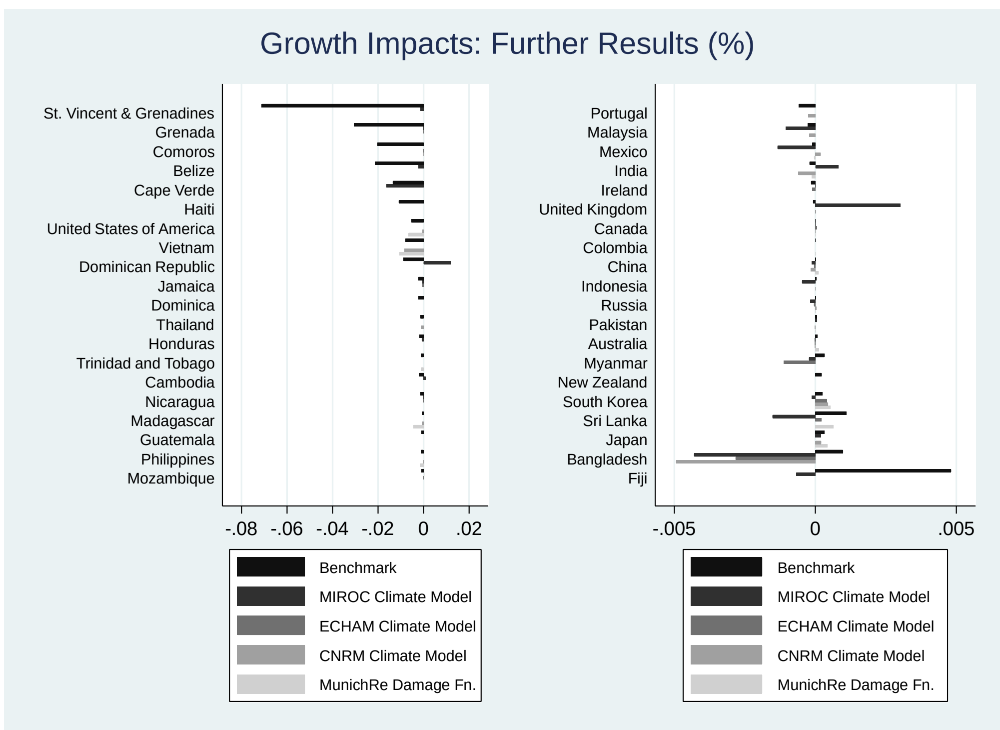

Figure A5: Growth Impacts with Alt. Climate Models, Damage Data

3 DICE Model Integration

3.1 Expected Cyclone Impacts: Alternative Climate Models

Table A7 presents results for expected global aggregate cyclone impacts across three additional climate models, above and beyond our benchmark. The results are broadly similar across models.

Table A7: Global Aggregate Annual Expected Cyclone Impacts (%/year)

	Future Climate (T_{2090})			
Climate Model:	Benchmark (GLDF)	MIROC	ECHAM	CNRM
TFP (DICE)				
Agg. Weight: GDP	.0329%	0.0354%	.0304%	0.0312%
Physical Capital				
Agg. Weight: Capital				
Damage Coefficients:				
Country-Fixed; U.S. sep.	.0110%	.00775%	.00568%	.00732%
Current GDP, Pop<5m; U.S. sep.	.0112%	.00745%	.00567%	.00695%
Future GDP, Pop<5m; U.S. sep.	.0087%	.00468%	.00321%	.00436%
Future GDP, Pop<5m	.0016%	.00172%	.00168%	.00161%
Fatalities				
Agg. Weight: Population				
Damage Coefficients:				
Country-Fixed	4.2e-05%	4.67e-05%	4.56e-05%	4.41e-05%
Current GDP, Pop<5m	3.9e-05%	4.55e-05%	4.08e-05%	4.28e-05%
Future GDP, Pop<5m	5e-06%	4.76e-06%	4.56e-06%	4.62e-06%

3.2 DICE Damage Function Coefficient Imputation

This section describes the derivation of the DICE climate change damage function coefficients based on the results of Table 8, which represent *total* expected cyclone depreciation. Holding socioeconomic factors constant, total future cyclone depreciation reflects a combination of baseline impacts and warming damages: $\delta^{Total}(T_\tau) = \underline{\delta}^{\text{Base}} + \delta^{\text{Additional}}(T_\tau)$. First, given the scientific literature's common finding of linearity in the global cyclone intensity-temperature relationship (see, e.g., Holland and Bruyere, 2014), we linearly interpolate from T_{2090} and specify $\delta^{\text{Additional}}(T_\tau) = \alpha T_\tau$. Table 8 provides pairs of 'observations' of total damages at current and future climates that we thus use to solve for slope parameters α via:

$$\alpha = \frac{\delta^{Total}(T_{2090}) - \delta^{Total}(T_{2015})}{(T_{2090} - T_{2015})} \tag{1}$$

The synthetic cyclone tracks from Emanuel et al. (2008) underlying our T_{2090} simulations reflect the IPCC's A1B emissions scenario, which different climate models estimate to result (on average) in $2.8°C$ warming over 1980-99 temperatures by 2100 (IPCC, 2007). Based on Hawkins et al.'s (2017) estimates that warming between 1986-2005 and 2015 was $0.45°$ to $0.2°C$, we thus have $T_{2090} - T_{2015} \approx 2.35°C$.

Given that global temperatures in 2015 were already around $1°C$ above pre-industrial levels, one additional question is whether to treat current cyclone patterns as already having been affected by this warming. A recent review by GFDL "conclude[s] that despite statistical correlations between SST [sea-surface temperatures] and Atlantic hurricane activity in recent decades, it is premature to conclude that human activity – and particularly greenhouse warming – has already caused a detectable change in Atlantic hurricane activity" (GFDL, 2018). In particular, they argue that, while a trend can be observed in recent years, over a longer time horizon back to the 1880s, one fails to detect a significant trend in cyclones (concurrent with the observed trend in warming) once observational biases are adjusted. In this case, the damage function would apply only to warming over the DICE model base year (2015), so that $\delta^{\text{Additional}}(T_t) = \alpha(T_t - T_{2015})$ (for $T_t > T_{2015}$). On the other hand, if anthropogenic warming has already been affecting cyclone patterns, the damage function is defined over warming since pre-industrial level as for other damages in DICE. Since both our overall global impact estimates and the difference between these scenarios are already small, we focus on the latter case where $\delta^{\text{Additional}}(T_t) = \alpha(T_t)$.

We thus back out annual impact coefficients via (1). For example, the TFP impact coefficient is calculated via:

$$\widehat{\alpha_A} = \frac{(.000329) - (.000288)}{2.35} = .0000173$$

The remaining parameters are computed analogously using the different impact pair estimates across alternative damage function coefficient scenarios in Table 8.

4 Theoretical Derivations

4.1 Stationary Equilibrium Growth

This section derives the paper's equations defining equilibrium growth (19), following the approach in Krebs (2003a,b). Country subscripts j are omitted for legibility. First, note that the household's problem can be written in recursive form as:

$$V(w, \widetilde{k}, \varepsilon) = \max u(c) + \beta E[V(w', \widetilde{k}', \varepsilon')] \tag{2}$$

subject to:

$$w' = w[1 + r(\widetilde{k}, \varepsilon)] - c \tag{3}$$

where $r(.)$ is as defined in paper equation (15). Substituting (3) into (2) and taking the first-order conditions (FOCs) for c and $\widetilde{k}'$ yields:

$$\begin{aligned} u'_c &= \beta E[V'_{w'}] \\ 0 &= \beta E[V'_{\widetilde{k}'}] \end{aligned} \tag{4}$$

Next, substituting in the decision rules $c = g(w, \widetilde{k}, \varepsilon)$ and $\widetilde{k}' = f(w, \widetilde{k}, \varepsilon)$ yields the Benveniste-Scheinkman conditions:

$$\begin{aligned} V'_w &= \beta E[V'_{w'}[(1 + r(\widetilde{k}, \varepsilon)]] \\ V'_{\widetilde{k}} &= \beta E[V'_{w'} w(1+\widetilde{k})^{-2} \left\{ [R^k(\widetilde{k}, \varepsilon) - \overline{\delta^k} - (1-\pi)\eta^k(\varepsilon)] - [R^h(\widetilde{k}, \varepsilon) - \overline{\delta^h} - (1-\pi)\eta^h(\varepsilon)] \right\}] \end{aligned}$$

Substituting based on (4) and iterating forward then yields the Euler equation and no-arbitrage condition, respectively:

$$\begin{aligned} u'_c &= \beta E[u'_{c'}[(1+r(\widetilde{k}',\varepsilon'))]] && (5)\\ 0 &= \beta E[u'_{c'}\frac{w'}{(1+\widetilde{k}')}\Big\{[R^k(\widetilde{k}',\varepsilon')-\overline{\delta^k}-(1-\pi)\eta^k(\varepsilon')]-[R^h(\widetilde{k}',\varepsilon')-\overline{\delta^h}-(1-\pi)\eta^h(\varepsilon')]\Big\}] && (6)\end{aligned}$$

Next, invoking the assumed utility function $u(c)=\frac{c^{1-\gamma}}{1-\gamma}$, the budget constraint (3), and the fact that $c'=\widetilde{c}[1+r(\widetilde{k}',\varepsilon')]w'$ (where $\widetilde{c}\equiv 1-\widetilde{s}$ denotes the consumption-out-of-wealth ratio), substitution and rearranging in (5) yields the desired result that:

$$\widetilde{s}=1-\widetilde{c}=\Big(\beta E[(1+r(\widetilde{k}',\varepsilon'))^{1-\gamma}]\Big)^{\frac{1}{\gamma}} \tag{7}$$

The same substitutions allow us to factor out as pre-determined terms $\widetilde{c}$ and $w'=(1+r)w-c$ in (6). Further noting that, in stationary equilibrium, $\widetilde{k}'=\widetilde{k}$, we obtain the desired condition:

$$0=\beta E[\frac{\Big\{[R^k(\widetilde{k}',\varepsilon')-\overline{\delta^k}-(1-\pi)\eta^k(\varepsilon')]-[R^h(\widetilde{k}',\varepsilon')-\overline{\delta^h}-(1-\pi)\eta^h(\varepsilon')]\Big\}}{(1+r(\widetilde{k}',\varepsilon'))^{\gamma}}] \tag{8}$$

Finally, the expression for average growth can be derived by again invoking $w'=[1+r(\widetilde{k},\varepsilon)]w-c$ and $c'=\widetilde{c}[1+r(\widetilde{k}',\varepsilon')]w'$. First, note that the definition of $\widetilde{c}$ implies that:

$$\begin{aligned} \widetilde{c} &= \frac{c}{[1+r(\widetilde{k},\varepsilon)]w} && (9)\\ &\rightarrow\ 1-\widetilde{c}=\frac{[1+r(\widetilde{k},\varepsilon)]w-c}{[1+r(\widetilde{k},\varepsilon)]w} \end{aligned}$$

Consequently, expected growth can readily be shown to equal paper equation (19), as desired:

$$\begin{aligned} E\left[\frac{c'}{c}\right] &= E\left[\frac{\widetilde{c}[1+r(\widetilde{k}',\varepsilon')]w'}{c}\right]=E\left[\frac{\widetilde{c}[1+r(\widetilde{k}',\varepsilon')]\{[1+r(\widetilde{k},\varepsilon)]w-c\}}{c}\right]\\ &= (1-\widetilde{c})(1+E[r(\widetilde{k}',\varepsilon')])=(\widetilde{s})(1+E[r(\widetilde{k}',\varepsilon')]) && (10)\end{aligned}$$

4.2 Storm Risk Impacts

We first substantiate the following claim about our benchmark model:

- #1: *Cyclone realizations have a negative effect on contemporaneous growth ($\frac{dg_t}{d\varepsilon_t}<0$).*

This claim follow from the equation for realized growth in stationary equilibrium (19) with the definition of portfolio returns (15) substituted in:

$$g_t = \frac{c_t}{c_{t-1}} = (\widetilde{s})[1+\omega_k(\widetilde{k})\{R^k(\widetilde{k},\varepsilon_t) - \overline{\delta^k} - (1-\pi)\eta^k(\varepsilon_t)\} \\ +(1-\omega_k(\widetilde{k}))\{R^h(\widetilde{k}) - \overline{\delta^h} - (1-\pi)\eta^h(\varepsilon_t)\}] \tag{11}$$

Differentiating (11) with respect to cyclone realizations yields:

$$\frac{dg_t}{d\varepsilon_t} \\ = (\widetilde{s})(1-\pi)\left[\omega_k(\widetilde{k})\{\frac{\partial R^k(.)}{\partial \varepsilon_t} - \frac{\partial \eta^k(.)}{\partial \varepsilon_t}\} + (1-\omega_k(\widetilde{k}))\{\frac{\partial R^h(.)}{\partial \varepsilon_t} - \frac{\partial \eta^h(.)}{\partial \varepsilon_t}\}\right] < 0 \tag{12}$$

where the inequality follows from the definition of factor returns (14) and our assumptions about the damage functions as increasing in cyclone intensity.

We next illustrate the following claims:

- #2: *An increase in cyclone risk has a theoretically ambiguous effect on average growth:* $\frac{d\overline{g}}{d\mu_\varepsilon} \lesseqqgtr 0$. *This effect may moreover be non-monotonic within a given country (i.e,. calibration).*
- #3: *An increase in cyclone risk may increase the savings rate (precautionary savings).*

We demonstrate these claims by construction, specifically by showcasing the possibility of both positive and negative growth impacts, and positive precautionary savings effects. In order to maintain analytic transparency, we now work with a simpler parameterization where, each period, there is just a binary probability ϕ that a cyclone occurs with intensity $\varepsilon_t = \overline{\varepsilon}$, whereas, with probability $1-\phi$, no cyclone occurs ($\varepsilon_t = 0$). We assume that there are no damages if no storm hits, that is, $\eta^k(0) = \eta^h(0) = \eta^A(0)$. The mean disaster realization is thus $\mu_\varepsilon = \phi\overline{\varepsilon}$. For clarity, we also separate the average depreciation term $\overline{\delta_k}$ back into its underlying components: $\overline{\delta_k} = \underline{\delta}_k + \pi\mu^k = \underline{\delta}_k + \pi\phi\eta^k(\overline{\varepsilon})$, and analogously for human capital. In this setting, expressions (7) and (8) become:

$$\widetilde{s} = \beta^{\frac{1}{\gamma}}\left[\phi\left\{(1+\left[\begin{array}{c}\omega_k(\widetilde{k})[R_k(\widetilde{k},\overline{\varepsilon}) - \underline{\delta}_k - \pi\phi\eta^k(\overline{\varepsilon}) - (1-\pi)\eta^k(\overline{\varepsilon})] \\ +(1-\omega_k(\widetilde{k}))[R_h(\widetilde{k},\overline{\varepsilon}) - \underline{\delta}_h - \pi\phi\eta^h(\overline{\varepsilon}) - (1-\pi)\eta^h(\overline{\varepsilon})]\end{array}\right])^{1-\gamma}\right\} \right. \\ \left. +(1-\phi)\left\{(1+\left[\omega_k(\widetilde{k})[R_k(\widetilde{k},0) - \underline{\delta}_k - \pi\phi\eta^k(\overline{\varepsilon})] + (1-\omega_k(\widetilde{k}))[R_h(\widetilde{k},0) - \underline{\delta}_h - \pi\phi\eta^h(\overline{\varepsilon})]\right])^{1-\gamma}\right\}\right]^{\frac{1}{\gamma}} \tag{13}$$

$$\phi\left[\frac{\left[R_k(\widetilde{k},\overline{\varepsilon}) - \underline{\delta}_k - \pi\phi\eta^k(\overline{\varepsilon}) - (1-\pi)\eta^k(\overline{\varepsilon})\right] - \left[R_h(\widetilde{k},\overline{\varepsilon}) - \underline{\delta}_h - \pi\phi\eta^h(\overline{\varepsilon}) - (1-\pi)\eta^h(\overline{\varepsilon})\right])}{(1+\left[\omega_k(\widetilde{k})[R_k(\widetilde{k},\overline{\varepsilon}) - \underline{\delta}_k - \eta^k(\overline{\varepsilon})(\pi\phi+1-\pi)] + (1-\omega_k(\widetilde{k}))[R_h(\widetilde{k},\overline{\varepsilon}) - \underline{\delta}_h - \eta^h(\overline{\varepsilon})(\pi\phi+1-\pi)]\right])^{\gamma}}\right] \\ +(1-\phi)\left[\frac{\left[R_k(\widetilde{k},0) - \underline{\delta}_k - \pi\phi\eta^k(\overline{\varepsilon})\right] - \left[R_h(\widetilde{k},0) - \underline{\delta}_h - \pi\phi\eta^h(\overline{\varepsilon})\right]}{(1+\left[\omega_k(\widetilde{k})[R_k(\widetilde{k},0) - \underline{\delta}_k - \pi\phi\eta^k(\overline{\varepsilon})] + (1-\omega_k(\widetilde{k}))[R_h(\widetilde{k},0) - \underline{\delta}_h - \pi\phi\eta^h(\overline{\varepsilon})]\right])^{\gamma}}\right] = 0$$

While it is possible to apply the implicit function theorem to these two equations to derive analytic expressions for $\frac{d\widetilde{k}}{d\overline{\varepsilon}}$, $\frac{d\widetilde{s}}{d\overline{\varepsilon}}$, and thus ultimately $\frac{d\overline{g}}{d\overline{\varepsilon}}$, we have not found these expressions to be instructive. We therefore analytically illustrate the possibility of higher average growth and savings due to higher storm risk in the simplest possible case where human and physical capital are perfectly symmetric. That is, assume that both types of capital are equally vulnerable to cyclone damages $\eta^k(\varepsilon_t) = \eta^h(\varepsilon_t) \equiv \eta(\varepsilon_t)$, enter production symmetrically (with Cobb-Douglas exponents $\alpha = 1 - \alpha = 0.5$), and have equal baseline depreciation rates $\underline{\delta}_k = \underline{\delta}_h \equiv \delta$. In this case, it is straightforward to show that the optimal capital share equation is solved by $\widetilde{k}^* = 1$, implying equal optimal investment in both types of capital in stationary equilibrium. The optimal savings rate (13) in the symmetric setting then reduces to:

$$\begin{aligned}\widetilde{s} &= \left(\beta E[(1 + r(\widetilde{k}', \varepsilon'))^{1-\gamma}]\right)^{\frac{1}{\gamma}} \qquad (14)\\ &= \beta^{\frac{1}{\gamma}}\left[\phi(1 + \frac{A(1-\eta^A(\overline{\varepsilon}))}{2} - \delta - \eta(\overline{\varepsilon})(\pi\phi + 1 - \pi))^{1-\gamma} + (1-\phi)(1 + \frac{A}{2} - \delta - \pi\phi\eta(\overline{\varepsilon}))^{1-\gamma}\right]^{\frac{1}{\gamma}}\end{aligned}$$

where A denotes total factor productivity with cyclone impact function $(1 - \eta^A(\varepsilon))$, where, for simplicity, we also assume that $\eta^A(\varepsilon) = \eta(\varepsilon)$. Here, the impact of a change in storm risk on optimal savings depends only on its direct effect in (14), and is given by:[2]

$$\frac{d\widetilde{s}}{d\overline{\varepsilon}} = \beta[\widetilde{s}]^{1-\gamma} \cdot \frac{(1-\gamma)}{\gamma} \cdot \left[\phi(1 + r(\overline{\varepsilon}))^{-\gamma}\{\frac{A}{2} + \phi\pi + 1 - \pi\} + (1-\phi)(1 + r(0))^{-\gamma}\{\phi\pi\}\right] \cdot (-1)\frac{\partial\eta}{\partial\overline{\varepsilon}} \qquad (15)$$

where the portfolio returns in case of a storm $r(\overline{\varepsilon}) = \frac{A(1-\eta^A(\overline{\varepsilon}))}{2} - \delta - \pi\phi\eta(\overline{\varepsilon}) - (1-\pi)\eta(\overline{\varepsilon})$ or no storm $r(0) = \frac{A}{2} - \delta - \pi\phi\eta(\overline{\varepsilon})$ and $\widetilde{s}$ are all as in (14).

Since depreciation damages are assumed to be increasing in storm intensity ($\frac{\partial\eta}{\partial\overline{\varepsilon}} > 0$), expression (15) immediately shows that *the equilibrium savings rate is increasing in average storm intensity if* $\gamma > 1$, unaffected by storm risk if $\gamma = 1$ (logarithmic preferences), and decreasing in storm risk if $\gamma < 1$:[3]

$$\frac{d\widetilde{s}}{d\overline{\varepsilon}} = \begin{cases} > 0 & \text{if } \gamma > 1 \\ = 0 & \text{if } \gamma = 1 \\ < 0 & \text{if } \gamma < 1 \end{cases} \qquad (16)$$

Given (10), the corresponding change in average growth due to storm risk is then given by:

$$\frac{d\overline{g}}{d\overline{\varepsilon}} = \frac{d\widetilde{s}}{d\overline{\varepsilon}}(1 + E[r(\varepsilon')]) + (\widetilde{s})\frac{d(1 + E[r(\varepsilon')])}{d\overline{\varepsilon}} \qquad (17)$$

[2] That is, there is no additional indirect effect via a change in $\widetilde{k}$.

[3] This conclusion follows from the fact that, over the permissible range of parameter values (where $1 + r(\overline{\varepsilon}) > 0$), all terms in (15) are positive except for $\left[\frac{-\partial\eta(.)}{\partial\overline{\varepsilon}}\right]$, which is negative, and $(1-\gamma)$, whose sign consequently determines the overall sign of (15).

where $\frac{d\widetilde{s}}{d\bar{\varepsilon}}$ is given by (15), $\widetilde{s}$ remains defined by (14), and:

$$E[r(\varepsilon')] = \frac{A}{2}[\phi(1-\eta(\bar{\varepsilon}))+1-\phi]-\delta-\pi\phi\eta(\bar{\varepsilon})-\phi(1-\pi)\eta(\bar{\varepsilon}) \tag{18}$$
$$\frac{d(1+E[r(\varepsilon')])}{d\bar{\varepsilon}} = \phi(-\frac{\partial\eta}{\partial\bar{\varepsilon}})(\frac{A}{2}+1)<0$$

In the relevant range of the parameter values (for which well-defined interior solutions exist), we therefore see that:

$$\frac{d\bar{g}}{d\bar{\varepsilon}} = \underbrace{\frac{d\widetilde{s}}{d\bar{\varepsilon}}}_{\lesseqqgtr 0}\underbrace{(1+E[r(\varepsilon')])}_{>0}+\underbrace{\widetilde{s}}_{>0}\underbrace{[\phi(-\frac{\partial\eta}{\partial\bar{\varepsilon}})(\frac{A}{2}+1)]}_{<0} \tag{19}$$

It immediately follows from (19) that average growth is unambiguously *decreasing* in storm risk whenever $\gamma \leq 1$, as this condition implies a negative effect of storm risk on savings as per (16). In contrast, if agents are sufficiently risk averse with $\gamma > 1$, average growth may be increasing in storm risk.
To complete the characterization of $\frac{d\bar{g}}{d\bar{\varepsilon}}$, we follow as in the empirical part of the paper:

$$\eta(\bar{\varepsilon}) = \xi_1(\bar{\varepsilon})^{\xi_2} \tag{20}$$

Figure A5 showcases this possibility by displaying average growth as a function of average storm risk $\mu_\varepsilon = \phi\bar{\varepsilon}$ (while varying $\bar{\varepsilon}$) for different values of γ in a calibration that assume the same functional form for $\eta(\bar{\varepsilon}) = \xi_1(\bar{\varepsilon})^{\xi_2}$ as in the benchmark, and sets the parameters to $\beta = 0.985$, $A = 1$, $\phi = 0.1$, $\delta = .1$, $\xi_1 = 0.5$, and $\xi_2 = 2$ as an example:

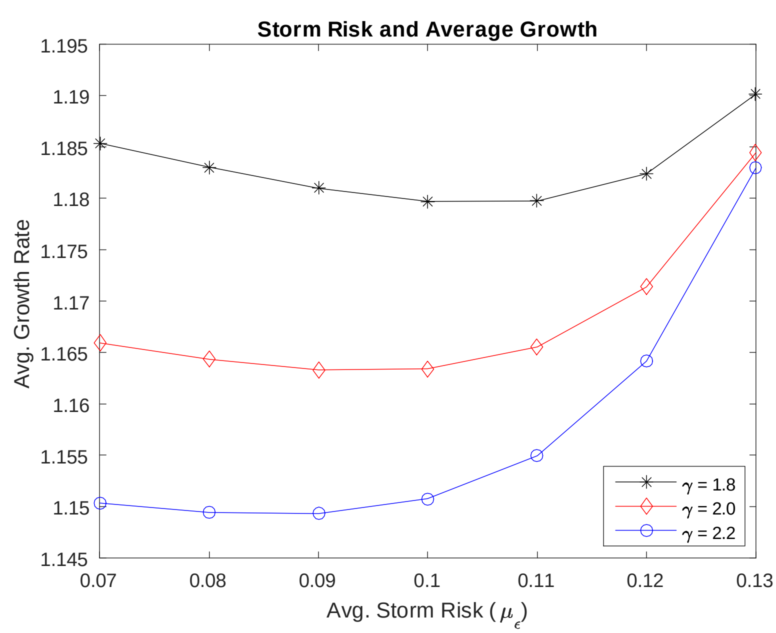

Figure A6

Figure A6 demonstrates that the effect of storm risk on growth $\frac{d\bar{g}}{d\bar{\varepsilon}}$ may be ambiguous in sign not only across but even *within* calibrations, concluding our illustration of Claim #2. We lastly illustrate the following claim:

- Claim #4: *Cyclone risk can affect growth and welfare in opposite ways.*

Given that we have already demonstrated that cyclone risk can decrease average growth (including in cases where $\gamma > 1$), we substantiate this case by showing that this same increase in cyclone risk results in a decline in welfare. Following the same approach as Krebs (2003b), we re-write household lifetime utility (focusing on the relevant case with $\gamma > 1$) as:

$$U_0 \equiv E_0 \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\gamma}}{1-\gamma} = \frac{c_0^{1-\gamma}}{1-\gamma} + \beta \frac{E_0[\{c_0 g(\widetilde{k}, \varepsilon)\}^{1-\gamma}]}{1-\gamma} + \beta^2 \frac{E_0[\{c_0 g(\widetilde{k}, \varepsilon) g(\widetilde{k}, \varepsilon)\}^{1-\gamma}]}{1-\gamma} \ldots \tag{21}$$

where initial consumption $c_0 = (1-\widetilde{s})(1 + r(\widetilde{k}_0, \varepsilon_0))w_0$ is pre-determined (since h_0, k_0, and ε_0 are given) except for the equilibrium savings rate $\widetilde{s}$, and $g(.)$ is the consumption growth factor $g_t \equiv \frac{c_t}{c_{t-1}} = (\widetilde{s})[1 + r(\widetilde{k}, \varepsilon_t)]$. Given the assumption of independently distributed shocks and following Krebs (2003b) one can write (21) as:

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\gamma}}{1-\gamma} = \frac{c_0^{1-\gamma}}{(1-\gamma)(1-\beta E_0[g(\widetilde{k}, \varepsilon)^{1-\gamma}])} \tag{22}$$

Intuitively, cyclone risk increases should always be welfare-decreasing in our setting as households could have chosen to save more and throw away more of their income even in the absence of such risk increases. In order to formally demonstrate welfare in the same setting giving rise to positive growth effects, we numerically evaluate (22) at the same parameters as in Figure A6 (evaluated variably for initial conditions $\varepsilon_0 = 0$ or $\varepsilon_0 = \bar{\varepsilon}$). Figure A7 confirms that welfare declines with cyclone risk.

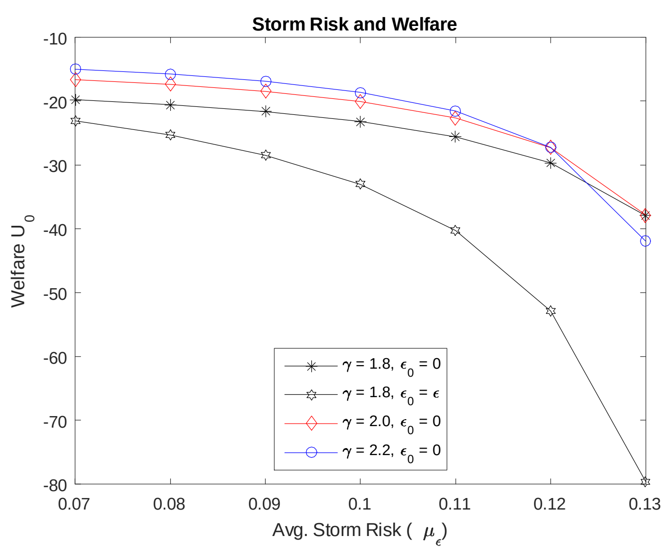

Figure A7

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