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THE RETURN OF ADAPTATION TO EXTREME WEATHER

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ABSTRACT

We estimate the return of climate adaptation by modeling the uncertain impact of global warming for extreme weather. Unexpected arrivals elevate extreme-weather risk, which leads households and firms to adapt and thereby lowering the damage of each subsequent arrival. Our approach provides country-specific estimates of disaster risk as extreme-weather events unfold, and state-dependent marginal effects of extreme-weather damage on economic growth. Applying our approach to cyclones and heatwaves from 1980-2019, average country income in 2019 is several percent lower absent state-dependent adaptation. Adaptation becomes significantly more valuable in the long run as the uncertainty regarding extreme weather is resolved.

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1 Introduction

Economic damages from extreme weather have increased sharply in recent decades.[1] Climate scientists link the increased frequency of extreme weather to global warming (National Academies of Sciences, Engineering, and Medicine (2016)). After the unprecedented floods in Brazil's Rio Grande Sul, which displaced 600,000 people and destroyed 200,000 homes, the magazine *The Economist* naturally wondered whether this is a harbinger of disasters to come, and whether and how society can adapt to extreme weather in the age of climate change? Such questions are also becoming commonplace with more frequent heatwaves during summer months (Perkins-Kirkpatrick and Lewis (2020)). Relative to carbon emissions abatement, climate adaptation has thus far been under-emphasized both in climate change research and policy discussion (Bouwer, Crompton, Faust, Höppe, and Pielke Jr (2007)).

We propose an empirical framework for estimating the economic effects of extreme-weather events in the presence of adaptation. Our approach takes into consideration three key features. First, there is considerable uncertainty regarding the consequence of global warming for extreme weather. For instance, according to a survey of tropical-cyclone models (Knutson, Camargo, Chan, Emanuel, Ho, Kossin, Mohapatra, Satoh, Sugi, Walsh, et al. (2020)), the median model projects a modest 13% increase in the frequency of major tropical cyclones in a 2^oc world relative to pre-industrial era. The most pessimistic climate model projects a two-fold increase, while the most optimistic model projects a slight decrease.

Second, society does not just observe, but learns from unfolding extreme events, attributing global warming to certain types of extreme weather events such as flooding and heatwaves (Sisco, Bosetti, and Weber (2017)). Third, learning induces a possibly non-linear relation between economic damages and disaster risks due to state-dependent adaptation. We use an economic specification of damage to economic growth that is guided by Hong, Wang, and Yang (2023),

[1] According to the National Oceanic and Atmospheric Administration (NOAA), the US since 1980 has experienced 391 events with CPI-adjusted losses reaching or exceeding a billion dollars and totalling 2.75 trillion dollars.

who recently generalized the neoclassical growth model with disasters (Rietz (1988), Barro (2006), Pindyck and Wang (2013)) to allow optimizing consumers and firms to learn and adapt.

Our approach involves a two-step estimation procedure to provide country-specific estimates of disaster risk as extreme-weather events unfold, and state-dependent marginal effects of extreme-weather damages on economic growth. We apply our approach to two panels of extreme-weather data: one on tropical cyclones making landfall, and one on extremely high annual temperatures that correspond to heatwaves during summer months. (See Dell, Jones, and Olken (2012) and Hsiang and Jina (2014)), among others, for analysis using data from the same sources.) Our paper estimates the economic effects of these extreme-weather events and quantifies the return to adaptation.

In the first step, we fit a model with a time-varying arrival rate for extreme-weather events in a given country. The model is characterized by three key parameters: the arrival rate in a bad climate state, the arrival rate in a good climate state, and the prior belief on the arrival rate of the bad state.[2] Unexpected arrivals increase the posterior probability that our model attaches to the bad climate state, and this probability can be thought of as a measure of the risk of future strikes. Over time, there is resolution of uncertainty on whether a country faces a good or bad climate state, i.e., mild or adverse consequences from climate change.

We set the prior belief to the historical arrival rate for a country between 1960 and 1980. Then using the history of extreme-weather arrivals in the country from 1980 to 2019, we use the simulated method of moments (Duffie and Singleton (1993)) to estimate the two remaining parameters using five moments from extreme-weather arrivals: the mean, variance, third moment, fourth moment and first-order autocorrelation coefficient. Our model generates highly non-linear updates of posteriors when a disaster strikes, depending on the risk a country faces. These revisions serve as the exogenous time-series variation for us to identify the return to

[2]Earlier work in asset pricing (Collin-Dufresne, Johannes, and Lochstoer (2016) and Wachter (2013)) uses learning to generate time-varying disaster risk (Gabaix (2012)) so as to explain asset-price behavior like the equity risk premium.

adaptation.

In the second step, we allow for economic damages arising from extreme-weather events to vary non-linearly with arrival risk as predicted by the model. Bad news elevates extreme-weather risk, which leads households and firms to learn and adapt, thereby lowering damages for each subsequent disaster arrival. For each country, we estimate a tractable regression that is motivated by a Taylor approximation of the nonlinear damage function in the Hong, Wang, and Yang (2023) model around the prior on disaster risk.

Absent learning or revision of priors, this second-step regression collapses to the linear specification often used to estimate the economic damage from extreme weather, but in a pooled panel setting. Though introducing an interaction term in the panel setting to allow economic damage to vary with a country's historical exposure to disasters can accommodate adaptation (see discussion of related literature below), it would not capture the state dependence suggested by learning. In particular, as disasters destroy capital, theory suggests that recovery and rebuilding of the capital stock should depend on the time-varying beliefs of households and firms regarding future strikes.

Our approach provides estimates of several objects of interest. First, the posterior estimates are instructive about how agents' beliefs about disaster risk change with climate conditions. Second, the country-level estimates shed light on the extent to which adaptation differs across countries, while still allowing an average effect to be estimated as a (cross-section) weighted average of country-level estimates using any weights of choice. In contrast, pooled regressions only give an estimate of the average effect. Third, the specification allows for a decomposition of the coefficient measuring marginal damage into two terms: (1) the impact of an extreme-weather arrival holding fixed beliefs and adaptation at the initial prior; and (2) the reduction in damage due to the change in adaptation that comes with a revision of beliefs from the prior.

Our empirical findings are as follows. First, we reject a time-invariant arrival-rate model of extreme weather in favor of a time-varying arrival-rate model. Unexpected arrivals of extreme-weather events are associated with more future arrivals. Hence, the arrival of an extreme weather event not only potentially damages economic activity but also serves as a signal that future such events are more likely, consistent with time-varying extreme-weather risk.

Second, we reject the time-invariant regression specification for damages in favor of state dependence due to learning and adaptation. The state-dependence implies that a country with low prior experience in extreme weather is less adapted or prepared and suffer more damages. But this country will make larger revision in its beliefs upon arrival of extreme weather and hence benefit more from adaptation (net of the costs), compared to a country at high risk and that has already converged in its belief.

Third, we conduct a number of additional analyses, including model diagnostics to verify that a linear model is misspecified and robustness checks to address common time trends. Evaluating a typical country in our cyclone sample at its prior risk equal to 0.3, a cyclone reduces GDP growth by 90 basis points. As this country's risk increases to 0.8, the damage to GDP growth per cyclone falls to 83 basis points. Evaluating a typical country in our extreme-temperatures sample at its prior risk of 0.1, an extreme-temperature event reduces GDP growth by 69 basis points. As this country's risk increases to 0.6, the damage per event falls to 63 basis points.

Finally, to gauge the aggregate returns to adaptation, we calculate a counterfactual of what income in 2019 would have been absent learning and state-dependent adaptation as captured by estimates of our time-varying nonlinear model. Country income in 2019 would on average be 7.5% lower for cyclones and four percent lower for heatwaves if damage and adaptation were fixed at prior risk levels.

We then use simulations to consider how income might evolve over the next century in the face of increasing extreme weather, and how that depends on learning and adaptation. We expand on the exercise of Burke, Hsiang, and Miguel (2015). We use SSP5 growth-rate projections (Kriegler, Bauer, Popp, Humpenöder, Leimbach, Strefler, Baumstark, Bodirsky, Hilaire, Klein, et al. (2017)) and then account for extreme weather using our model of time-varying risk and economic damage estimated from 1980-2019. For the cyclone (heatwave) sample, mean income in 2100 would be 33.3% (36%) lower under the scenario where damage and adaptation were fixed are prior risk levels than under the learning scenario with state-dependent adaptation to extreme weather. The difference in the return of adaptation out of sample compared to in sample— around 5 times larger—has to do with the importance of uncertainty resolution and learning over the long run regarding global warming for extreme weather in a given country.

Related literature. A widely-used approach to estimating the value of adaptation to disasters such as tropical cyclones (Bakkensen and Mendelsohn (2016), Hsiang and Narita (2012), Hsiang and Jina (2014)) is to measure how economic damage conditional on a disaster arrival significantly declines cross-sectionally with the historical experience of a locale with disasters (see, e.g., Dell, Jones, and Olken (2014) for a review).[3] Locales or countries with more prior experience are found to have less damage per disaster, consistent with adaptation. Studies examining the value of adaptation for temperature also utilize aspects of this approach (Auffhammer (2022), Gourio and Fries (2020), Carleton, Jina, Delgado, Greenstone, Houser, Hsiang, Hultgren, Kopp, McCusker, Nath, Rising, Rode, Seo, Viaene, Yuan, and Zhang (2022)).

This time-invariant approach is a special case of our setting when we assume that there is no learning, i.e. the level of adaptation is fixed at prior risk levels. However, the assumption of no learning is unlikely to hold[4], and hence leads to regression misspecification. Even in our short sample period, countries have seen significant time-series fluctuations in their disaster risk. Importantly, we solely utilize the time series of a country to identify the return to state-dependent adaptation, whereas the literature uses cross-locale variation in prior risks or disaster experiences to value adaptation.

A fundamental challenge in the literature is to consider how adaptation will affect outcomes

[3]This time-invariant approach, which goes back to earlier work on identifying the impact of temperature on agricultural yields (Deschênes and Greenstone (2007) and Schlenker and Roberts (2009)), relies on location and time fixed effects to address unobserved heterogeneities in the panel data.

[4]For instance, Barreca, Clay, Deschenes, Greenstone, and Shapiro (2016) document a declining relationship over time in temperature-mortality relationship due to increasing adaptation in the form of air conditioning.

in the long run, i.e., standing today, how would income in 2100 differ with adaptation? Taking into account learning and state-dependent adaptation is particularly crucial for this exercise. A country at low prior risk standing in 2019 but which then receives bad realizations and moves to high risk over time has scope to adapt. Hence, ignoring this learning dimension will overstate damages for these countries going forward.

By explicitly modeling the learning or belief process in the first-stage, we are able to not only estimate the returns to adaptation in sample, but to also assess the value of adaptation in the long-run by simulating the evolution of beliefs based on the parameters of the disaster process that we have estimated for each country.

Such projections are valuable inputs for calibrating integrated assessment models (Nordhaus (2017), Golosov, Hassler, Krusell, and Tsyvinski (2014)), as is emphasized by Barnett, Brock, and Hansen (2020). At the same time, we do not model the potential spillovers of learning and adaptation across countries. Such a spatial dimension and the role of government policies or heterogeneity are addressed typically in a within-country setting (Bilal and Rossi-Hansberg (2023), Hsiao (2023), Fried (2022)), though without learning and state-dependent adaptation. It would be fruitful to combine both the learning and the spatial dimensions in future research.

2 Data

We consider two widely-studied extreme-weather events in the literature: tropical cyclones and abnormal temperatures. We first describe the data in Section 2 and then present some key stylized facts in Section 3 to motivate the importance of integrating time-varying extreme-weather risk as a state variable into estimation of economic damages.

Tropical cyclones. Our data comes from the International Best Track Archive for Climate Stewardship (IBTrACS) database. It is the most complete global database for tropical cyclone observations. Our largest sample contains annual observations for the real GDP per capita growth rate and cyclone landfalls across 109 countries from 1980 to 2019 with 4,264 county-year observations in total.[5] These are the same set of countries and places as in Hsiang and Jina (2014), but excludes Taiwan for which there is no GDP data from the World Bank Development Indicator. For countries covering large areas — such as the U.S., China, and Canada, we consider data only from the eastern regions that are the most prone to cyclone landfall to avoid any potential bias that might arise if we include large areas mostly unaffected by cyclones. Let $\text{Landfall}_{i,t}$ be an indicator variable that equals one if and only if country i experienced at least one cyclone landfall that is "tropical storm" or higher in year t.

To concisely summarize the data, we assign the 109 countries into four regions: North Atlantic (including North America, the Caribbean, and West Europe), West Pacific (including Oceania), North India (including North India, Middle East, North Africa, and Central Europe), and South Atlantic (including Latin America and Sub-Saharan Africa). Globally, a country experiences a tropical cyclone landfall once every 7.4 years on average, as the disaster arrival rate is 0.135 per annum. There is variation across regions, with West Pacific countries getting hit more frequently (at a rate of 0.515 per annum).

Temperature. Our temperature panel contains annual observations of temperature across 139 countries from the year 1980 to 2019, similar to the one used in Dell, Jones, and Olken (2014) and Burke, Hsiang, and Miguel (2015)).[6] The data, which come from Willmott and Matsuura (2018), contain 0.5 degree gridded monthly average temperature for all land areas over the period 1900-2017. Data for 2018 and 2019 are taken from Berkeley Earth.[7] As in Burke, Hsiang, and Miguel (2015), we first aggregate the 0.5 degree grid cell temperature values to the country-month level, weighting by population density in the year 2000 using data from

[5]We use pre-1980 data, from 1960-1979, to inform the prior beliefs.

[6]Our temperature sample starts in 1980 so as to overlap with our cyclones sample and with economic data. Another reason is that data from recent decades are more likely to be informative about the consequences of climate change than data from earlier decades (see Section 5.1). We use pre-1980 data, from 1960-1979, to set the prior beliefs.

[7]Data source: `http://berkeleyearth.org/`.

Table 1: Summary statistics of extreme weather data, 1980:2019

This table shows the summary statistics of cyclone (Panel A) and extreme temperature arrivals (Panel B) for our sample of global country. The regions for cyclone in Panel A are: North Atlantic (including North America, the Caribbean, and West Europe), West Pacific (including Oceania), North India (including North India, Middle East, North Africa, and Central Europe), and South Atlantic (including Latin America and Sub-Saharan Africa). The regions for heatwaves in panel B are: (1) EUNA: Europe and North America, (2) ASME: Asia, Middle East and North Africa, (3) CLAC: Caribbean and Latin America, and (4) SSAF: Sub-Saharan Africa.

Panel A: Cyclone arrival frequency			
Region	(1) Total # of country-year obs.	(2) Total # of cyclone landfall obs.	(3) Freq. of landfall = (2)/(1): Disaster arrival intensity λ
North Atlantic	1249	181	0.145
West Pacific	501	258	0.515
North India	561	52	0.093
South Atlantic	1953	82	0.042
Global	4264	573	0.134

Panel B: Heatwave arrival frequency			
Region	(1) Total # of country-year obs.	(2) Total # of heatwave disaster obs.	(3) Freq. of heatwave = (2)/(1): Disaster arrival intensity λ
EUNA	1319	298	0.226
ASME	1431	284	0.198
CLAC	1031	249	0.242
SSAF	1742	382	0.219
Global	5523	1213	0.220

the Gridded Population of the World hosted by CIESIN at Columbia University.[8] Then we aggregate to the country-year level by averaging monthly values across all months in a year for each country. We define a country as being hit by heatwaves if the mean summer temperature is, relative to historical summer norms, above 1^{o}C.[9]

For this data, we classify countries into the following regions: (1) EUNA (Europe and North America), (2) ASME (Asia, Middle East and North Africa), (3) CLAC (Caribbean and Latin America), and (4) SSAF (Sub-Saharan Africa).[10] Panel B of Table 1 shows the summary statistics of summer extreme temperature of 1.0°C+ in each global region in our sample. The typical country faces an arrival rate of 0.22 or is hit by a summer extreme temperature once every 5 years or so.

Economic Data The key economic indicators of interest — the growth rate of real GDP per capita (g), investment ratio (i) (to lagged output), depreciation rate (δ), and Tobin's q. Tobin's (average) q is calculated using the market value of the stock market of that country divided by the book value of capital stock of that country. In addition, we calculate the GDP growth rate net of the difference between the investment and depreciation rates ($g - (i - \delta)$), as it will be the a natural variable of interest according to our model of the impact of extreme weather on the macroeconomy.

These economic variables are constructed using COMPUSTAT and World Bank data sources. Panel A of Table 2 reports the mean of the economic data for the cyclone sample. The mean GDP growth rate is 1.75% (st.dev. of 4.8%). The mean investment ratio is 0.21 (st.dev. of 0.08).

[8]See Gridded Population of the World (GPW), v3, `https://sedac.ciesin.columbia.edu/data/collection/gpw-v3`.

[9]Heatwaves occur in the summer and can last anywhere from days to weeks. We will refer to heatwaves and an extremely hot summer interchangeably.

[10]In Dell, Jones and Olken (2012), there are 6 regions in total, with a separate Middle East & North Africa and an Eastern Europe & Central Asia region. Since the number of observations in the separate Middle East & North Africa and Eastern Europe & Central Asia regions are small, we merge these two regions with other bigger regions to have a more balanced number of observations in each region. We merge the Middle East & North Africa region with the Asia region to form our region (2), and assign the countries in the Eastern Europe & Central Asia region to our region (1) and (2) accordingly, so we have 4 regions in total.

The mean Tobin's q is 2.45 (st.dev. 4.70). The net GDP growth rate has a mean of -0.17 with a standard deviation of 0.26, suggesting that investment net of depreciation is an important driver of GDP growth. As seen in Panel B of Table 2, the mean of the economic indicators for the extreme temperature sample are comparable to cyclone sample.

Table 2: Summary statistics of economic variables

This table shows the summary statistics of the economic variables for our sample of global countries. Panel A and B show the summary statistics for the cyclone and heatwave samples respectively. GDP denotes growth rate of real GDP per capita (in percentages). Investment ratio denotes investment scaled by lagged output. GDPnet denotes GDP growth net of $(i_{t-1} - \delta)$ (lagged investment rate minus depreciation). Tobin's q denotes market value of equity market divided by book value of capital. The sample is from 1980 to 2019.

Panel A: Cyclone					
	Mean	S.D.	Median	P10	P90
GDP (%)	1.75	4.80	2.11	-3.56	6.53
Investment ratio	0.21	0.08	0.20	0.12	0.31
GDPnet (%)	-0.17	0.26	-0.13	-0.45	0.06
Tobin's q	2.45	4.70	1.50	0.61	3.65

Panel B: Heatwave					
	Mean	S.D.	Median	P10	P90
GDP (%)	1.65	5.96	2.02	-3.71	6.68
Investment ratio	0.22	0.08	0.21	0.13	0.32
GDPnet (%)	-0.18	0.30	-0.15	-0.53	0.08
Tobin's q	2.33	3.95	1.51	0.64	3.52

3 Stylized Facts

We start with a constant-coefficient linear panel regression model that is widely used to estimate the impact to an economic outcome Y_{it} from extreme-weather arrivals (see, e.g., Dell, Jones, and Olken (2014)):

$$Y_{it} = \phi D_{it} + u_i + v_t + \varepsilon_{it}, \tag{1}$$

where D_{it} is an indicator variable that equals 1 when country i is hit by an extreme event in year t. In the literature, the main dependent variable of interest Y_{it} is typically GDP growth of a country. The regression includes u_i a country fixed effect and v_t a time fixed effect.[11] Thus in this linear model (1), the coefficient ϕ captures the impact of an extreme event on economic outcome Y_{it}.

Table 3: Panel regressions of economic variables on extreme weather arrivals

This table shows the result from a baseline climate-economy panel regression that regresses an economic variable on an indicator for extreme weather events (tropical cyclone or heatwave arrivals). Panel A shows the cyclone sample results while Panel B shows the heatwave sample results. The dependent variables are GDP growth net of $(i_{t-1} - \delta)$ (column 1), investment ratio (scaled by lagged output) (column 2), Tobin's q (column 3), and scaled future arrival, defined as the number of future arrivals in a 3-year bin from $t + 1$ to $t + 3$ divided by 3 (column 4). The main explanatory variable is the extreme weather arrival indicator at t, i.e., D_t. We control for country fixed effects and year fixed effects in all regressions. t-statistics with clustered robust standard errors are shown in parentheses below the estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively. The sample is from 1980 to 2019.

Panel A: Cyclone				
	(1) GDPnet	(2) Investment ratio	(3) Tobin's q	(4) Future arrivals
$\hat{\phi}$	-0.916***	-1.005***	-0.107**	0.036**
	(-5.04)	(-4.12)	(-2.29)	(2.50)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: Heatwave				
	(1) GDPnet	(2) Investment ratio	(3) Tobin's q	(4) Future arrivals
$\hat{\phi}$	-0.767***	-0.855***	-0.172***	0.078***
	(-4.11)	(-3.59)	(-2.86)	(3.14)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

In Table 3, we report results for four definitions of outcome Y_{it}: GDP growth, aggregate investment, Tobin's q, and scaled future extreme-weather arrivals. In column (1), we report the impact of an extreme event for GDP growth that is adjusted for investment and depreciation. The coefficient of interest is -0.916 with a t-statistics of -5.04 for tropical cyclones and -0.767 with a t-statistic of -4.11 for heatwaves. The economic effect of an extreme-weather event for a typical country in our sample is quite adverse — lowering economic growth of 77 to 92 bps.

[11]Alternatively, the literature sometime replaces the time fixed effect with a region x time fixed effect.

These are well-known findings in the literature.

In columns (2) and (3), we consider the investment-to-lagged output ratio and Tobin's q as the dependent variables of interest. We find that there is also a pronounced decline in both investment and Tobin's q. This set of findings (columns (2)-(3)) are inconsistent with a neoclassical model of investment with time-invariant arrival rate of disasters (Pindyck and Wang (2013)). To see why, first observe that the arrival of a disaster destroys capital stock, which of course leads to a drop in contemporaneous growth rate of output. However, investment and Tobin's q are forward looking variables. If agents in the economy perceive the risk of extreme weather as being unchanged, then they should not change their investment plans and Tobin's q should be unchanged. If anything, a disaster that destroys capital should mechanically lead to a higher investment-to-capital output ratio.

In column (4) the dependent variable Y_{it} is the number of extreme-weather arrivals for country i in a 3-year bin from $t+1$ to $t+3$ divided by 3, i.e. $Y_{it} = \frac{1}{3}(D_{it+1} + D_{it+2} + D_{it+3})$. We find that the arrival of an extreme-weather event is also associated with the country experiencing more frequent strikes over the next three years. That is, the risk of extreme-weather events is time-varying and persistent. Hence, to simultaneously rationalize columns (1)-(4) one can model time-varying disaster risk so that agents learn as this risk varies. The reason investment and Tobin's q are lower following a disaster is that agents in the economy perceive extreme-weather risk as being elevated. Rather than invsting, society presumably shifts those resources to costly adaptation to better protect capital.

Papers in the empirical literature on damages to GDP growth do not explicitly model time-varying risk (see further discussion in Section 4.2). As such, we now turn to a state-dependent approach to modeling damages to economic growth, which can help us improve on the empirical specifications used in the literature. We are particularly focused on developing empirical specifications that allow us to estimate the return of adaptation to extreme weather.

4 Extreme-Weather Damages: Theory and Estimation

Our empirical approach builds on a couple of key features of Hong, Wang, and Yang (2023), who generalize the neoclassical growth model to allow optimizing agents to adapt to disasters. In their continuous-time model, an economy (subsequently indexed by i, and suppressed in this subsection to simplify notation), disasters arrive according to a Poisson process with intensity λ which can take on one of two values: λ_G (good) or λ_B (bad), with $\lambda_B > \lambda_G$.The representative agent (of economy i) has a prior belief π_0 that the true value of λ is λ_B. At each t, the agent forms a posterior belief $\pi_t = P_t(\lambda = \lambda_B)$ based on observed signals, where $P_t(\cdot)$ is the conditional probability at t. A higher value of π_t corresponds to a belief that state B is more likely. The expected disaster arrival rate at t given π_t is

$$E_t(\lambda; \pi_t) = \lambda_B \pi_t + \lambda_G (1 - \pi_t)$$

Signals arrive in the form of jumps $d\mathcal{J}_t$, which equals one if there is a disaster and zero otherwise.[12] Given a pre-jump belief of π_{t-}, belief evolves according to $d\pi_t = \sigma_\pi(\pi_{t-})(d\mathcal{J}_t - \lambda_{t-}dt)$. Specifically, after a disaster at t, beliefs change in an unfavourable way to

$$\pi_t^{\mathcal{J}} \quad = \quad = \pi_{t-} + \sigma(\pi_{t-}) = \frac{\pi_{t-}\lambda_B}{E_t(\lambda_t; \pi_{t-})} > \pi_{t-}. \tag{2}$$

where $\sigma(\pi_{t-}) = \frac{\pi_{t-}(1-\pi_{t-})(\lambda_B - \lambda_G)}{\lambda(\pi_{t-})}$ is the size of the jump (i.e. revision in prior) with the arrival of an event. If there is no arrival over interval dt (i.e. $d\mathcal{J}_v = 0$ for $v \in (s, t)$), then beliefs evolve according to a logistic differential equation $\frac{d\pi_t}{dt} = -\sigma_\pi(\pi_{t-})E_t(\lambda; \pi_{t-})$ whose closed-form

[12]Note that if the number of arrivals per interval of time is Poisson distributed, the length of time between occurrences has an exponential distribution.

solution is given by

$$\pi_t^{\mathcal{N}\mathcal{J}} = \frac{\pi_s \exp\Big(- (\lambda_B - \lambda_G)(t-s)\Big)}{1 + \pi_s \Big[\exp\Big(- (\lambda_B - \lambda_G)(t-s)\Big) - 1\Big]}.$$

Their model predicts that agents will adapt to disasters, in the sense that economic outcomes (such as economic growth, Tobin's q and equity risk premium) will be different from the case when there is no learning. For example, output growth g_t (adjusted for investment and depreciation) will take the form

$$g_t = (i(\pi_{t-}) - \delta)dt + F(\pi_{t-})dJ_t + \sigma dW_t. \tag{3}$$

where i is the investment-to-capital ratio, δ is the depreciate rate, $F(\pi_{t-})$ is an adaptation function that mediates damage to growth caused by the jump dJ_t and depends on beliefs π_t, and dW_t is an idiosyncratic Brownian shock. The output response to disasters ($dJ_t = 1$) is state dependent with two features: it is time varying (to the extent that π_{t-} varies with t) and possibly non-linear (to the extent that $F(\cdot)$ is non-linear). As π_{t-} rises, there is more adaptation spending which lowers economic damage.

4.1 Estimating Time-Varying Extreme-Weather Risk

Both features of the model can be seen by simulating the model in discrete time given country-specific parameters $\theta = (\lambda_B, \lambda_G)$. We initialize $\bar{\lambda}_0 = \pi_0\lambda_B + (1-\pi_0)\lambda_G$ with π_0 set to a country's 1960-1979 mean arrival rate. For $t > 1$, we simulate a Poisson jump arrival based on the mean $\bar{\lambda}_{t-1} = \lambda_B\pi_{t-1} + \lambda_G(1 - \pi_{t-1})$. Defining $D_t = 1$ when an arrival occurs, posterior beliefs are updated as[13]

$$\pi_t = \begin{cases} \dfrac{\pi_{t-1}\lambda_B}{\pi_{t-1}\lambda_B + (1-\pi_{t-1})\lambda_G} & \text{if} \quad D_t = 1 \\ \dfrac{\pi_{t-1}\exp(-(\lambda_B - \lambda_G))}{1 + \pi_{t-1}[\exp(-(\lambda_B - \lambda_G)) - 1]} & \text{if} \quad D_t = 0\ . \end{cases} \tag{4}$$

Since countries are heterogeneous, we simulate one model for each country $i = 1, \ldots, N$. Though the true country-specific parameters $\{\theta^0\}_{i=1}^N$ are unknown, we have data on extreme weather events $D_i = (D_{i1}, \ldots, D_{iT})'$ from which we can compute sample moments $\hat{\psi}(D_i, \theta_i^0)$ for each i. Assuming that the binding function $\psi(\cdot)$ is invertible, we can estimate θ_i country-by-country using moments $\bar{g}_i = \hat{\psi}(D_i, \theta_i^0) - \hat{\psi}(\theta)$ whose asymptotic variance Ω_i can be consistently estimated by $\hat{\Omega}_i$. As $\psi(\cdot)$ is not tractable, we approximate it by simulations. Let $\hat{\psi}^S(\theta) = \frac{1}{S}\sum_{s=1}^S \hat{\psi}(D_i^s, \theta)$ be the moments computed from data D_i^s simulated under θ using the s draw of errors, $s = 1, \ldots, S$. Let $\bar{g}_i^S = \hat{\psi}(D_i, \theta_i^0) - \hat{\psi}^S(\theta)$. Under regularity conditions in (Duffie and Singleton (1993)), the SMM estimator $\hat{\theta}_i^S = \text{argmin}_\theta \bar{g}_i^S(\theta)'\hat{\Omega}_i^{-1}\bar{g}_i^S(\theta)$ is root-T consistent and asymptotically normal.

4.2 Estimating State-Dependent Damages

Studies in the climate economics literature recognize the potential importance of adaptation in making inferences about damage to GDP growth from extreme weather. They augment the linear model (1) for GDP growth by estimating the following panel regression:

$$g_{it} = \phi D_{it} + (\psi \cdot n_i) \times D_{it} + u_i + v_{jt} + \varepsilon_{it}, \tag{5}$$

where n_i is the variable measuring the number of extreme weather events a country i has experienced historically, u_i is a country fixed effect, and v_{jt} is a region-by-time fixed effect.

[13] See also By Lipster and Shiryaev (2001, Theorem 19.6) for optimal filtering of point processes, and Example 1 on p.333.

Adaptation studies typically find that ψ is negative, i.e., countries with more extreme weather arrivals historically (measured by high n_i values) would experience lower damage for an given event D_{it}. Thus in this reduced-form model (5), the coefficient ϕ captures the conditional damage without adaptation and the coefficient ψ captures the adaptation effect.

Though simple and intuitive, there are several limitations to this regression. While the model allows for heterogeneity through individual and time fixed effects, a linear model with time constant parameters would not encompass the possible effects of learning and state-dependent adaptation. But when the coefficients are heterogeneous, pooled estimation has its drawbacks. As reviewed in Baltagi (2008) in the context of linear models, if the slope parameters are homogeneous, pooling is efficient when N is large and T is small. But pooling becomes less appealing when the slope coefficients are heterogeneous especially in the presence of dynamics. Pesaran and Smith (1995) showed that the average effect will be inconsistent if the omitted heterogeneity induces a correlation between the serially correlated regressors and the regression error.

An alternative to pooling is unit by unit estimation which will yield consistent estimates when T is large. Arguably, we have enough disaster observation for each country to consider individual level estimation. The main appeal is that there is more flexibility to estimate a model with the desired state dependent effects at the country level. After country-by-country regressions, we can still compute the average.

Equation (3) suggests a flexible alternative to the linear model

$$g_{it} - (i_{it-1} - \delta_{it-1}) = \mu_i + F(\pi_{it-1})D_{it} + \varepsilon_{it}, \tag{6}$$

where $F(\pi_{it-1})$ is the adaptation-induced damage function. Rather than modeling the growth rate g_{it}, we will instead work with GDP growth net of the difference between the investment rate and depreciation rate, i.e. $g_{it}^n = g_{it} - (i_{it-1} - \delta_{it-1})$. That is, we will net out the previous level of investment and also adjust for depreciation to give us a mean zero dependent outcome. Note that all variables in the regression are country-specific. The linear model in Equation 1 obtains as a special case when $F(\pi_{it-1})$ is a constant $\zeta_{1i} = F(\pi_{i0})$, i.e. when there is no learning. Then

$$g_{it}^n = \mu_i + \zeta_{1i} D_{it} + \varepsilon_{it}. \tag{7}$$

The growth of an economy depends on investment (based on π_{it-1}). We expect the constant term μ_i to be zero. (See also discussion in Section 2.).

If we were only interested in a 'ghat' that allows for time-varying parameters, we could use a non-parametric model (such as a kernel, a neural-net, or a random forest) with $\hat{\pi}_{it}$ and D_{it} as predictors. But we are interested in the marginal effects of learning and adaptation, so the 'beta-hat' is of interest. We use a first-order Taylor expansion of $F(\pi_{it-1})$ around π_{i0} to obtain

$$\begin{aligned} g_{it}^n &= \mu_i + \underbrace{F(\pi_{i0})}_{\substack{\text{damage at}\\ \text{prior adaptation}}} D_{it} + \underbrace{F'(\pi_{i0})(\pi_{it-1} - \pi_{i0})}_{\substack{\text{return to state-dependent}\\ \text{adaptation}}} D_{it} + \varepsilon_{it} \\ &= \mu_i + \beta_{1i} D_{it} + \beta_{2i} \tilde{\pi}_{it-1} D_{it} + \varepsilon_{it} \\ &= \mu_i + \chi_{it} + \varepsilon_{it} \end{aligned} \tag{8}$$

where $\tilde{\pi}_{it-1} = (\pi_{it-1} - \pi_{i0})$ and $\chi_{it} = \beta_{1i} D_{it} + \beta_{2i} \tilde{\pi}_{it-1} D_{it}$ is the total damage in the presence of learning and adaptation. The $F(\pi_{i0})$ term is economic damage with adaptation fixed at prior risk π_{i0}. The $F'(\pi_{i0})\tilde{\pi}_{it-1}$ term is the return to state-dependent adaptation induced by learning or revision of beliefs, which is net of the costs of adaptation to society.

Note that $F(\pi_{i0})$ and $F'(\pi_{i0})$ suffice for identifying the first-order effects of D_t, being

$$E[g_{it}^n | D_{it} = 1] = \underbrace{F(\pi_{i0})}_{\beta_{i1}<0} + \underbrace{F'(\pi_{i0})}_{\beta_{i2}>0} \tilde{\pi}_{it-1} \tag{9}$$

The constraints $\beta_1 < 0$ and $\beta_2 > 0$ will be imposed in estimation. Equation (8) nests the linear model (7) in which F is constant (no state-dependent adaptation) and $(\pi_{t-1} - \pi_0) = 0$ (no learning). Equation (8) also nests (5) in which D_{it} is not interacted with past beliefs, π_{it-1}. Omitting dependence on π_{i0} and π_{it-1} could bias the estimates of economic damages.

5 Estimation Results

This section has four parts. Subsection 1 presents results for first step estimation of the structural model for extreme weather arrivals. Subsection 2 presents the second stage estimates of the damage function. Subsection 3 explores the relation between the first step estimates of π_{it} and the β_i parameters of the damage function in the second step.

5.1 First-Stage Estimates of Extreme-Weather Risk

For a given definition of extreme weather (which can be cyclone or extreme temperature), the structural parameters of the model in Section 4 are $\theta = (\lambda_B, \lambda_G)'$. Countries' π_0 values are fixed to their pre-1980 historical extreme-weather arrival frequencies. From 4, for tropical cyclones, the mean of $\hat{\pi}_0$ is 0.33 and the median is 0.2. For heatwaves, the mean of $\hat{\pi}_0$ is 0.11 and the median is 0.05. Countries standing in 1980 face a greater prior risk from cyclones than heatwaves.

We estimate θ_i for each country $i = 1, \ldots, N$ by simulated method of moments. The five sample moments matched to the model are the mean (M1), variance (Var), 3rd central moment (M3), 4th central moment (M4), and first-order autocorrelation (AC). The country-specific moments are given in Table A.1 and A.2 of the Appendix. As we alluded to in Section 2, we are using only the recent four decades of data to discipline our time-varying risk model. We think this is reasonable choice since the recent decades are likely to be more informative about a changing climate than data early in the twentieth century.

The estimates of θ_i are summarized in Table 4. For the tropical cyclone sample in Panel A, the mean of $\hat{\lambda}_{Bi}$, the estimated arrival rate in the bad state, is 0.84 (or once in every 1.2 years), with 95% of the estimates being significant. The mean estimate of λ_{Gi} is 0.16 (or once in every 6.5 years), with 95% of the estimates being significant. For the extreme temperature sample, the mean estimate of λ_{Bi} is 0.727, with 98.3% of the estimates being significant. For estimates of $\lambda_{G,i}$, the mean is 0.138 with again 98.3% of the estimates being significant.

Table 4: Estimates of the arrival model

This table shows the summary statistics over all countries of country-level parameter estimates of the time-varying arrival-rate model of extreme weather in Section 4. $\hat{\pi}_{0,i}$ is set to a country's arrival rate in 1960-1979 sample. Estimates for $\lambda_{B,i}$ and $\lambda_{G,i}$, $\hat{\lambda}_{B,i}$ and $\hat{\lambda}_{G,i}$, are from simulated method of moments targeting the five moments over the sample of 1980-2019 as specified in Appendix Tables A.1 and A.2. % Sig. in the second column denotes the percentage of country-level estimates that are significant at the 5% level.

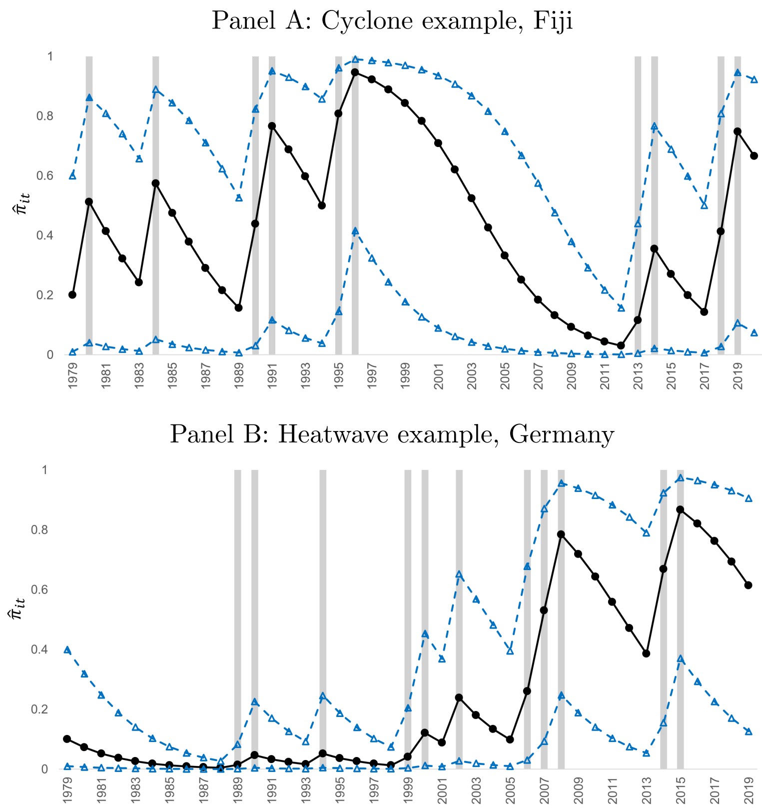
	Mean	% Sig.	Median	Min	Max
Panel A: Cyclone					
$\hat{\pi}_{0,i}$	0.33		0.2		
$\hat{\lambda}_{B,i}$	0.841	95.1%	0.802	0.638	0.989
$\hat{\lambda}_{G,i}$	0.155	95.1%	0.059	0.026	0.347
Panel B: Heatwave					
$\hat{\pi}_{0,i}$	0.11		0.05		
$\hat{\lambda}_{B,i}$	0.727	98.3%	0.731	0.639	0.933
$\hat{\lambda}_{G,i}$	0.138	98.3%	0.136	0.023	0.199

Cyclones in Fiji and heatwaves in Germany. To better understand the implications of time-varying arrival model, Panel A of Figure 1 plots the path of $\hat{\pi}_{it}$ implied by the cyclone model estimated from data for Fiji, along with the actual arrivals of cyclones (the gray bars). In this case, the cluster of arrivals in the 1990s lead the model to shift its posterior to near 1. But the absence of subsequent cyclones until 2013 leads the posterior to shift down to close to 0 in the late 2000s until recently when $\hat{\pi}_{it-1}$ started to shift up again due to another cluster of arrivals.

Panel B performs a similar plot, but using heatwave data for Germany. The path of $\hat{\pi}_{it}$ for Germany's extreme-temperature is quite different. The $\hat{\pi}_{it}$ series stays close to zero until a cluster of arrivals in the 2000s lead the risk posterior to rise dramatically. In spite of several abnormally hot summers in the late eighties and early nineties, $\hat{\pi}_{it}$ does not shoot up because the prior risk π_{it} is close to zero. According to Equation 2, the size of the jump with the arrival of an event is given by $\sigma(\pi_{t-}) = \frac{\pi_{t-}(1-\pi_{t-})(\lambda_B-\lambda_G)}{\lambda(\pi_{t-})}$. Notice that $\sigma(\pi_{t-})$ is nonlinear in π_{t-}, and equal to 0 when π_{t-} equals 0 or 1. When the risk is extremely low or extremely high, the arrival of an event triggers only a small revision in posteriors, i.e. society is already pretty sure that it is at low or high risk. The largest revisions are typically for intermediate values of π_{t-}.

Figure 1: Arrivals and evolution of $\hat{\pi}_{it}$: two illustrative examples

This figure shows the arrivals and evolution of $\hat{\pi}_{it}$ for two illustrative examples: Fiji with cyclone data (Panel A) and Germany with heatwave data (Panel B). In each example, the path of $\hat{\pi}_{it}$ computed from the fixed prior $\hat{\pi}_{i0}$ is plotted in the solid black line, and the ones from $\hat{\pi}_{i0}\pm$(the standard deviation of arrivals in the pre-1980 period) are plotted in dotted lines. The gray bars indicate years when there is an arrival.



5.2 Second-Stage Estimates of the Damage Function

The average effect of economic damages is typically estimated by pooled estimation of a linear model controlling for time and fixed effects. We differ in that we allow the damage function to vary with π_{i0} and π_{it-1}, and we impose sign restrictions on the parameters. Furthermore, we perform constrained time series estimation country-by-country, and then aggregate the individual estimates to obtain an estimate of the average effect of interest. The cost to flexibility is that the sample size for the country level regressions is limited by data availability which might affect the estimate of the average effect.

Before turning to non-linear estimation, we want to be confident that our country-by-country approach gives estimates of the average that are similar to panel estimation of the constant parameter linear model $g_{it}^n = \mu + \zeta_{1i} D_{it} + \epsilon_{it}$. To this end, Figure 2 plots the density, estimated using the Epanchnikov kernel, of the individual $\hat{\zeta}_{1i}$ estimated from the linear model (7). Also shown is the simple average $\hat{\zeta}_1 = \frac{1}{N}\sum_i \hat{\zeta}_{1i}$, as well as the pooled panel estimate $\tilde{\zeta}_1$ (black dotted line). They are -0.90 (the average) and -0.93 (the pooled) for the cyclone data, and -0.69 (the average) and -0.68 (the pooled) for the extreme temperature data. We see that $\hat{\zeta}_1$ and $\tilde{\zeta}_1$ are quite similar.

We thus proceed with second-stage estimation of a model with learning and adaptation, ie.

$$g_{it}^n = \mu_i + \beta_{1i} D_{it} + \beta_{2i} \tilde{\pi}_{i,t-1} D_{it} + \varepsilon_{it}$$

For each country i, the damage parameter β_{1i} is constrained to be negative and the adaptation parameter β_{2i} is constrained to be positive. The density of the estimates are shown in Figure 3. For both the cyclone and extreme temperature data, the density of $\hat{\beta}_{1i}$ is slightly skewed. From $\hat{\beta}_{1i}$ and $\hat{\beta}_{2i}$, we define $\hat{\beta}_1 = \frac{1}{N}\sum_{i=1}^N \hat{\beta}_{1i}$ and $\hat{\beta}_2 = \frac{1}{N}\sum_{i=1}^N \hat{\beta}_{2i}$ and use bootstrap to obtain their standard errors.[14] We obtain a $\hat{\beta}_1$ of -0.904 with a standard error of 0.38 in

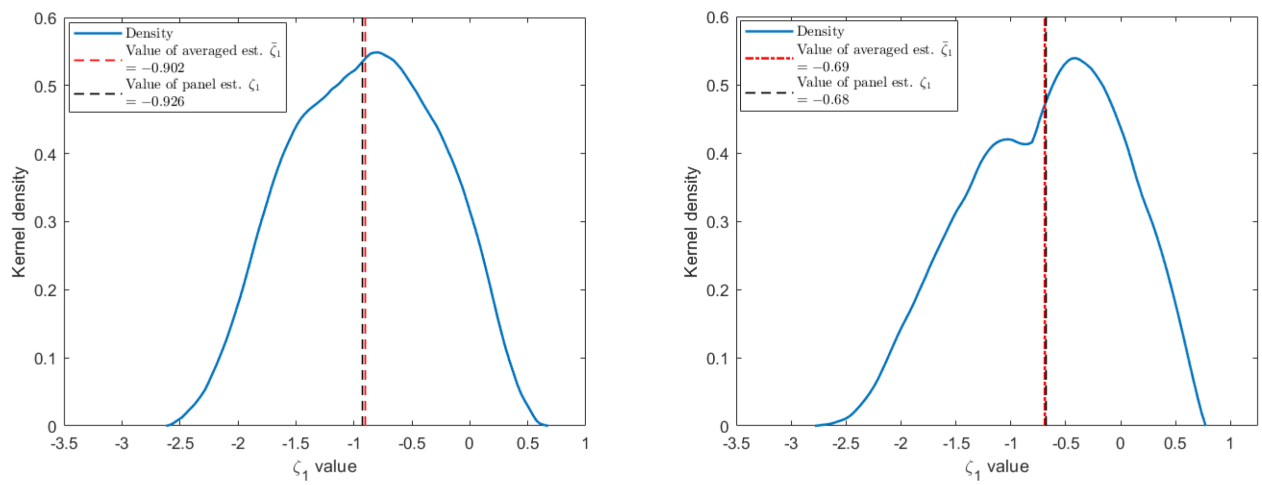
[14]Precisely, estimation using the b-th bootstrap sample of data for country i gives $\hat{\beta}_{1i}^b$. This yields an average estimate in the b-replication of $\hat{\beta}_{1i}^b = \frac{1}{N}\sum_{i=1}^N \hat{\beta}_{1i}^b$. The standard error of $\hat{\beta}_1$ is estimated by the standard

Figure 2: Density of $\hat{\zeta}_{1i}$

This figure plots the density (estimated using the Epanchnikov kernel) of the individual $\hat{\zeta}_{1i}$ estimated from the linear model (7). The blue solid line is the density. The red dashed line is $\hat{\zeta}_1 = \frac{1}{N}\sum_{i=1}^{N}\hat{\zeta}_{1i}$. The black dashed line is the estimate of the average effect from a linear panel regression of growth on arrivals with country and region-by-year fixed effects.

Panel A: Cyclone data

Panel B: Heatwave data



the cyclone data, and -0.693 with a standard error of 0.21 in the extreme temperature data; both significant at the 5% level. Interestingly, $\hat{\beta}_1$ implied by the non-linear model is close to the average estimate $\hat{\zeta}_1$ and the pooled estimate $\tilde{\zeta}_1$ for the linear model shown earlier in Figure 2. However, while a linear model constrains β_{2i} to zero, our model with adaptation treats this as a free parameter. The bottom of Figure 3 shows that many of the $\hat{\beta}_{2i}$ are non-zero. The average estimate $\hat{\beta}_2$ is 0.145 with a standard error of 0.06 for the cyclone data, and is 0.126 with a standard error of 0.05 for the extreme temperature data. Both estimates are significant at the 5% level.

To put these estimates into context, the arrival of a cyclone leads to a decline of 90.4 basis points of economic growth for a typical country at its prior risk (the mean π_0 is 0.3). Suppose that the country's risk increases by 0.5 from its prior, i.e. $(\pi_{t-1} - \pi_0)$ is 0.5, so that its π_{t-1} equals 0.8. This would mean that an extreme-weather arrival reduces economic growth only

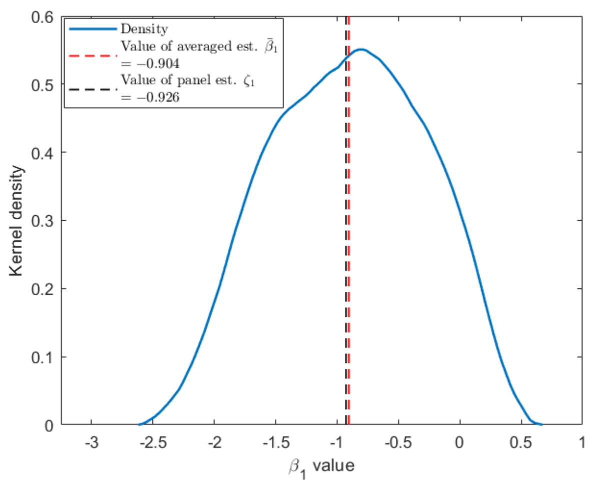
deviation in $\{\hat{\beta}_1^b\}, b = 1, \dots B$. Similar calculations are performed for $\hat{\beta}_2$.

Figure 3: Density of $\hat{\beta}_{1i}$ and $\hat{\beta}_{2i}$

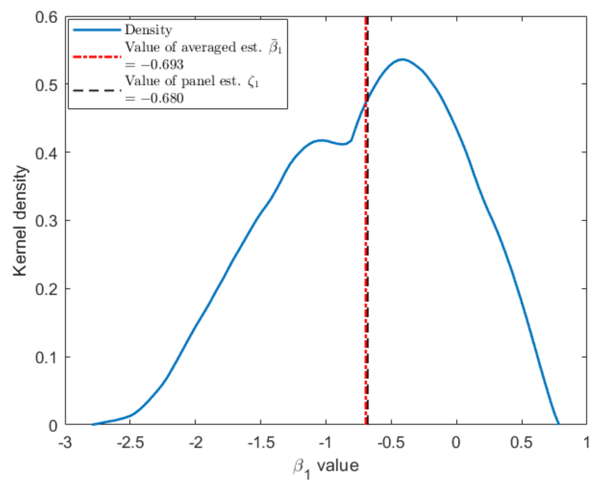
This figure plots the density (estimated using the Epanchnikov kernel) of the individual $\hat{\beta}_{1i}$ and $\hat{\beta}_{2i}$ estimated from the non-linear model (8). The blue solid line is the density. The red dashed line is the simple average over countries, and the black dashed line is the estimate from a pooled linear regression of growth on arrivals with country and region-by-year fixed effects.

Panel A: Density plot of $\hat{\beta}_{1i}$

Cyclone $\hat{\beta}_{1i}$

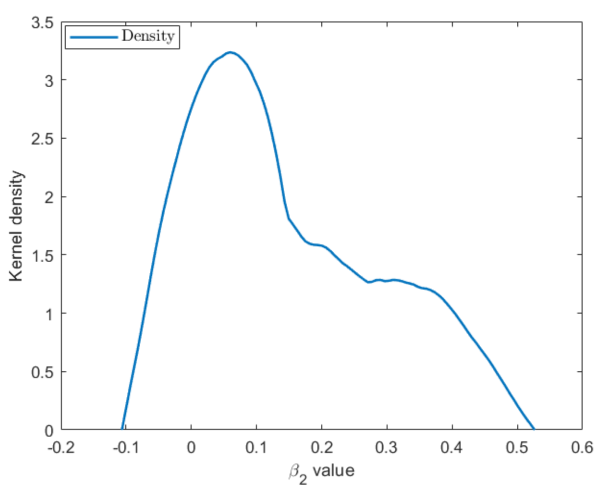


Heatwave $\hat{\beta}_{1i}$

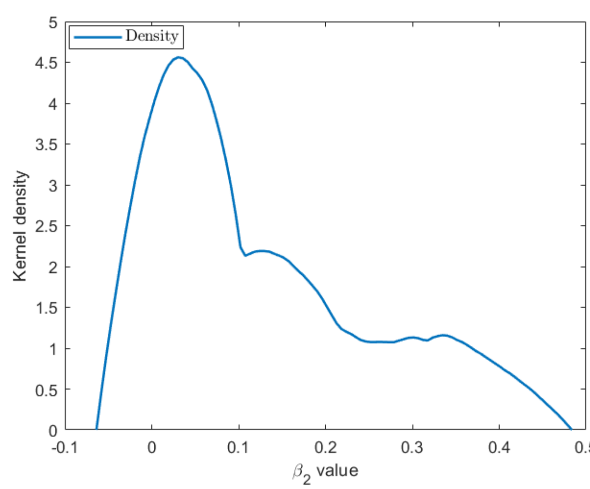


Panel B: Density plot of $\hat{\beta}_{2i}$

Cyclone $\hat{\beta}_{2i}$



Heatwave $\hat{\beta}_{2i}$



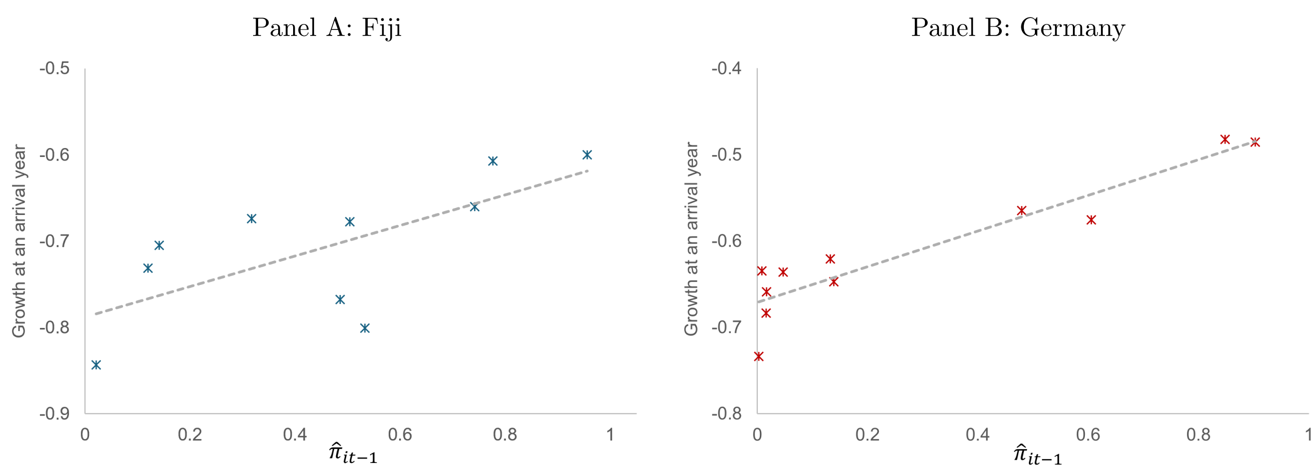
by $0.904 - 0.145 \times 0.5$ or 0.83. In other words, state-dependent adaptation on net ameliorates damage due to cyclones by 7 basis points.

The benefits of state-dependent adaptation are similar for extreme temperature. For the typical country at its risk prior which is 0.1, the damage to growth from an episode of extreme temperature is 69.3 basis points. If that country's risk rises by 0.5 to 0.6, the damage per arrival of an extreme-weather event falls to 63 basis points. This is a 6.3 basis points reduction.

GDP growth of Fiji and Germany. To better understand the variation we are using to isolate β_{2i}, we return to our Fiji and Germany examples. Figure 4 contains scatter plots of GDP growth (net of $(i_t - \delta)$) against $\hat{\pi}_{it-1}$ at extreme-weather arrival years for our two illustrative country examples. For Fiji, $\hat{\beta}_{1i} = -0.93$ and $\hat{\beta}_{2i} = 0.15$. For Germany, $\hat{\beta}_{1i} = -0.72$ and $\hat{\beta}_{2i} = 0.12$. The positive estimate of β_{2i} can be seen from the positive slopes of the scatterplots. The higher is $\hat{\pi}_{it-1}$, the smaller is the damage to GDP growth with an arrival. The coefficient β_{1i} is determined by a comparison of these arrival year observations with non-arrival year observations, which are not shown.

Figure 4: Scatter plots of GDP growth against $\hat{\pi}_{it-1}$ at arrival years, two illustrative examples

This figure scatter plots GDP growth (net of $(i_{t-1} - \delta)$) against $\hat{\pi}_{it-1}$ at extreme-weather arrival years for our two illustrative country examples. For Fiji, ($\hat{\beta}_{1i} = -0.93$, $\hat{\beta}_{2i} = 0.15$). For Germany, ($\hat{\beta}_{1i} = -0.72$, $\hat{\beta}_{2i} = 0.12$).



6 Model Diagnostics

Our approach differs from the approach in the literature in the following dimensions. First, we convert historical weather experience into an extreme-weather risk prior using a Bayesian learning model. Second, we incorporate learning and revision of priors into the country-by-country estimation. This learning term would ordinarily be swept up in the error term. But we show that explicitly accounting for the revisions in priors is important for long-horizon projections. Third, we allow for a nonlinear relationship between adaptation and risk priors. This non-linearity is typically absent in current models which assume that the effect of a disaster arrival on GDP growth is decreasing linearly in arrival experience.

In this section, we provide diagnostics to show (i) limitations of a time-invariant structural model for extreme weather arrivals model used in the first stage; (ii) limitations of linear model used in the second stage; (iii) new insights from our approach over linear event studies in estimating the damage function.

6.1 Disaster Arrivals: Constant versus State-Dependent Parameters

We first test for adequacy of our 2-parameter (unrestricted) time-varying extreme-weather arrivals model against a restricted time-invariant Poisson arrivals model. This restricted model which sets $\lambda_B = \lambda_G$ is also estimated using SMM with the five moments specified in Appendix Tables A.1 and A.2. The distance statistic is the difference between the value of the SMM objective function in the restricted Poisson model and our unrestricted extreme-weather arrivals model (both evaluated at their respective SMM estimates) multiplied by T. This test statistic has an asymptotic χ^2 distribution with one degree of freedom.

In Table 5, we present the result of this test, which shows the percentage of countries that rejects the null (restricted model). It is clear that for the vast majority of countries, we reject a time-invariant Poisson arrival model of extreme weather in favour of our time-varying arrival rate model at the usual significance levels. For instance, for cyclones, 92.8% of the countries are rejected at the 10% significance level and 76.8% at the 5% significance level. For extreme temperatures, 95% of countries are rejected at the 10% significance level and 87.6% at the 5% significance level.

6.2 Linear vs Nonlinear Damage Function

We can check the adequacy of the linear model (7) used in the second stage. Let $\hat{\varepsilon}_t$ be the residuals from estimation of (7) for a given country. Theory suggests that economic outcomes should depend not only on D_t, but also on π_t in a possibly non-linear way. Consider the regression

$$\hat{\varepsilon}_t = \gamma_0 + \gamma_1 D_t + \gamma_2 D_t \pi_{t-1} + \gamma_3 \pi_{t-1} + \text{err}_t. \tag{10}$$

Under the null hypothesis that the linear model is correct, π_t and the interaction term should have no explanatory power and the R^2 of the above regression should be small. The LM test statistic $T \cdot R^2$ has a χ^2 distribution with two degrees of freedom. As shown below, the results resoundingly reject the null hypothesis. On average, the R^2 in these regressions is over 0.18, indicating non-trivial explanatory power in the omitted terms. Table 5 shows the percentage of countries for which the LM test rejects the null hypothesis of the linear model being correctly specified. We can see that for most of countries, the LM test rejects at the usual statistical significance levels. This result suggests omitted non-linear terms from the linear model that can explain nearly 20% of the variations in the residuals.

6.3 Residual serial correlation test of nonlinear model

To further confirm the adequacy of our model with learning and adaptation, we conduct tests for first-order residual serial correlations of our nonlinear model in Section 4.2 with the estimates given in Section 5.2. We find no evidence of serial correlation in Table 5. For the 10% level of

Table 5: Specification Tests: % of countries rejecting null hypothesis H_0 at 10 and 5% significance levels

This table presents the results of our model diagnostics. The first row shows the summary statistics over all countries of country-level model specification tests for testing the first-stage 2-parameter extreme-weather arrival model versus the restricted simple Poisson arrival model (one constant λ) estimated using SMM with the five moments specified in Table A.3. The second row shows the summary statistics over all countries of country-level LM tests for the adequacy of the linear damage function model against the alternative adaptation model with additional $D_t\pi_{t-1}$ and π_{t-1} terms. The third row shows the summary statistics of country-level Breusch–Godfrey tests for 1st-order residual serial correlations in the adaptation regression.

Model	Equation	H_0	Cyclone		Heatwave	
			10%	5%	10%	5%
Disaster Arrival	(4)	$\lambda_B = \lambda_G$	92.8	76.8	95.0	87.6
Residual of linear model	(10)	$\gamma_1 = \gamma_2 = \gamma_3 = 0$	91.3	72.5	92.6	71.2
Residual of nonlinear model	(8)	Breusch-Godfrey	2.2	0	4.1	0

significance, we find that only in 3% of countries can we reject the null hypothesis of no serial correlation in the residuals for cyclones. For the 5% level of significance, it is 0%. For the extreme temperature model, only in 4% of the countries can we reject the null at the 10% level and 0% at the 5% level of significance.[15]

6.4 Robustness Check

Detrending. For our key estimation equation (8), we detrend the variables as follows. For any variable w_{it} where i indexes country and t indexes time, define $\bar{w}_{i\cdot} = (1/T)\sum_{t=1}^{T} w_{it}$, $\bar{w}_{\cdot t} = (1/N)\sum_{i=1}^{N} w_{it}$, $\bar{w} = (1/N)(1/T)\sum_{i=1}^{N}\sum_{t=1}^{T} w_{it}$, and the detrended version of w_{it} is $\ddot{w}_{it} = w_{it} - \bar{w}_{i\cdot} - \bar{w}_{\cdot t} + \bar{w}$. Then we estimate the following detrended version of our main equation (8) country by country

$$\ddot{y}_{it} = \alpha_i + \beta_{i1}\ddot{D}_{it} + \beta_{i2}\ddot{x}_{it} + \epsilon_{it}$$

[15]Because the residuals from our nonlinear model are serially uncorrelated, it does not matter if we also control for lagged GDP growth and the interaction of lagged GDP growth with the disaster arrival indicator D_{it} in our empirical analysis.

where $y_{it} = g_{it} - (i_{it-1} - \delta_{it-1})$, $x_{it} = \tilde{\pi}_{it-1} D_{it}$, and α_i is statistically equal to zero. This detrending is equivalent to removing the country and time effects from a pooled panel regression model.[16] We show the detrended results in Figure A.1. The estimates of β_1 and β_2 are quite close to our baseline model estimates in Figure 3. Hence detrending has no impact on our main findings.

Panel regression estimates of the state-dependent model. We estimate our state-dependent model in a pooled panel regression with country and year fixed effects as another robustness check. The estimates, which are similar to those that we obtain by averaging our country-by-country estimates, are shown in Table A.4.

7 Counterfactuals

7.1 In Sample: 1980-2019

We are interested in comparing the real GDP per capita in 2019 to the counterfactual 2019 income assuming that there had been no learning and state-dependent adaptation over our sample of 1980-2019. We can make this comparison using the actual in sample GDP growth rates g_{it} for our countries along with estimates of our non-linear time-varying extreme-weather risk model from Section 5.

The counterfactual GDP per capita in each year of our sample is:

$$GDP_{it}^{CF} = GDP_{it-1}^{CF} \times (1 + g_{it} - \hat{\beta}_{i2} \tilde{\pi}_{it-1} D_{it}), \tag{11}$$

where GDP^{CF} denotes the counterfactual real GDP per capita, $\tilde{\pi}_{it-1} = (\pi_{it-1} - \pi_{i0})$ and D_{it} equals 1 if the country is hit by a disaster and zero otherwise.[17] $\hat{\beta}_{i2}$ is from our estimates

[16] See Greene (2012), chapter 11.4 for reference.

[17] Strictly speaking, $\hat{\beta}_{i2}$ is estimated using growth rates of GDP net of $(i_{t-1} - \delta)$. However, the growth rates of GDP and GDP per capita are extremely correlated.

summarized in Figure 3. Equation 11 is a recursive relationship where the initial condition is set to the 1980 real GDP per capita.

Table 6 reports the 2019 country real per capita GDP compared to the counterfactual if there were no learning and state-dependent adaptation for cyclones and heatwaves, respectively. The counterfactual 2019 income for tropical cyclones would be 6.5% lower for the mean or median country income. For heatwaves, the counterfactual 2019 income is around 4% lower.

Panel A of Figure 5 plots the evolution of in-sample and counterfactual country incomes for our cyclone sample. We can see from this figure (and also the summary statistics in Table 6) that the return to adaptation varies across countries — higher for very high and very low income countries. Panel B of Figure 5 plots the evolution of actual and counterfactual incomes absent adaptation for heatwaves. Notice that the countries in the heatwaves sample differ somewhat from the tropical cyclone samples, which is reflected in the larger standard deviation in the heatwave sample.

Table 6: Summary statistics of counterfactual real GDP per capita in 2019

This table presents the summary statistics of the counterfactual real GDP per capita across countries in 2019 by shutting down the state-dependent adaptation channel and using the in-sample extreme weather arrival data. Real GDP per capita is in thousands of constant 2015 USD.

Counterfactual real GDP per capita in 2019				
	Cyclone sample		Heatwave sample	
	In-sample at 2019	Counterfactual	In-sample at 2019	Counterfactual
Mean	14.2	13.3	15.2	14.6
S.D.	19.5	19.1	21.5	21.9
Median	5.2	4.7	4.9	4.6
P25	2.0	1.5	1.6	1.5
P75	14.5	11.4	19.0	16.0

Evolution of $\hat{\pi}_{it}$ in sample. To see why income absent adaptation is lower, it is instructive to see how $\hat{\pi}_{it}$ changes over our sample. Figure 6 plots $\hat{\pi}_{it}$ for 1989, 1999, 2009 amd 2019.

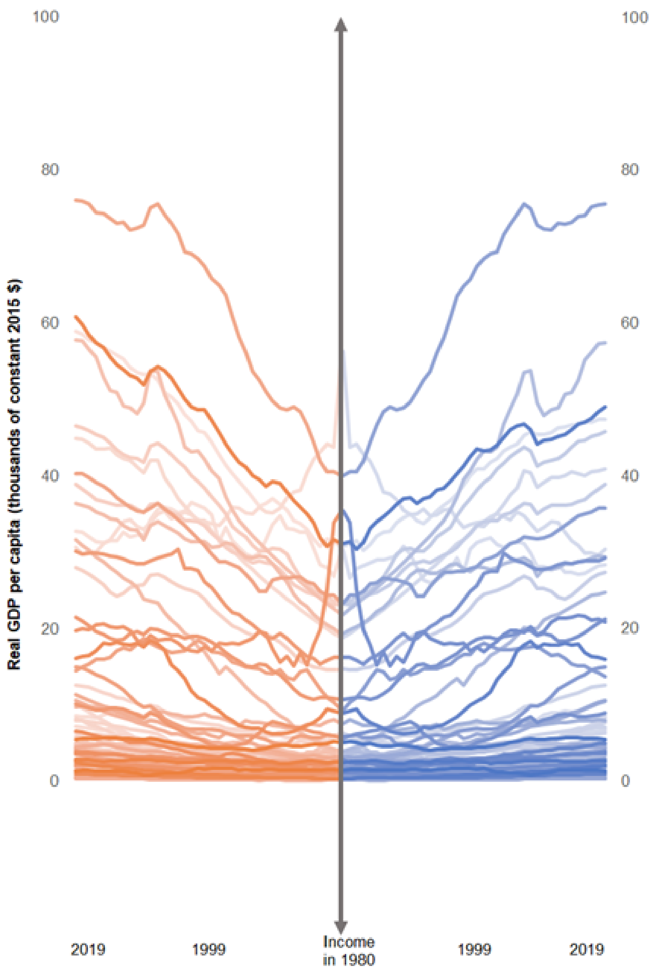
Consider the heatwave or extreme temperature sample. Here, we see that in 1979 there is little risk of heatwaves as most countries' values of $\hat{\pi}_{it}$ are at around 0.2. However, over the

Figure 5: In-sample counterfactual real GDP per capita absent learning and state-dependent adaptation

This figure shows the in-sample counterfactual (without state-dependent adaptation) real GDP per capita compared to the actual time-series of real GDP per capita from 1980 to 2019. Panel A shows the results for the cyclone sample and Panel B for the heatwave sample. The left figure in each panel (Actual) shows the actual in-sample time-series paths of real GDP per capita, while the right figure shows the counterfactual income with no learning and state-dependent adaptation. Real GDP per capita is shown in thousands of constant 2015 USD.

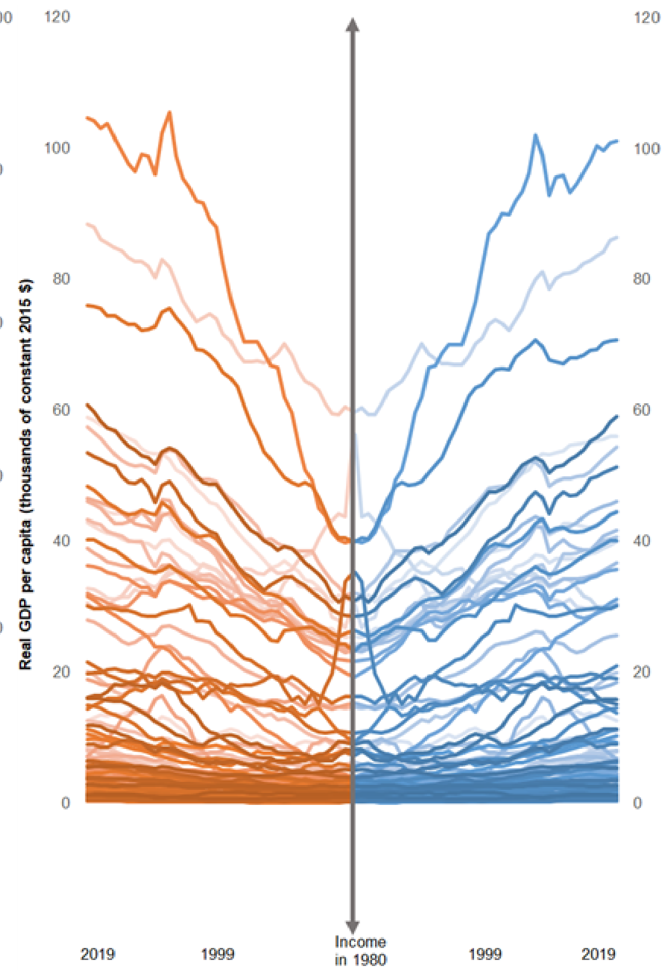
Panel A: Cyclone sample

Left: Actual. Right: Counterfactual



Panel B: Heatwave sample

Left: Actual. Right: Counterfactual

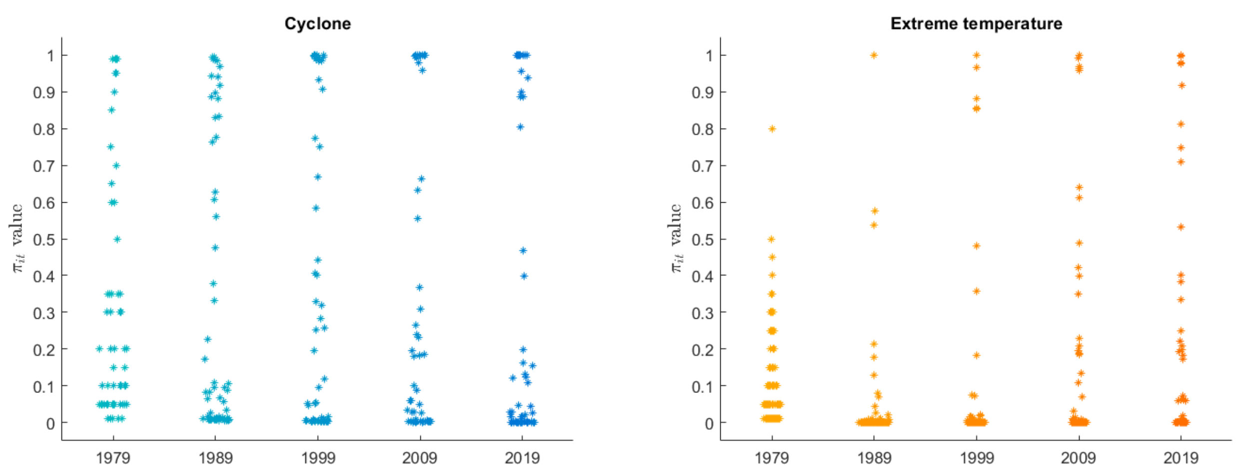


ensuing decades, some of these countries transition to higher $\hat{\pi}_{it}$.[18] The benefit of adaptation is largest for the countries that start from a low $\hat{\pi}_{it}$ in the beginning of the sample and move to a high $\hat{\pi}_{it}$ at the end of the sample. The reason is that these countries are being hit more frequently by disasters and hence lack of adaptation gets penalized more in Equation (11). At the same time, countries that start with a moderate risk and transition to lower $\hat{\pi}_{it}$ over time would be less likely to get hit and hence the adjustment accounting for adaptation matters less for these countries.

A similar logic applies to tropical cyclones. Notice that for cyclones, we see a more dispersed π_{i0} across countries in 1979 than for heatwaves. For instance, there are some countries with values of π_{it} above 0.8, but most the countries are clustered below 0.2. Over time, notice that there are more countries at the extremes of the π_{it} distribution.[19]

Figure 6: In-sample evolution of π_{it}

This figure plots the in-sample evolution of π_{it} from 1979 to 2019. The scatter plot of π_{it} values is shown at each decade end. The darker color the more country observations for those values of π_{it}.



[18]These countries, all with priors between 0.15 and 0.3, include Zambia, Nicaragua, Lebanon, Norway, Mongolia, Spain, The Bahamas, Algeria, Kuwait, Tunisia.

[19]These countries include Honduras, Cambodia, El Salvador, Belize, Fiji, Panama, Dominican Republic, Costa Rica, Guatemala, Nicaragua.

7.2 Out of Sample: 2020 to 2099

Another way to demonstrate the usefulness of our model is to consider the following common exercise in the climate literature, which is to project the impact of extreme weather events on economic growth over the coming century. We use the estimates from our constant-coefficient model and varying-coefficient model to generate projected future changes in GDP (i.e., growth rates). In particular, the evolution of real GDP per capita in country i in year t is given by:

$$GDP_{it} = GDP_{it-1} \times (1 + \eta_{it} + \chi_{it} D_{it}), \tag{12}$$

where GDP denotes the real GDP per capita. We take 2019 to be $t = 0$. The exercise starts from $t = 1$ and ends in $t = 101$ for year 2100.

In Equation (12), η_{it} is the growth rate of GDP of country i in year t absent any climate (extreme weather) damage. As in the literature (e.g., Burke et al., 2015), we take this base growth rate from the SSP5.[20] D_{it} as before is the dummy variable denoting the extreme weather arrival event for country i in year t. The key quantity is χ_{it}, which is the estimated damage of an extreme weather event. We consider two different models for χ_{it}:

a. The damage estimates from the time-invariant regression model. In this case, χ_{it} is a constant, $\forall(i,t)$, i.e. where adaptation is fixed at prior risk. We call this projection "Fixed Adaptation".

b. The damage estimates from the time-varying model with learning and adaptation, which are shown in Figure 3. In this case, $\chi_{it} = \left(F(\pi_{i0}) + F'(\pi_{i0})\widetilde{\pi}_{it-1} \right)$, which depends on beliefs π_{it-1}. We call this projection "State-dependent Adaptation".

We use the time-varying extreme-weather arrivals model to simulated paths of future extreme weather arrivals. This simulation is rather similar to the one used in our earlier simulated

[20]SSP5: Shared Socio-Economic Pathway, Scenario 5, called "Fossil-Fueled Development" — see Kriegler, Bauer, Popp, Humpenöder, Leimbach, Strefler, Baumstark, Bodirsky, Hilaire, Klein, et al. (2017)

method of moments estimation for beliefs in Section 4. Specifically, for any country i at future year t, we simulate the extreme weather arrival at t from the mixed Poisson process: with probability π_{it-1} we draw from the high Poisson jump arrival rate λ_{iB}, and with probability $(1 - \pi_{it-1})$ we draw from the low arrival rate λ_{iG}. Then we update beliefs π_{it} according to the belief-updating equation in Section 4. The simulation runs iteratively from $t = 1$: year 2020 to $t = 101$: year 2100 (remember we have already estimated all the learning parameters $\theta = (\pi_{i0}, \lambda_{iB}, \lambda_{iG})'$ in Section 4 for each country), and we obtain the simulate path of future extreme weather arrivals (as well as future beliefs).

Table 7: Summary statistics of projected real GDP per capita in 2100

This table presents the summary statistics of projected real GDP per capita across countries in 2100 using SSP5 and simulated arrivals from the time-varying extreme-weather arrivals model (Section 4) for both the cyclone and the heatwave sample. Real GDP per capita is in thousands of constant 2015 USD. We consider two scenarios: adaptation fixed at prior risk and state-dependent adaptation.

Projected real GDP per capita in 2100, time-varying arrivals model simulation				
	Cyclone sample		Heatwave sample	
	Fixed	State-dependent	Fixed	State-dependent
Mean	59.2	88.0	49.8	77.7
S.D.	37.1	50.0	34.0	56.6
Median	48.9	72.9	38.2	55.8
P5	20.5	39.1	16.7	25.1
P25	32.1	53.0	25.3	40.6
P75	75.3	105.6	69.1	99.3
P95	123.6	189.2	115.4	194.2

In Table 7, we report the projections for GDP in 2100, both for the cyclone sample and the extreme temperature sample. For the tropical cyclones sample, there is a significant difference in projected income depending on whether one accounts for learning and state-dependent adaptation. Using the constant-coefficient model that does not account for heterogeneity in state-dependent adaptation across countries, the mean income is 59.2 thousand dollars. Adding learning and state-dependent adaptation increases income from 59.2 thousand to 88.0 thousand dollars. That is, income with fixed adaptation would be nearly 32% lower than with state-dependent adaptation. For extreme temperature, income with fixed adaptation would be nearly

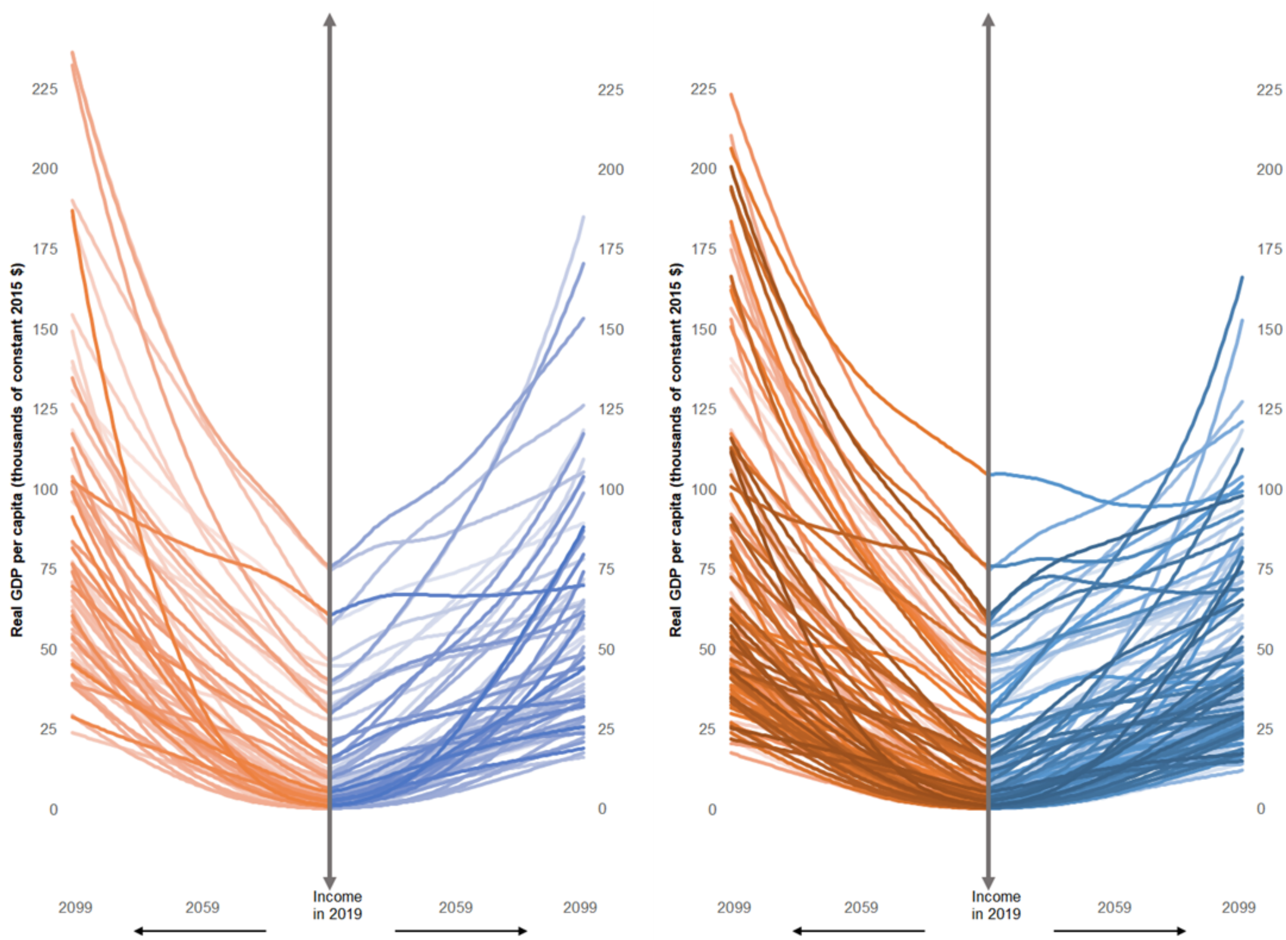
36% lower than with state-dependent adaptation. In other words, ignoring learning considerably overstates the damage from extreme-weather risks over long horizons.

Figure 7: Projections of real GDP per capita

This figure shows projections of real GDP per capita using simulated arrivals from the Bayesian learning model. Panel A shows the results for the cyclone sample and Panel B for the heatwave sample. The left figure in each panel (State-dependent Adaptation) uses adaptation estimates from the varying coefficient model and belief updates according to the simulated arrivals, while the right figure (Fixed Adaptation) uses damage estimates from the constant coefficient model. Real GDP per capita is shown in thousands of constant 2015 USD. Projections are shown from 2019 to 2100. We run 10,000 simulations for each country and take the median of the simulations as its projection. The baseline GDP growth projections without extreme weather damages come from the SSP5 (Shared Socio-Economic Pathway, Scenario 5, called "Fossil-Fueled Development" — Kriegler, Bauer, Popp, Humpenöder, Leimbach, Strefler, Baumstark, Bodirsky, Hilaire, Klein, et al. (2017)).

Panel A: Cyclone sample **Panel B: Heatwave sample**

Left: State-dependent Right: Fixed Left: State-dependent Right: Fixed



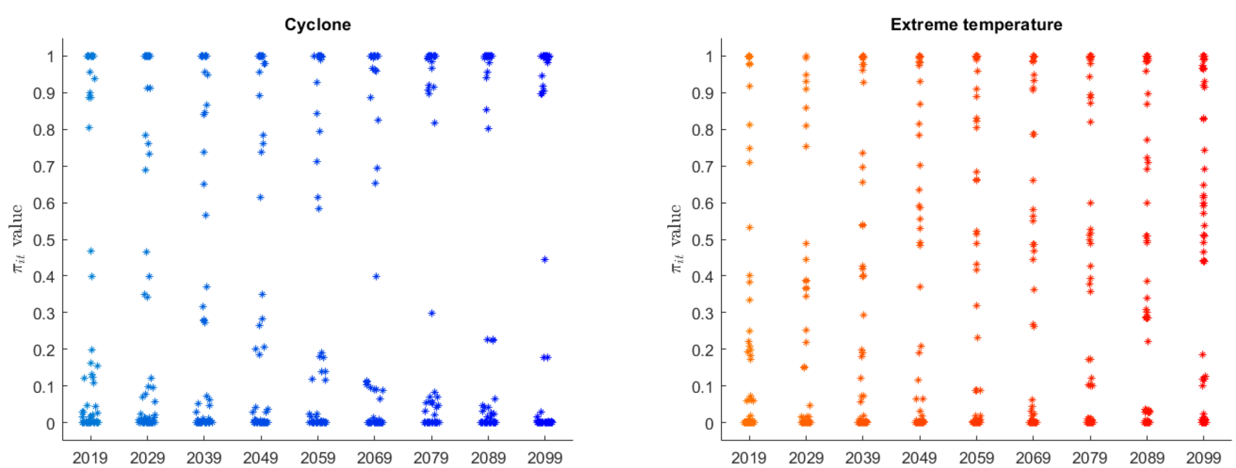
To see these differences country by country, in Figure 7, we report the projections for GDP using simulations of the time-varying arrivals model of Section 4. In Panel A, for the tropical cyclones sample, there is a significant difference depending on whether we account for learning (left side of the graphs) versus not doing so (right side of the graphs). The same is true for the extreme temperature sample in Panel B.[21]

Resolution of uncertainty in long run. To understand why adjusting for learning is more important for sample projections than in-sample counterfactuals, we plot in Figure 8 the evolution of π_{it} for all countries from the beginning of the end of our sample in 2019 to the end of projection period in 2099. We show the scatter plot of π_{it} values.

Compare the cyclone-risk evolution out of sample in Figure 8 to the analogous in-sample Figure 6. We can see considerably more dispersion in outcomes across countries in 2100. The same is true for the heatwave sample. This dispersion driven by uncertainty resolution means that adaptation becomes more valuable over the long run.

Figure 8: Evolution of π_{it} over time

This figure plots the evolution of π_{it} over time at each decade end from the sample end to the projection end. The scatter plot of π_{it} values is shown at each decade end.



[21]In Table A.5, we show that the results from a second-order Taylor approximation of the non-linear damage function are the same as those from a first-order Taylor approximation.

8 Conclusion

Global warming is expected to lead to more frequent occurrences of extreme weather but the effects for any given region is highly uncertain. As society learns from the arrivals of these events and changes spending on adaptations, the damage from extreme weather will vary over time. This learning channel is absent in linear models of economic damage with homogeneous and time-invariant parameters. We develop an approach to account for learning and adaptation. Our approach provides country-specific estimates of disaster risk as extreme-weather events unfold, and state-dependent marginal effects of extreme-weather damage on economic growth. Using data for tropical cyclones and extreme temperature from 1980-2019, we find that income in 2019 absent learning and state-dependent adaptation would be several percent lower. The return to state-dependent adaptation rises considerably in the future due to the resolution of uncertainty regarding extreme weather at long horizons.

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Appendices

Table A.1: Cyclone sample moments for each country

ISO Code	Country Name	M1	Var	M3	M4	AC
AUS	Australia	0.976	0.024	-0.023	0.022	0.975
BGD	Bangladesh	0.195	0.157	0.096	0.083	0.050
BHS	Bahamas, The	0.098	0.088	0.071	0.065	0.025
BLZ	Belize	0.293	0.207	0.086	0.078	0.100
BRA	Brazil	0.049	0.046	0.042	0.040	0.000
BRN	Brunei Darussalam	0.220	0.171	0.096	0.083	0.075
BWA	Botswana	0.049	0.046	0.042	0.040	0.000
CAN	Canada	0.634	0.232	-0.062	0.071	0.425
CHN	China	0.976	0.024	-0.023	0.022	0.975
COL	Colombia	0.049	0.046	0.042	0.040	0.000
CRI	Costa Rica	0.293	0.207	0.086	0.078	0.100
CUB	Cuba	0.463	0.249	0.018	0.063	0.125
DOM	Dominican Republic	0.293	0.207	0.086	0.078	0.075
ESP	Spain	0.098	0.088	0.071	0.065	0.000
FJI	Fiji	0.244	0.184	0.094	0.082	0.100
FRA	France	0.049	0.046	0.042	0.040	0.000
GBR	United Kingdom	0.073	0.068	0.058	0.054	0.000
GIN	Guinea	0.049	0.046	0.042	0.040	0.000
GNB	Guinea-Bissau	0.049	0.046	0.042	0.040	0.000
GRL	Greenland	0.049	0.046	0.042	0.040	0.000
GTM	Guatemala	0.220	0.171	0.096	0.083	0.075
HND	Honduras	0.220	0.171	0.096	0.083	0.075
HTI	Haiti	0.171	0.142	0.093	0.081	0.050
IDN	Indonesia	0.220	0.171	0.096	0.083	0.075
IND	India	0.805	0.157	-0.096	0.083	0.375
IRL	Ireland	0.049	0.046	0.042	0.040	0.000
IRN	Iran, Islamic Rep.	0.049	0.046	0.042	0.040	0.000
ISL	Iceland	0.049	0.046	0.042	0.040	0.000
JAM	Jamaica	0.049	0.046	0.042	0.040	0.000
JPN	Japan	0.976	0.024	-0.023	0.022	0.950
KHM	Cambodia	0.244	0.184	0.094	0.082	0.100
KOR	Korea, Rep.	0.707	0.207	-0.086	0.078	0.450
LAO	Lao PDR	0.902	0.088	-0.071	0.065	0.850
LKA	Sri Lanka	0.049	0.046	0.042	0.040	0.000

Cyclone sample moments for each country, continued

ISO Code	Country Name	M1	Var	M3	M4	AC
MDG	Madagascar	0.829	0.142	-0.093	0.081	0.675
MEX	Mexico	0.976	0.024	-0.023	0.022	0.950
MNG	Mongolia	0.049	0.046	0.042	0.040	0.000
MOZ	Mozambique	0.561	0.246	-0.030	0.064	0.325
MUS	Mauritius	0.049	0.046	0.042	0.040	0.000
MWI	Malawi	0.049	0.046	0.042	0.040	0.000
MYS	Malaysia	0.220	0.171	0.096	0.083	0.075
NAM	Namibia	0.049	0.046	0.042	0.040	0.000
NGA	Nigeria	0.049	0.046	0.042	0.040	0.000
NIC	Nicaragua	0.317	0.217	0.079	0.076	0.100
NOR	Norway	0.049	0.046	0.042	0.040	0.000
NZL	New Zealand	0.122	0.107	0.081	0.073	0.050
OMN	Oman	0.049	0.046	0.042	0.040	0.000
PAK	Pakistan	0.098	0.088	0.071	0.065	0.000
PAN	Panama	0.293	0.207	0.086	0.078	0.100
PHL	Philippines	0.951	0.046	-0.042	0.040	0.900
PNG	Papua New Guinea	0.049	0.046	0.042	0.040	0.000
PRI	Puerto Rico	0.122	0.107	0.081	0.073	0.050
PRT	Portugal	0.049	0.046	0.042	0.040	0.000
RUS	Russian Federation	0.610	0.238	-0.052	0.068	0.350
SEN	Senegal	0.073	0.068	0.058	0.054	0.025
SLB	Solomon Islands	0.073	0.068	0.058	0.054	0.025
SLV	El Salvador	0.293	0.207	0.086	0.078	0.100
SWZ	Eswatini	0.049	0.046	0.042	0.040	0.000
THA	Thailand	0.780	0.171	-0.096	0.083	0.625
TTO	Trinidad and Tobago	0.049	0.046	0.042	0.040	0.000
SGP	Singapore	0.220	0.171	0.096	0.083	0.075
TZA	Tanzania	0.561	0.246	-0.030	0.064	0.600
USA	United States	0.976	0.024	-0.023	0.022	0.975
VEN	Venezuela, RB	0.073	0.068	0.058	0.054	0.025
VNM	Vietnam	0.976	0.024	-0.023	0.022	0.950
VUT	Vanuatu	0.122	0.107	0.081	0.073	0.025
YEM	Yemen, Rep.	0.049	0.046	0.042	0.040	0.000
ZAF	South Africa	0.049	0.046	0.042	0.040	0.000
ZWE	Zimbabwe	0.122	0.107	0.081	0.073	0.025

Table A.2: Heatwave sample moments for each country

ISO Code	Country Name	M1	Var	M3	M4	AC
AGO	Angola	0.200	0.160	0.096	0.083	0.154
ALB	Albania	0.425	0.244	0.037	0.065	0.308
ARE	United Arab Emirates	0.150	0.128	0.089	0.079	0.103
AUS	Australia	0.225	0.174	0.096	0.083	0.205
AUT	Austria	0.200	0.160	0.096	0.083	0.051
BDI	Burundi	0.425	0.244	0.037	0.065	0.308
BEL	Belgium	0.325	0.219	0.077	0.075	0.154
BEN	Benin	0.050	0.048	0.043	0.041	0.000
BFA	Burkina Faso	0.350	0.228	0.068	0.072	0.256
BGR	Bulgaria	0.300	0.210	0.084	0.078	0.205
BHS	Bahamas, The	0.350	0.228	0.068	0.072	0.205
BOL	Bolivia	0.250	0.188	0.094	0.082	0.205
BRA	Brazil	0.300	0.210	0.084	0.078	0.231
BWA	Botswana	0.375	0.234	0.059	0.070	0.154
CAF	Central African Republic	0.175	0.144	0.094	0.082	0.154
CAN	Canada	0.200	0.160	0.096	0.083	0.051
CHE	Switzerland	0.100	0.090	0.072	0.066	0.026
CHL	Chile	0.025	0.024	0.023	0.023	0.000
CHN	China	0.050	0.048	0.043	0.041	0.000
CIV	Cote d'Ivoire	0.150	0.128	0.089	0.079	0.077
CMR	Cameroon	0.275	0.199	0.090	0.080	0.256
COD	Congo, Dem. Rep.	0.175	0.144	0.094	0.082	0.103
COG	Congo, Rep.	0.050	0.048	0.043	0.041	0.000
COL	Colombia	0.225	0.174	0.096	0.083	0.205
CPV	Cabo Verde	0.225	0.174	0.096	0.083	0.154
CRI	Costa Rica	0.600	0.240	-0.048	0.067	0.436
CUB	Cuba	0.025	0.024	0.023	0.023	0.000
CYP	Cyprus	0.075	0.069	0.059	0.055	0.000
DEU	Germany	0.275	0.199	0.090	0.080	0.128
DNK	Denmark	0.250	0.188	0.094	0.082	0.128
DOM	Dominican Republic	0.100	0.090	0.072	0.066	0.051
DZA	Algeria	0.525	0.249	-0.012	0.063	0.385
ECU	Ecuador	0.250	0.188	0.094	0.082	0.205
EGY	Egypt, Arab Rep.	0.300	0.210	0.084	0.078	0.282
ESP	Spain	0.400	0.240	0.048	0.067	0.231
ETH	Ethiopia	0.275	0.199	0.090	0.080	0.205
FIN	Finland	0.450	0.248	0.025	0.064	0.308
FJI	Fiji	0.225	0.174	0.096	0.083	0.205
FRA	France	0.250	0.188	0.094	0.082	0.103
GAB	Gabon	0.125	0.109	0.082	0.073	0.103
GBR	United Kingdom	0.050	0.048	0.043	0.041	0.000
GEO	Georgia	0.250	0.188	0.094	0.082	0.154
GHA	Ghana	0.200	0.160	0.096	0.083	0.154
GIN	Guinea	0.275	0.199	0.090	0.080	0.231
GMB	Gambia, The	0.225	0.174	0.096	0.083	0.205
GNB	Guinea-Bissau	0.100	0.090	0.072	0.066	0.026
GNQ	Equatorial Guinea	0.325	0.219	0.077	0.075	0.282
GRC	Greece	0.125	0.109	0.082	0.073	0.051
GTM	Guatemala	0.900	0.090	-0.072	0.066	0.872
HND	Honduras	0.500	0.250	0.000	0.063	0.359
HUN	Hungary	0.275	0.199	0.090	0.080	0.103
IRL	Ireland	0.075	0.069	0.059	0.055	0.026
IRN	Iran, Islamic Rep.	0.350	0.228	0.068	0.072	0.256
IRQ	Iraq	0.375	0.234	0.059	0.070	0.256
ISL	Iceland	0.200	0.160	0.096	0.083	0.077
ISR	Israel	0.075	0.069	0.059	0.055	0.051
ITA	Italy	0.250	0.188	0.094	0.082	0.154
JAM	Jamaica	0.050	0.048	0.043	0.041	0.000
JOR	Jordan	0.250	0.188	0.094	0.082	0.231
JPN	Japan	0.075	0.069	0.059	0.055	0.026
KEN	Kenya	0.300	0.210	0.084	0.078	0.205
KHM	Cambodia	0.075	0.069	0.059	0.055	0.026
KOR	Korea, Rep.	0.050	0.048	0.043	0.041	0.000
KWT	Kuwait	0.475	0.249	0.012	0.063	0.333

Heatwave sample moments for each country, continued

ISO Code	Country Name	M1	Var	M3	M4	AC
LAO	Lao PDR	0.225	0.174	0.096	0.083	0.128
LBN	Lebanon	0.600	0.240	-0.048	0.067	0.538
LKA	Sri Lanka	0.150	0.128	0.089	0.079	0.077
LSO	Lesotho	0.225	0.174	0.096	0.083	0.205
LUX	Luxembourg	0.150	0.128	0.089	0.079	0.051
LVA	Latvia	0.575	0.244	-0.037	0.065	0.385
MAR	Morocco	0.375	0.234	0.059	0.070	0.256
MDG	Madagascar	0.250	0.188	0.094	0.082	0.231
MEX	Mexico	0.225	0.174	0.096	0.083	0.205
MLI	Mali	0.275	0.199	0.090	0.080	0.128
MNG	Mongolia	0.475	0.249	0.012	0.063	0.333
MOZ	Mozambique	0.100	0.090	0.072	0.066	0.026
MRT	Mauritania	0.100	0.090	0.072	0.066	0.026
MUS	Mauritius	0.125	0.109	0.082	0.073	0.077
MWI	Malawi	0.450	0.248	0.025	0.064	0.333
MYS	Malaysia	0.025	0.024	0.023	0.023	0.000
NAM	Namibia	0.450	0.248	0.025	0.064	0.256
NER	Niger	0.125	0.109	0.082	0.073	0.077
NGA	Nigeria	0.075	0.069	0.059	0.055	0.026
NIC	Nicaragua	0.525	0.249	-0.012	0.063	0.385
NLD	Netherlands	0.375	0.234	0.059	0.070	0.179
NOR	Norway	0.325	0.219	0.077	0.075	0.205
NPL	Nepal	0.100	0.090	0.072	0.066	0.051
NZL	New Zealand	0.025	0.024	0.023	0.023	0.000
OMN	Oman	0.225	0.174	0.096	0.083	0.205
PAK	Pakistan	0.075	0.069	0.059	0.055	0.026
PAN	Panama	0.150	0.128	0.089	0.079	0.051
PER	Peru	0.300	0.210	0.084	0.078	0.231
PNG	Papua New Guinea	0.225	0.174	0.096	0.083	0.205
POL	Poland	0.300	0.210	0.084	0.078	0.128
PRT	Portugal	0.125	0.109	0.082	0.073	0.051
PRY	Paraguay	0.250	0.188	0.094	0.082	0.205
QAT	Qatar	0.400	0.240	0.048	0.067	0.282
RWA	Rwanda	0.350	0.228	0.068	0.072	0.205
SAU	Saudi Arabia	0.175	0.144	0.094	0.082	0.103
SDN	Sudan	0.175	0.144	0.094	0.082	0.128
SEN	Senegal	0.325	0.219	0.077	0.075	0.231
SLE	Sierra Leone	0.050	0.048	0.043	0.041	0.000
SLV	El Salvador	0.625	0.234	-0.059	0.070	0.513
SWE	Sweden	0.175	0.144	0.094	0.082	0.077
SWZ	Eswatini	0.225	0.174	0.096	0.083	0.103
SYR	Syrian Arab Republic	0.325	0.219	0.077	0.075	0.205
TCD	Chad	0.225	0.174	0.096	0.083	0.128
TGO	Togo	0.275	0.199	0.090	0.080	0.231
THA	Thailand	0.025	0.024	0.023	0.023	0.000
TTO	Trinidad and Tobago	0.300	0.210	0.084	0.078	0.231
TUN	Tunisia	0.550	0.248	-0.025	0.064	0.462
TUR	Turkey	0.250	0.188	0.094	0.082	0.179
TZA	Tanzania	0.025	0.024	0.023	0.023	0.000
UGA	Uganda	0.300	0.210	0.084	0.078	0.205
URY	Uruguay	0.050	0.048	0.043	0.041	0.000
USA	United States	0.125	0.109	0.082	0.073	0.051
VEN	Venezuela, RB	0.225	0.174	0.096	0.083	0.128
VUT	Vanuatu	0.250	0.188	0.094	0.082	0.231
ZAF	South Africa	0.200	0.160	0.096	0.083	0.179
ZMB	Zambia	0.475	0.249	0.012	0.063	0.282
ZWE	Zimbabwe	0.300	0.210	0.084	0.078	0.205

Table A.3: Summary statistics of sample moments across all countries

This table shows the summary statistics of country-level cyclone and heatwave sample moments across all countries. M1 is the mean of arrivals, Var is the variance, M3 is the 3rd central moment, M4 is the 4th central moment, and AC is the first-order autocorrelation, defined as the sample analogue of $\mathbb{E}[D_t D_{t-1}]$.

Panel A: Cyclone sample moments					
	Mean	S.D.	Median	P10	P90
M1	0.29	0.32	0.12	0.05	0.95
Var	0.10	0.07	0.07	0.05	0.21
M3	0.04	0.05	0.04	-0.04	0.09
M4	0.06	0.02	0.05	0.04	0.08
AC	0.19	0.31	0.05	0.00	0.90
Panel B: Heatwave sample moments					
	Mean	S.D.	Median	P10	P90
M1	0.25	0.16	0.23	0.05	0.45
Var	0.16	0.07	0.17	0.05	0.24
M3	0.06	0.04	0.08	0.02	0.10
M4	0.07	0.02	0.07	0.04	0.08
AC	0.17	0.14	0.15	0.00	0.31

Table A.4: Panel regression estimates of the state-dependent model

This table shows the estimation results of our state-dependent model in a pooled panel regression. t-statistics (with bootstrapped standard errors) are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

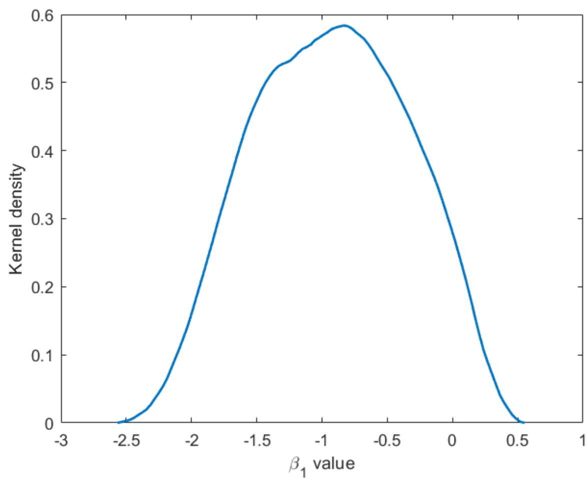
	Cyclone	Heatwave
$\hat{\beta}_1$	-0.992***	-0.682***
	(-15.0)	(-13.4)
$\hat{\beta}_2$	0.177**	0.148***
	(2.28)	(2.63)
Country FE	Yes	Yes
Year FE	Yes	Yes

Figure A.1: Density of $\hat{\beta}_{1i}$ and $\hat{\beta}_{2i}$ after detrending

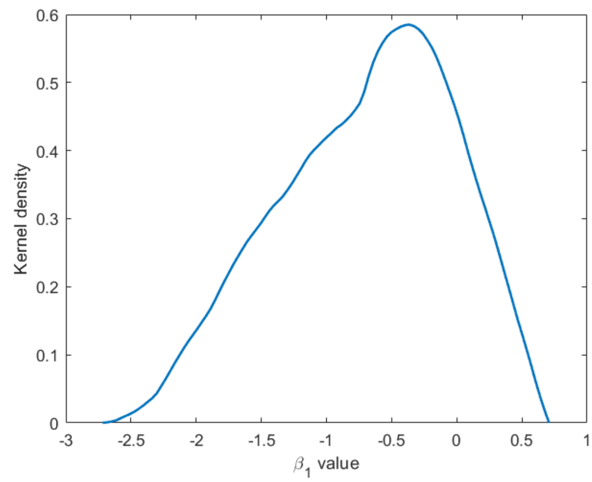
This figure plots the density (estimated using the Epanchnikov kernel) of the individual $\hat{\beta}_{1i}$ and $\hat{\beta}_{2i}$ estimated from the detrended version of our main equation (8).

Panel A: Density plot of $\hat{\beta}_{1i}$

Cyclone $\hat{\beta}_{1i}$

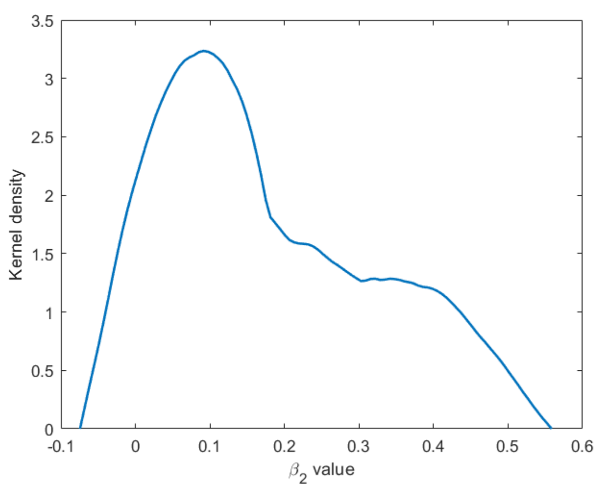


Heatwave $\hat{\beta}_{1i}$



Panel B: Density plot of $\hat{\beta}_{2i}$

Cyclone $\hat{\beta}_{2i}$



Heatwave $\hat{\beta}_{2i}$

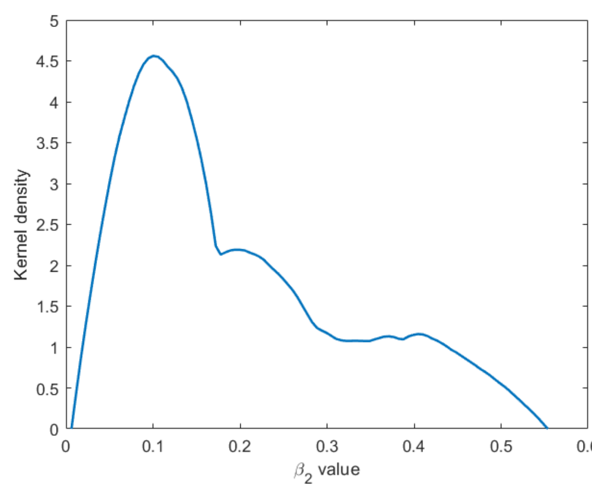


Table A.5: Summary statistics of projected real GDP per capita in 2100, higher order Taylor approximation

This table presents the summary statistics of projected real GDP per capita across countries in 2100 using the Bayesian model simulation for both the cyclone and the heatwave sample. Real GDP per capita is in thousands of constant 2015 USD. Adaptation is our main adaptation function with the first-order Taylor approximation. Adaptation order 2 is the adaptation function with the second-order Taylor approximation.

Projected real GDP per capita in 2100, higher order Taylor approximation				
	Cyclone sample		Heatwave sample	
	Adaptation	Adaptation order 2	Adaptation	Adaptation order 2
Mean	88.0	89.6	77.7	80.5
S.D.	50.0	50.5	56.6	57.0
Median	72.9	74.4	55.8	58.2
P5	39.1	40.0	25.1	26.1
P25	53.0	54.6	40.6	41.9
P75	105.6	110.2	99.3	101.6
P95	189.2	195.3	194.2	198.3