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A New Perspective on Temperature Shocks

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ABSTRACT: Prevailing research suggests that climate change disproportionately burdens emerging markets and developing economies with greater output losses compared to advanced economies, positing that colder regions are less impacted than their warmer counterparts. This study revisits the empirical relationship between temperature fluctuations and real growth, with a novel focus on differentiating between transitory versus permanent temperature shifts, aligning naturally with the definitions of weather and climate change, respectively. Our findings reveal that richer and colder economies exhibit better adaptation only in response to weather shocks, whereas the pattern reverses for climate change disturbances, challenging the conclusions of previous studies.

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WORKING PAPERS

A New Perspective on Temperature Shocks

Prepared by Nooman Rebei[1]

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1 Introduction

Surface temperature, at a global and country levels, is known to display and upward trend (non-stationary). Conventional empirical models designed to assess the impact of climate change on aggregate output often struggle to distinctly identify permanent changes in temperature. Instead, many studies incorporate temperature using levels, growth rates, or a combination of both to explain the dynamics of output growth. In the field of time series analysis, it is a well-established fact that regressions involving non-stationary or trending variables generally result in statistical inconsistencies and can frequently be spurious.

Research that examines the role of climate change effects on economic growth include Dell, Jones, and Olken (2012), Burke, Hsiang, and Miguel (2015), Tol (2018), Acevedo, Mrkaic, Novta, Pugacheva, and Topalova (2020), and Waidelich, Batibeniz, Rising, Kikstra, and Seneviratne (2024); who highlight a significant and non-linear impact of temperature on economic productivity, revealing that productivity declines sharply at higher temperatures.[1] Letta and Tol (2019) and Henseler and Schumacher (2019) report similar results for total factor productivity growth. In an attempt to account for long-term shifts of temperature, some proposed averaging the weather variables over a certain number of years and running longer-difference estimates. Results remain qualitatively similar. Nath, Ramey, and Klenow (2023) challenge the quantitative findings as they show that output growth losses are amplified due to omitted lags and serial correlation of temperature. Further, they develop a model where the impact of temperature shocks, as opposed to temperature levels, on output depends on the country's average temperature.[2] They still find that hot countries will be harmed by warming and cold countries less affected.

Few papers show distinct results as they find substantial heterogeneity across countries in the impulse responses of real growth. Kahn et al. (2021) take the persistence of climate change more seriously by introducing deviations of temperature and precipitation from their long-term moving average historical norms instead of their levels. Interestingly, shifts in weather patterns, indicative of climate change, impact not only countries with low incomes or those situated in warm climates but also affect advanced economies and regions with cooler climates. Similar findings are illustrated by Berg, Curtis, and Nelson (2023) from a country-specific time series perspective using local projections. Bilal and Känzig (2024) estimate significantly larger impacts of climate change than previously reported. By analyzing natural fluctuations in

[1] The general approach consists of using within-country and across-country year-to-year fluctuations in temperature and precipitation to identify their causal effect on aggregate output growth, both contemporaneously and over the medium term.

[2] In the process of identifying temperature shocks, Nath et al. (2023) adopt an autoregressive process for temperature including variables that are still trending.

global temperatures, they document that global temperature shocks lead to adverse economic effects even in higher-income, colder regions. Their findings are motivated by the observation that global temperature shocks correlate much more strongly with extreme weather events compared to country-specific temperature changes.

Despite the obvious evidence that trending temperature is a characterization of climate change, the existing literature is silent about this central identification issue. Furthermore, global and country-specific long-term scenarios of temperatures are attributed to very persistent pathways for greenhouse gas concentrations and the amount of warming that could occur by the end of the century.[3] To fill this gap, two motivations drive our inquiry. First, temperature is trending and it is important to revisit the empiric of the relation between climate change and real growth while explicitly distinguishing between permanent and transitory temperature shifts. The second motivation consists of the heterogeneous climate change witnessed during the recent decades at the country level. We document evidence showing that advanced economies (AEs) are becoming hotter at a faster pace than emerging markets and developing economies (EMDEs). This could have a different implications in the long term depending on the sensitivity of the economic environment to rising temperatures.

We also find the motivation of our analysis in the literature examining the fundamental aspects of temperature time series, aiming to detect the source of non-stationarity and differentiate between linear and stochastic trends. Results are inconclusive when tests on individual time series are adopted,[4] An alternative methodology to identify the driver of temperature trend is through testing the cointegration between temperature and radiative forcing. In the positive case, temperature should share a common stochastic trend with the variable measuring radiative forcing.[5] Kaufmann, Kauppi, Mann, and Stock (2013) adopt cointegration and error correction approach to explore the relationship between temperature and radiative forcing, uncovering evidence that temperature anomalies exhibit stochastic rather

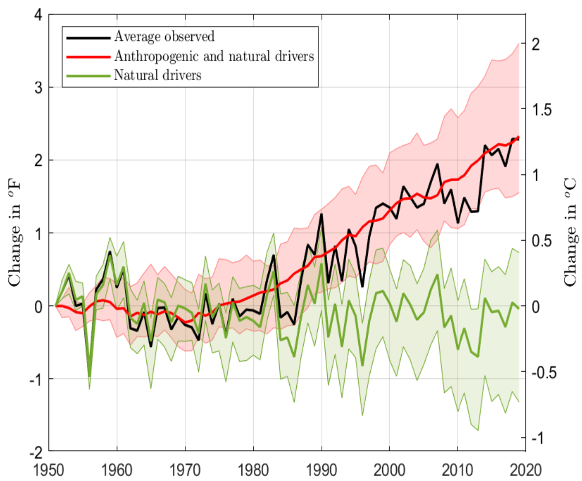
[3]The development of pathways to understand future environmental changes is spearheaded by two distinct research initiatives: the "Representative Concentration Pathways" (RCPs) and the "Shared Socioeconomic Pathways" (SSPs). RCPs provide scenarios that outline various levels of greenhouse gases and other radiative forcings, offering insights into potential future atmospheric compositions without incorporating socioeconomic storylines. On the other hand, SSPs take a comprehensive approach by modeling potential shifts in socioeconomic factors over the coming century, including changes in population, economic growth, education levels, urbanization trends, and the pace of technological innovation.

[4]Numerous research efforts have found evidence supporting the existence of a stochastic trend, as indicated by works from Gordon (1991), Woodward and Gray (1993, 1995), and Kärner (1996). On the other hand, a significant number of studies have identified evidence suggesting the presence of a deterministic trend, potentially accompanied by highly persistent noise, as seen in the research by Bloomfield (1992), Bloomfield and Nychka (1992), Baillie and Chung (2002), and Fomby and Vogelsang (2002).

[5]Such cointegration would align with the theory that economic activity and atmospheric lifetimes introduce a stochastic trend to radiative forcing, which in turn affects temperature trends.

than deterministic trends. Based on trend-stationary long memory models, Chang et al. (2020) reach the same findings. Based on our regressions, Figure 1 illustrates the stochastic trend and the non-persistent component of average global temperature, which are very similar to science-based results illustrated in IPCC (2021).

Figure 1: Global Surface Temperature



Our modeling strategy follows Uribe (2022) and Rebei and Sbia (2021) to account for temporary and permanent shocks for temperature and real output. The model is framed using detrended endogenous variables and external shocks. Given that both the external shocks and stochastic trends are not directly observable, the majority of the model's variables are considered latent. However, the estimation leverages the model's ability to provide accurate predictions for variables that can be observed. The likelihood of the data is computed using the Kalman filter, and Bayesian techniques are applied in the econometric estimation. Our analysis yields three principal findings. First, in recent decades, there has been a noticeable upward trend in temperature across countries, with significant disparities. Notably, cold countries have witnessed the most substantial changes—around 0.5°C higher than hot regions. Second, the previously reported pattern where poor and hot countries appear more affected by increasing temperatures holds true only in the context of non-persistent shocks. The impact of climate change turns out to be more pronounced in colder and wealthier nations and less pronounced in hotter and poorer nations, resulting in an average output loss of 6 percent and 1 percent, respectively, under the most severe temperature increase scenario. Third, temperature shocks account for approximately one-quarter of the observed variations in aggregate economic activity in rich countries, while their impact is significantly lower in poor and hot countries. Moreover, only one-quarter of the contribution of temperature shocks is attributed to temporary disturbances, while the remaining three-quarters are driven by the permanent effects of climate change.

Our findings challenge the existing literature, which posits that colder and wealthier regions are less impacted by climate change than warmer regions due to an assumed, but unproven, greater capacity for adaptation. Burke et al. (2024) examine the extent to which societies are adapting to climate change by analyzing a broad array of longitudinal datasets across different geographies and sectors. Empirical results suggest an observed lack of adaptation including in advanced economies. We attribute our results to the fact that in wealthier countries, temperature trends are more pronounced in colder regions, accompanied by a higher frequency and greater damages from natural disasters. Similarly, Bilal and Känzig (2024) identify extreme climatic events as the primary transmission channel of climate change impacts.

The remainder of this paper is organized as follows. Section 2 describes the underlying assumptions of the empirical model used to disentangle permanent and temporary temperature components and how they affect output growth. Section 3 displays the estimation methodology. Section 4 explores the empirical implications from the country-specific regressions. Section 5 undertakes a cross-country analysis of forecast error variances. A robustness check, consisting of potential reverse causality, is considered in Section 6. Finally, we present concluding remarks in Section 7.

2 Model

Weather describes the short-term state of the lower atmosphere, encompassing elements such as precipitation, temperature, humidity, wind speed and direction, and atmospheric pressure. These conditions are in constant motion, leading to frequent weather changes, as seen with events like the Indian Summer Monsoon Rainfall and the El Niño-Southern Oscillation. In contrast, climate refers to atmospheric trends and shifts observed over extended periods of time.

To differentiate the effects of weather and climate on temperature, we can assume that temperature consists of both a transitory component and a permanent one. In the simplest setting, expressing variables in logarithms, one can formalize this as follows:

$$T_t = \Psi_t^T + \phi_t^T, \tag{1}$$

where $\Psi_t^T = \Psi_{t-1}^T + \nu_t^T$ and $\phi_t^T = \rho\phi_{t-1}^T + \eta_t^T$. The two temperature innovations ν_t^T and η_t^T are i.i.d. shocks; however, they imply persistent and temporary effects, respectively.

It is important to note that based on the specification of temperature in Equation 1, this variable is assumed non-stationary by definition.

Now, let's assume a more general process of evolution of temperature by allowing it to be autocorrelated—due to the cumulative CO_2 emissions. Since the observed temperature has a unit root that could be attributed to a stochastic trend, we define a "detrended" measure of temperature $\hat{T}_t = T_t - \Psi_t^T$. Then, we can express the following autoregressive equation:

$$\hat{T}_t = \sum_{i=1}^{p} \rho_j \hat{T}_{t-j} + \kappa \Delta \Psi_t^T + \phi_t^T. \tag{2}$$

Similarly, we assume that real GDP has a stochastic trend, $\hat{\Psi}_t^Y$, that could be affected by an exogenous trend, $\Psi_t^Y = \Psi_{t-1}^Y + \nu_t^Y$, and the long-term temperature trend, Ψ_t^T (to be statistically tested based on the estimation outcome). Hence, $\hat{Y}_t = Y_t - \hat{\Psi}_t^Y$, where $\hat{\Psi}_t^Y = \Psi_t^Y + \lambda \Psi_t^T$.

We define the law of motion of the detrended real GDP as follows:

$$\hat{Y}_t = \sum_{j=1}^{p} \beta_j \hat{Z}_{t-j} + \theta \Delta \Psi_t^Y + \gamma \Delta \Psi_t^T + \alpha \phi_t^T + \phi_t^Y, \tag{3}$$

where $\hat{Z}_{t-j} = \left\{ \hat{T}_{t-j}, \hat{Y}_{t-j} \right\}_{j=1}^{p}$.[6]

By construction, $\Delta \Psi_t^Y$ and $\Delta \Psi_t^T$ denote changes in the non-stationary innovations while ϕ_t^Y and ϕ_t^T correspond to temporary shocks.

The observable variables used in the estimation of the empirical model are growth rates of temperature and real GDP. The observable variables are linked to the variables included in the unobservable system Equations 2 and 3 through the following relations

$$\Delta T_t = \hat{T}_t - \hat{T}_{t-1} + \Delta \Psi_t^T, \tag{4}$$

and

$$\Delta Y_t = \hat{Y}_t - \hat{Y}_{t-1} + \left(\Delta \Psi_t^Y + \lambda \Delta \Psi_t^T \right). \tag{5}$$

For more generality, we allow shocks to weather and climate change to be serially correlated. Formally, the transitory and permanent components evolve according to

$$\begin{bmatrix} \Delta \Psi_{t+1}^T \\ \phi_{t+1}^T \\ \Delta \Psi_{t+1}^Y \\ \phi_{t+1}^Y \end{bmatrix} = \Theta \begin{bmatrix} \Delta \Psi_t^T \\ \phi_t^T \\ \Delta \Psi_t^Y \\ \phi_t^Y \end{bmatrix} + \Sigma \begin{bmatrix} \mu_t^T \\ \eta_t^T \\ \mu_t^Y \\ \eta_t^Y \end{bmatrix} \tag{6}$$

where Θ and Σ are 4-by-4 diagonal matrices; μ_t^i and η_t^i ($i = T, Y$) are i.i.d. normally distributed disturbances.

[6] Other papers such as Burke et al. (2015) and Kahn et al. (2021) include precipitation variables in the regression arguing that they could also capture climate change. On the other hand, others like Nath et al. (2023) and Bilal and Känzig (2024) find they were not significant and their presence did not change the estimated impulse responses.

We denote o_t be the vector of variables observed in year t, which corresponds to $o_t = [\Delta T_t \ \Delta Y_t]'$. The state-space representation of the system composed of Equations (2) to (6) can be written as follows:

$$\zeta_{t+1} = A\,\zeta_t + B\,\varepsilon_{t+1}$$
$$o_t = C' + D'\,\zeta_t,$$

where $\zeta_t = [\hat{Z}_{t-1} \ldots \hat{Z}_{t-p+1} \ \ u_t]'$, $u_t = [\Delta\Psi_t^T \ \ \phi_t^T \ \ \Delta\Psi_t^Y \ \ \phi_t^Y]'$, and $\varepsilon_t = [\mu_t^T \ \ \eta_t^T \ \ \mu_t^Y \ \ \eta_t^Y]'$. The matrices A, B, C, and D are known functions of ρ_j, β_j^i (for $i = T, Y$; and $j = 1, ..., p$), κ, γ, α, and λ. Let's define I_i as an identity matrix of order i, $\emptyset_i$ is a square matrix of order i with all elements equal to zero, while $\emptyset_{i,j}$ denotes a matrix of order i by j with all entries equal to zero. Further, let q and n denote, respectively, the number of the number of shocks ($= 4$) and the number of endogenous variables included in the empirical model ($= 2$). We also define

$$G \equiv \begin{bmatrix} \rho_1 \ \ldots \ \rho_p & \emptyset_{1,p} \\ \beta_1^T \ \ldots \ \beta_p^T & \beta_1^Y \ \ldots \ \beta_p^Y \end{bmatrix}, \quad H \equiv \begin{bmatrix} \kappa & 1 & 0 & 0 \\ \gamma\lambda & \alpha & \gamma & 1 \end{bmatrix}$$

Hence, for $p \geq 2$, we have

$$A = \begin{bmatrix} G & H\Theta \\ \begin{bmatrix} I_{n(p-1)} & \emptyset_{n(p-1),n} \end{bmatrix} & \emptyset_{n(p-1),q} \\ \emptyset_{q,np} & \Theta \end{bmatrix}, \quad B = \begin{bmatrix} H\Sigma \\ \emptyset_{n(p-1),q} \\ \Sigma \end{bmatrix}$$

$$C = [\mathbb{E}(\Delta\Psi_t^T) \ \ \mathbb{E}(\Delta\Psi_t^Y)] \ \text{ and } \ D = [M_\zeta \ \ \emptyset_{n,n(p-2)} \ \ M_u],$$

where the matrices M_ζ and M_u take the form

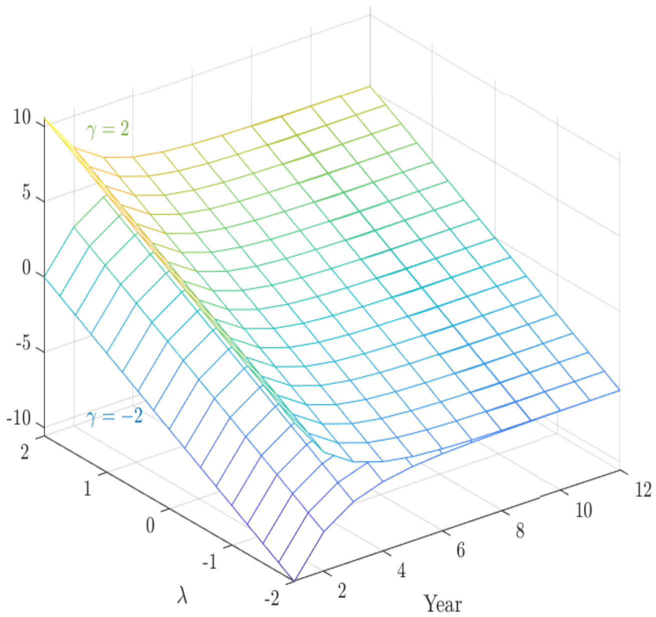
$$M_\zeta = \begin{bmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & -1 \end{bmatrix} \ \text{ and } \ M_u = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \lambda & 1 & 0 & 0 \end{bmatrix}.$$

To gain deeper insights into how persistent shocks on temperature affect real output, we first calibrate a simplified version of the model and then iteratively simulate the impulse-response functions using different values for the two key parameters λ and γ. Figure 2 illustrates the sensitivity of output level responses to a sudden permanent increase of 1^oC.[7] For significantly negative values of λ, the output response

[7]This is only valid conditional on a one-off permanent shock, the parameter γ still plays a crucial role in the shock decomposition including the permanent ones during the estimation process; besides SSPs and RCPs scenarios would imply a sequence of shocks until 2100 and the response of output would depend on γ in the long-term.

reaches a new low, with the transition primarily influenced by γ, which determines the speed of convergence. After the sixth year, the output response becomes insensitive to the transition parameter γ and is instead driven entirely by the long-term equilibrium relationship, as indicated by the cointegration term λ. This highlights the underlying short- and long-term conditional moments that could help identify the key parameters of the proposed model.

Figure 2: Output growth response to a permanent increase of temperature of 1^oC



Notes: The average temperature is assumed to be 68^oF (20^oC); and 1^oC increase would correspond to a shock of magnitude 2.64 percent.

3 Estimation

The two observable variables considered in the regressions are real output and surface temperature. We use real GDP from Penn World Table PWT version 10.01 as it provides the most extensive data both in terms of country coverage and years availability. Temperature is measured as the observed annual average mean surface air temperature reported by the World Bank database—Climate Change Knowledge Portal.[8] The model is estimated using data from twenty advanced economies and twenty emerging markets and developing economies.[9]

[8]The Climatic Research Unit (CRU) at the University of East Anglia generates observed, historical climate data. This data is available at a resolution of $0.5^o \times 0.5^o$ ($50km \times 50km$).

[9]AEs correspond to: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Iceland, Italy, Japan, Korea, Netherlands, Norway, Portugal, Spain, Sweden, United Kingdom, and United States. EMDEs include: Argentina, Bangladesh, Brazil, Chile, China, Cameroon, Egypt, India, Kenya, Madagascar, Malaysia, Mexico, Morocco, Nepal, Pakistan, Romania, South Africa, Thailand, Tunisia, and Turkey.

Table 1 presents the prior distributions for the parameters of our model, following the Minnesota prior framework, a well-established method for setting macroeconomic priors in VAR coefficient analysis. This approach assumes that treating each variable in the system as an independent random walk is a reasonable representation of their time series behavior. Consequently, this assumption suggests that a variable's own historical data (own lags) typically provide more information than the historical data of other variables. Furthermore, it posits that more recent data points (lags) of a variable offer more insight than older ones, emphasizing the importance of recent trends over distant past behavior. Formally, the coefficients in the diagonal of the autocorrelation matrix in Equation 5 are a priori independent and normally distributed, with means and standard deviations set to 0.5 and 0.15, respectively. Furthermore, we choose flat prior distributions for the B matrix coefficients capturing the contemporaneous reaction of the endogenous variables to structural shocks—Gamma (Normal) distributions with mean values set to 1 (0) and standard deviations equal to 2 or 1. Permanent and temporary components of temperature and output exhibit a degree of persistence captured by the diagonal of the matrix Θ. Autocorrelations follow prior Beta distributions with mean 0.2 and standard deviations set to 0.15. Finally, we assume inverse Gamma prior distributions for the standard errors of the structural shocks as well as measurement errors.[10]

Table 1: Prior Distributions

Parameter	Distribution	Mean	Std. Dev.
$A_1(j,j)$ for $j=1$	Normal	0.5	0.15
$A_i(j,k)$ for $i=2,...,L$	Normal	0	0.15
$-B_{1,1}\,(=\kappa)$	Gamma	1	1
$B_{2,1}/\gamma\,(=\lambda)$	Normal	0	2
$B_{2,2}\,(=\alpha)$	Normal	0	1
$-B_{2,3}\,(=\gamma)$	Gamma	1	1
$diag(\Theta)$	Beta	0.2	0.15
$diag(\Sigma)$	Inv-Gamma	1	2

To determine the appropriate lag length for the autoregressive segment, we conduct a comparison of the marginal likelihoods across models featuring 1 to 4 lags. Notably, for most countries, the posterior odds ratio test demonstrates a strong preference for the model with $L=2$, indicating a higher Log data density.

[10] For simplicity measurement errors are i.i.d. shocks showing no persistence.

To extract posterior distributions for our estimated parameters, we employ the Metropolis-Hastings algorithm, initiating a Monte-Carlo Markov Chain (MCMC) consisting of 500,000 draws. We discard the initial 20 percent of these samples as a burn-in phase to eliminate the potential effect of the chain initialization. For the analysis of impulse responses presented in the following section, we create posterior means and error bands based on a subsample of 10,000 draws, using a random selection process with replacement.

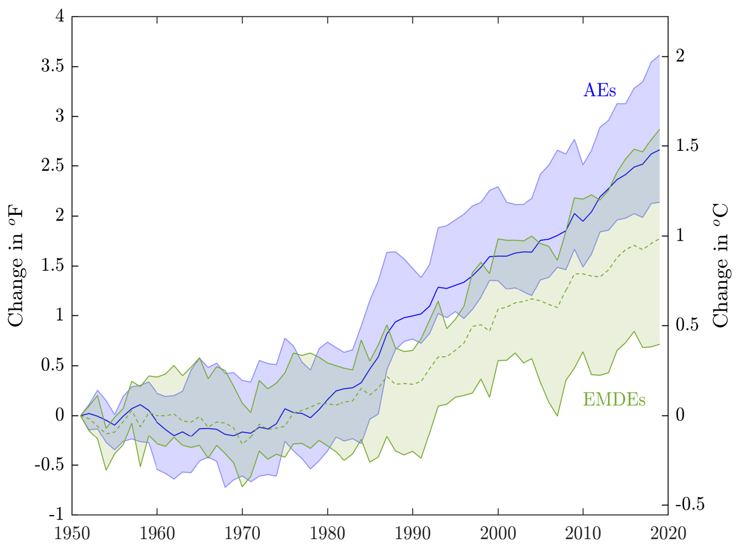
4 Empirical Results

4.1 Trend characteristics and cointegration

The estimated model allows us to examine the evolution of two key unobserved variables, the temperature trend component, Ψ_t^T, and the underlying cyclical component, ϕ_t^T, since 1950, as characterized in Equation 2.

Figure 3 displays the posterior median temperature stochastic trends in AEs against EMDEs along with their corresponding 90 percent posterior bands. From the figure we find that there is no statistically meaningful upward shift in average temperatures in the two groups of countries until the 1970s. Then, there is a persistent increasing temperature in both AEs and EMDEs during the 1980s, which is statistically similar. Importantly, the speed at which climate change materializes is more pronounced in colder countries starting from 1990, leading to an average absolute increase of temperature of 1.5^{o}C, 0.5^{o}C larger than what hot countries have registered.

Figure 3: Temperature Stochastic Trends: AEs versus EMDEs



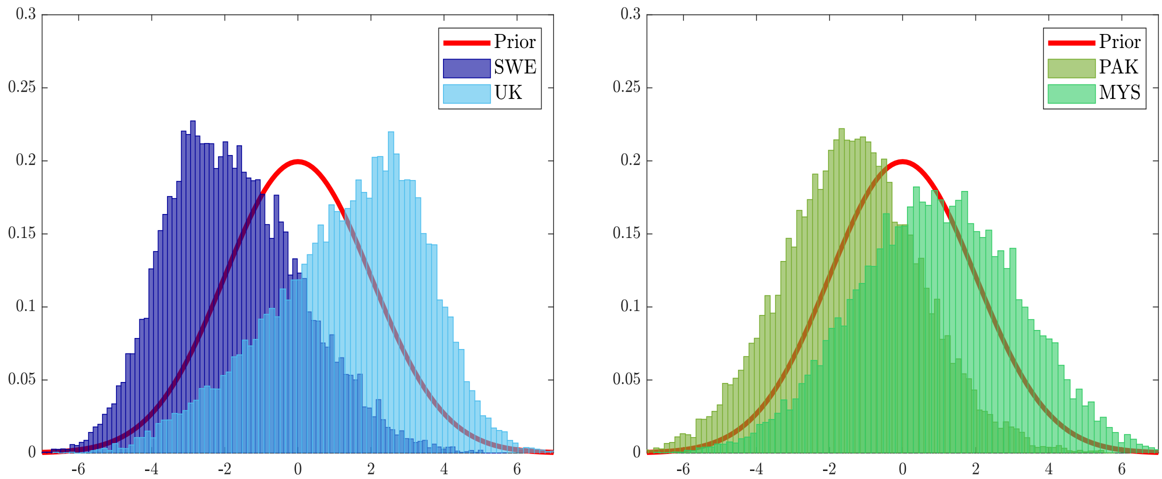
Since we define persistent fluctuations of temperature as an outcome of permanent shocks, the uneven estimated trend with adverse consequences only in countries with cold climates should be attributed to larger shocks on the permanent component.[11] In other terms, climate change shocks are larger in cold climates or high-income countries, which could yield larger economic losses despite their higher capacity to deal with changes in temperature (capacity to adapt).

Another important determinant of the the effect of climate change on economic activity is captured by the the coefficient λ, as discussed in the previous section. Figures 4a and 4b display the posterior distributions of the highest versus lowest cointegration coefficients estimated in the groups of AEs and EMDEs, respectively.

Figure 4: Posterior Distributions of the parameter λ

(a) AEs

(b) EMDEs



While the long-run relation between output and temperature does not have a structural interpretation, it does measure the conditional reduced-form relationship between the two, which can provide a summary of the climate change impact on economic activity in the long run. From the figures, we find that the response can have a positive or negative sign regardless of the level of income and historical average temperature. Besides, there is some evidence that growth effects of persistent weather shocks are more dispersed in cold climates with the most severe negative (positive) effect is registered in Sweden (UK) with a long-term impact of 3 percent loss (gain) in output following a 1 percent permanent change in temperature. In contrast, lower income countries exhibit a squeezed distribution of the long-term correlation varying between only -2 and 2 percent. In conclusion, while rich countries are found to

[11] As shocks are interpreted in deviations and not in absolute terms, permanent shocks on temperature in cold countries would be much larger to reflect on a average absolute increase of 1.5°C.

be disproportionately affected by weather shocks, poor countries are by no means immune to climate change once we consider real output loss as a metric.

4.2 Permanent climate shock transmission

Country-specific impulse response functions are simulated following an annual 0.04^{o}C permanent shocks over the period 2019–2100 (when compared to a baseline scenario under which temperature in each country increases according to its historical trend of 1950–2019).[12] This broadly corresponds to 3.5^{o}C permanent increase of temperature by 2100. Figures 5a and 5b display the posterior averages of the long-term impact on output with countries grouped based on income level and historical average temperature, respectively. As previously discussed, the cointegration coefficient, λ, significantly influences the sign and magnitude of the responses. However, other estimated parameters, such as the degree of shock persistence (see Equation 6), could also affect the output's reaction to permanent temperature shocks.

In response to a positive (unfavorable) permanent temperature surprise, real output in most AEs countries significantly declines, with a larger effect on higher income countries also exhibiting low historical average temperatures. Only four countries could benefit from permanent rise of temperature, with Ireland as an outlier registering output gains slightly below 8 percent. All the remaining AEs are estimated to suffer output declines. The Nordic region (Denmark, Finland, Iceland, Norway, and Sweden) along with USA are the most significantly affected, with losses between 12 percent (in USA) and 18 percent (in Sweden), assuming a severe scenario of climate change.

Considering the responses from EMDEs to persistent temperature increases, it is observed that the cross-country heterogeneity is not as significant as in AEs. The long-term reaction of output ranges from a decrease of 14 percent (Malaysia) to an increase of 9 percent (Nepal). A reduced number of countries are expected to benefit from climate change leading to an average loss of output around 1 percent by the end of the century in EMDEs or hot countries—6 percent lower than the average of AEs.

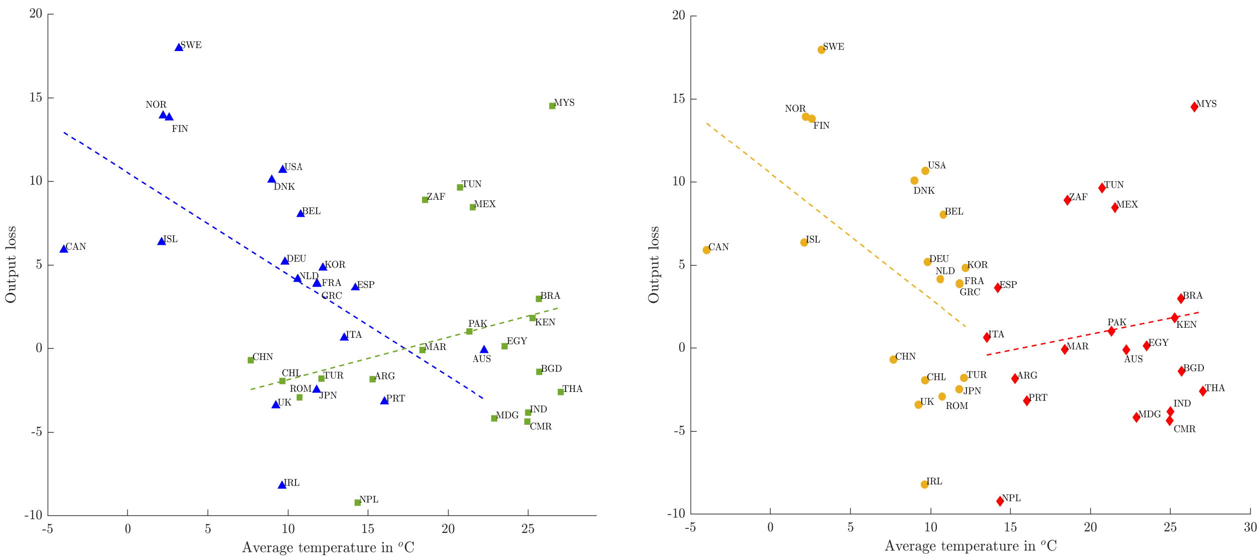
Figures 5a and 5b also present a comprehensive comparison of the long-term relationship between income levels and vulnerability to climate change, differentiating between AEs and EMDEs, as well as between historically cold and hot countries. The figures provide visual confirmation that the poorest countries, also hottest, are estimated to experience significantly lower economic growth deterioration to positive

[12]Note that depending on the historical average of temperature, country-specific sizes of the annual shocks should be adopted in the simulations of the impulse-responses functions. Hence, for cold countries the size of innovations should be larger compared to that considered in the case of hot countries.

persistent temperature shocks. This evidence reverses the common wisdom that climate change is largely affecting poor and hot countries whereas rich and cold countries could rather benefit from rising temperature associated with climate change.

Figure 5: Distribution of Output Loss by 2100

(a) Income group effect (b) Average temperature effect



Notes: Blue triangles: AEs. Green squares: EMEDEs. Orange dots: Cooler group. Red diamonds: Hotter group. Dashed lines: Group trend.

4.3 Transitory weather shock transmission

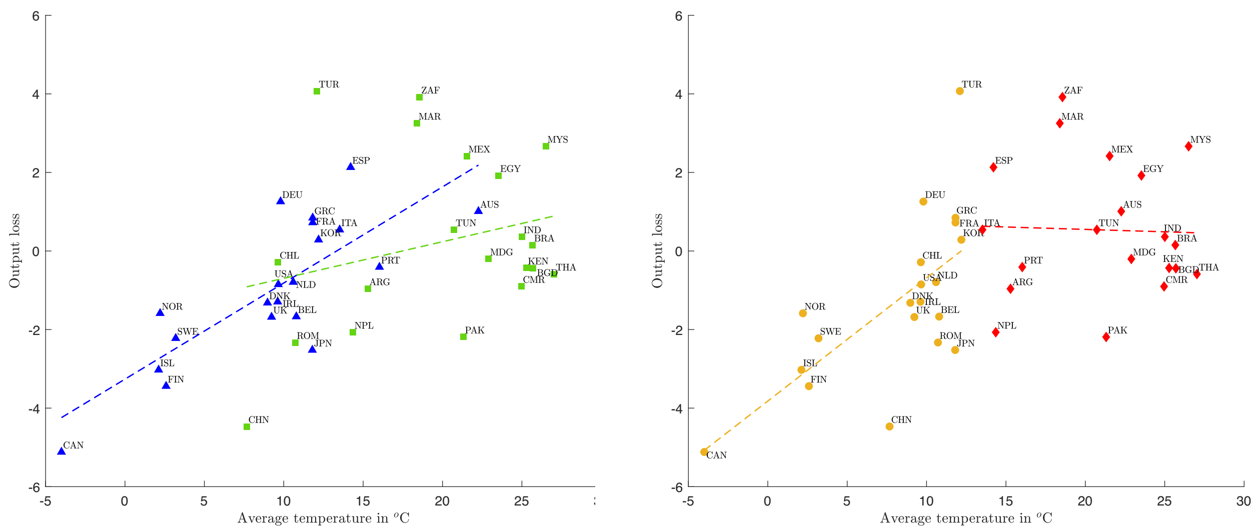
To examine the impact of stationary change in temperature on real output, we consider the case of 1^{o}C shock on the transitory component, ϕ_t^T. Although the shock is allowed to persist over time, its posterior average autocorrelation is generally estimated at low levels, consistent with its very nature.

Figures 6a and 6b display the absolute maximum impulse responses of output in the twenty AEs and EMDEs to a temporary shock. Detailed impulse-response functions with confidence intervals are reported in Appendix A.2. The figures also include trends of country subgroups based on income levels and average historical temperatures. Real output reaches its maximum response with a delay that could reach four years following the shock depending on the estimated auto- and cross-correlation coefficients of the model. All EMDEs experience an contemporaneous overshooting as a reaction to the sudden temporary change in temperature. By contrast, most of AEs exhibit hump-shaped response functions. Focusing on the posterior average conditional comovement between real output and weather shocks reveals interesting results, which are threefold. First, during upturns of temperature, the distributions of responses are almost centered around zero regardless of countries' grouping. Second, several countries exhibit opposite sign reactions following temporary versus permanent temperature shocks. For instance, Canada and Nordic region are estimated to benefit from non-persistent rise in temperature, ranging between 1 and 5 percent, as opposed to dramatic losses once we consider permanent shifts. This finding is also present in several EMDES such as Argentina, Pakistan, Nepal, and Romania. The novel aspect of the result documented here proves that stationary and nonstationary temperature shocks—namely, weather and climate change, respectively—have significantly distinguishable effects on economic activity that could yield responses of opposite signs for the same country. Third, consistent with existing findings in the literature, there is a negative relation between the degree of wealth in a country and output losses from (temporary) surges in temperature. As reported in Figure 6b, this pattern is also evident when considering the historical average temperature. This correlation has been interpreted as reflecting the extensive adaptive capacity of advances economies. Hence, a possible explanation for our findings is that the adaptation capacity in AEs helps mitigate short-term temperature fluctuations but is insufficient to address the long-term detrimental effects of climate change, which manifest as permanent disturbances in our model.

Figure 6: Distribution of Output Loss Following a Temporary +1^{o}C Shock

(a) Income group effect

(b) Average temperature effect



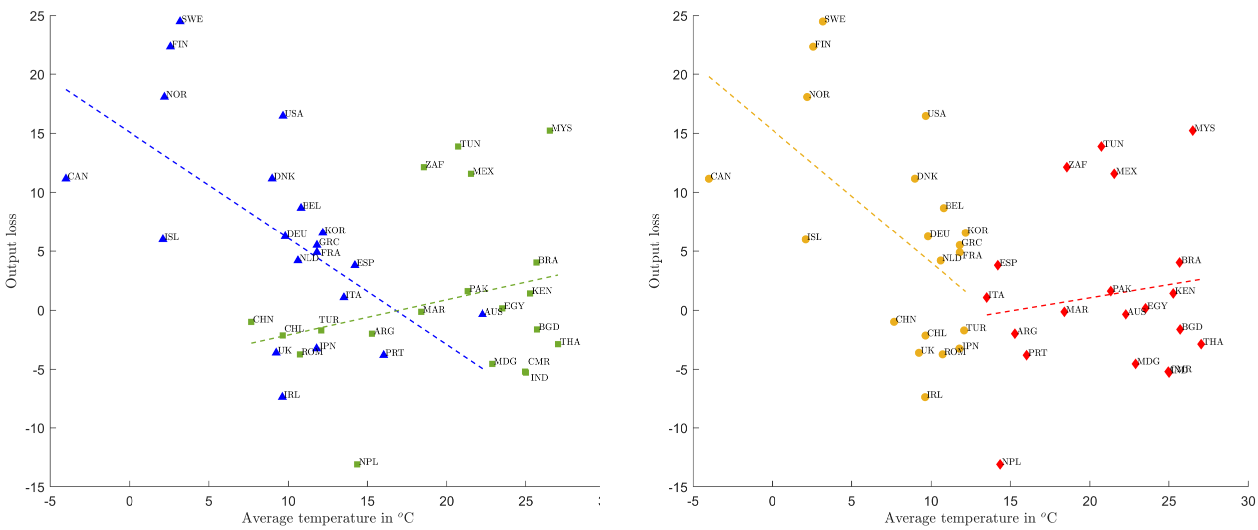
4.4 Climate projection data (SSP5-8.5)

To ensure better comparability with previous papers, we also conducted a counterfactual exercise where temperature increases followed commonly adopted country-specific temperature pathways. From the Shared Socioeconomic Pathways (SSP), we adopt the SSP5–8.5 scenario representing the high end of the range of future pathways—corresponding to RCP8.5 as defined in Representative Concentration Pathways (RCPs).

The methodology involves using the Kalman filter to extract the shocks from the model. The process is as follows: First, we represent the model in its state-space form. Second, we apply the Kalman filter to construct the likelihood function of the observed data and estimated the structural parameters of the model.[13] Third, using these estimated parameters, we determine the values of the model perturbations over the sample period, conditional on all observed data corresponding to forecasts of temperature from 2020 to 2100 as defined in the SSP5–8.5 scenario.[14] Applying this methodology results in a structure of the underlying persistent and non-persistent shocks that exhibits both positive and negative values, in contrast to the simplistic scenario adopted previously.

Figure 7: Distribution of Output Loss by 2100: SSP5–8.5

(a) Income group effect (b) Average temperature effect



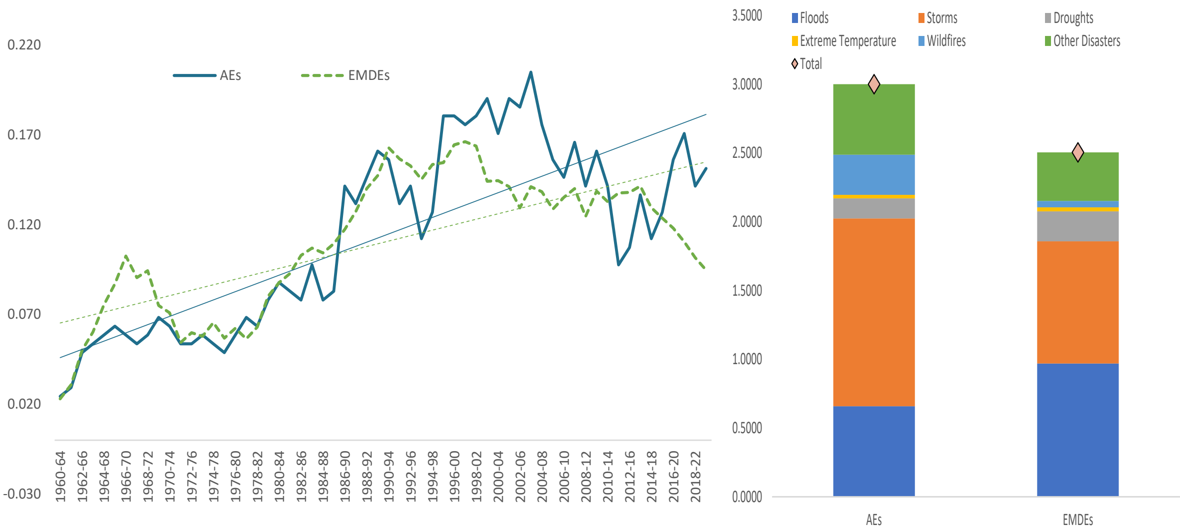
[13]Values of the structural parameters, including shock volatilities, are set to their posterior median point estimates.

[14]See Bauer, Haltom, and Rubio-Ramírez (2003) for details on using the Kalman filter to smooth the shocks in endogenous models.

Figures 7a and 7b depict county-level long-term output changes in response to the derived sequence of shocks. Among AEs, permanent temperature shocks result in real output changes ranging from -25 to $+8$ percent. The Nordic region, Canada, and the United States experience the most significant output losses. In EMDEs, output responses range from -15 to $+13$ percent, with Malaysia, Tunisia, South Africa, and Mexico estimated to suffer the most from climate change. Overall, most countries are more affected than under the initial scenario, which assumes an annual temperature increase of 0.04^{o}C.

Figure 8: Comparative Analysis of Natural Disasters

(a) Frequency (5-year moving average) (b) Incidences (2004-23)



The inverse relationship between losses and historical temperature aligns with our initial findings. This effect is particularly prominent in colder countries, which typically belong to the group of advanced economies. As historical average temperatures rise, the case of EMDEs, output losses become less sensitive to the effects of climate change. There are two possible and non-mutually exclusive explanations for the higher adverse effects of persistent temperature increases in AEs compared to EMDEs. First, as shown in Figure 3, AEs are experiencing a precipitous rise of temperature in absolute terms (0.5^{o}C higher than EMDEs). This reflects in more prominent size of permanent temperature shocks in deviations from the historical trend. Second, It is widely believed that in the context of future global climate change, factors such as rising sea levels, increasing frequency of natural disasters, and biodiversity loss could negatively impact economic activity. Based on the EM-DAT database, we contract times series of five-year average frequency of natural disasters in

AEs and EMDEs along with aggregated incidences measured as percentage of GDP.[15] Figure 8a illustrates the upward trend in the global frequency of natural disasters. Notable differences in the long-term trajectories of natural disaster frequency may explain the greater vulnerability of AEs to climate change. In addition, Figure 8b shows the impact of historical incidents, measured as average capital loss in percent of GDP, over the last two decades. Once again, wealthy countries have experienced greater capital loss due to natural disasters, particularly following storms and wildfires. Bilal and Känzig (2024) demonstrate that when global temperature, rather than local temperature, is used in regressions linking output growth to climate change, the correlation between the two variables is stronger, as extreme weather events are more closely linked to global temperature variations.

5 How Important are Temperature Shocks for Economic Activity

So far, we have examined the dynamic effects of weather and climate shocks. A natural question that arises is whether temperature shocks are important from an economic point of view. This section delves into the relative importance of temperature shocks in influencing fluctuations in country temperatures and economic activities. Specifically, we investigate whether changes in temperature serve as a significant indicator of shifts in real output and whether persistence is a major driver of business cycles.

Tables 2 and 3 show the amount of temperature forecast error variances at different horizons for AEs and EMDEs, respectively, that are attributable to the structural shocks identified by our model.[16] Results show that in the present sample of 20 AEs, the vast majority of fluctuations in average temperature is driven by stationary shocks. The median share of Ψ_t^T in the forecast error across the ranges from 1 percent at the 1-year horizon to 35 percent at the long-run horizon showing an increase over time for all countries. This suggests that climate change has a heterogeneous effect on this group of countries with the most affected are Portugal, Spain, and Australia. Transitory shocks to in EMDEs are equally important drivers of country-specific temperatures in average and across horizons, while the spread of variance decomposition contribution is significantly lower compared to AEs. In particular,

[15] The EM-DAT database provides foundational data on more than 22,000 significant disasters worldwide, spanning from 1900 to 2023. This comprehensive repository is sourced from a diverse array of contributors, including United Nations agencies, non-governmental organizations, insurance firms, research institutions, and media outlets.

[16] In addition to the structural shocks reported in the tables, the model reflects measurement error shocks, which are not reported as their contributions to the forecast error variances—mainly owing to the low values of the posterior median standard deviations of these shocks.

long-run forecast errors attributable to permanent shocks range from 19 to 43 percent with the largest levels are recorded in Tunisia, Egypt, and Chile.

Table 2: Variance Decomposition of the Change in Temperature (AEs)

Shock	$\Delta\Psi_t^T$				ϕ_t^T			
Horizon	1	2	3	∞	1	2	3	∞
AUS	21.7	28.9	29.2	29.4	75.5	69.3	69.0	68.9
BEL	7.9	9.7	9.9	10.0	91.5	89.9	89.7	89.7
CAN	1.1	1.4	1.5	1.5	98.8	98.5	98.4	98.4
DEU	7.2	8.7	8.9	8.9	92.4	91.0	90.8	90.8
DNK	4.1	5.3	5.4	5.4	95.5	94.4	94.4	94.3
ESP	26.5	32.6	32.7	32.8	72.0	66.5	66.4	66.3
FIN	1.9	2.2	2.2	2.2	98.0	97.7	97.7	97.7
FRA	17.9	20.5	20.7	20.7	80.9	78.7	78.6	78.5
GRC	17.9	20.4	20.6	20.6	80.9	78.8	78.7	78.6
IRL	23.0	27.6	27.8	27.9	75.4	71.2	71.1	71.0
ISL	19.1	22.1	22.1	22.3	80.5	77.7	77.6	77.5
ITA	22.2	28.0	28.2	28.3	76.0	70.9	70.7	70.6
JPN	20.1	23.9	24.1	24.2	78.2	75.0	74.8	74.8
KOR	15.9	19.1	19.4	19.4	83.1	80.2	80.0	79.9
NLD	21.4	22.1	22.1	22.2	78.0	77.5	77.4	77.4
NOR	5.2	6.3	6.4	6.5	94.1	93.2	93.1	93.0
PRT	27.1	34.3	34.4	34.6	70.4	64.2	64.1	63.9
SWE	2.3	2.7	2.7	2.8	97.5	97.2	97.1	97.1
UK	8.0	10.3	10.5	10.6	90.9	88.9	88.7	88.7
USA	15.4	17.4	17.5	17.5	83.2	81.6	81.7	81.7

Note:The table displays the percentage of the temperature growth variance attributed to the country specific nonstationary temperature shock, $\Delta\Psi_t^T$ and stationary shocks, ϕ_t^T. These values are averaged from 10,000 samples of the posterior distribution for the variance decomposition.

Table 3: Variance Decomposition of the Change in Temperature (EMDEs)

Shock	$\Delta\Psi_t^T$				ϕ_t^T			
Horizon	1	2	3	∞	1	2	3	∞
ARG	18.9	24.7	24.9	25.0	78.7	73.8	73.6	73.5
BGD	18.2	24.3	25.0	25.1	77.3	72.4	72.1	72.0
BRA	15.1	21.8	22.3	22.4	79.3	74.3	74.0	73.9
CHL	21.6	27.9	28.1	28.3	75.4	70.1	69.9	69.8
CHN	18.4	22.9	23.2	23.3	79.4	75.5	75.3	75.2
CMR	17.0	23.2	23.7	23.8	76.5	72.1	72.0	71.9
EGY	26.6	33.8	33.9	34.1	71.7	65.2	65.1	64.9
IND	19.1	25.1	25.4	25.5	75.9	71.3	71.2	71.1
KEN	17.1	23.1	23.8	23.9	78.0	73.4	73.2	73.2
MAR	22.0	27.3	27.5	27.6	76.1	71.5	71.3	71.2
MDG	19.5	25.9	26.2	26.4	75.5	70.6	70.4	70.3
MEX	20.6	27.8	28.0	28.2	74.7	69.1	69.0	68.8
MYS	16.4	26.4	27.0	27.8	75.8	67.7	67.3	66.8
NPL	19.4	23.9	24.3	24.3	78.1	74.4	74.2	74.2
PAK	19.5	24.9	25.1	25.2	78.4	73.7	73.6	73.5
ROM	20.9	24.1	24.3	24.4	78.3	75.4	75.2	75.1
THA	20.5	25.9	26.2	26.3	75.7	71.5	71.3	71.3
TUN	33.6	42.5	42.7	43.1	63.4	55.6	55.4	55.1
TUR	15.9	18.6	18.7	18.7	83.4	81.0	80.9	80.9
ZAF	23.1	26.7	27.1	27.1	74.1	71.1	71.0	70.9

One corollary of these findings is that the significant impact of temporary shocks on the volatility of temperature growth rates could lead to the misidentification of the permanent climate change component if a researcher uses the temperature variable in level or growth form in regression analysis. In such cases, the majority of temperature fluctuations are temporary rather than permanent, resulting in a conditional correlation between output and temperature shocks that could be similar to our identified responses following perturbations on the non-persistent component. In fact, we find that adverse temporary shocks on temperature are affecting mostly hot and poor countries, which corresponds to what the literature reports as it abstracts from the distinction between persistent and non-persistent determinants of temperature.

Rows of Table 4 show that, on average, temperature shocks significantly contribute to the volatility in real activity. Namely, 24 and 12 percent of to output growth fluctuations are attributed to jointly temporary and permanent temperature disturbances in AEs and EMDEs, respectively. The explanatory preponderance of permanent temperature shocks in accounting for movements in output manifests itself in the context of AEs—19 percent in average and approximately twice as much as in EMDEs. These results find their roots in the sizable stochastic shocks combined with the large cointegration coefficient estimated in the context of AEs.

Table 4: Variance Decomposition of the Change in Real GDP

Shock	$\Delta\Psi_t^T$	ϕ_t^T	$\Delta\Psi_t^Y$	ϕ_t^Y		$\Delta\Psi_t^T$	ϕ_t^T	$\Delta\Psi_t^Y$	ϕ_t^Y
AUS	18	5	52	24	ARG	5	2	74	19
BEL	21	6	53	19	BGD	6	2	79	13
CAN	31	7	46	15	BRA	4	1	86	8
DEU	12	4	73	10	CHL	4	2	77	17
DNK	35	5	44	15	CHN	5	3	88	4
ESP	9	5	77	9	CMR	4	1	82	12
FIN	25	5	60	9	EGY	7	4	77	11
FRA	11	4	69	14	IND	13	3	67	17
GRC	12	4	68	14	KEN	6	1	61	31
IRL	10	3	78	9	MAR	8	3	32	56
ISL	28	6	56	10	MDG	7	1	78	13
ITA	12	4	70	14	MEX	8	3	77	12
JPN	7	3	81	8	MYS	17	3	67	12
KOR	10	3	79	8	NPL	16	5	60	19
NLD	17	5	64	12	PAK	17	7	54	17
NOR	31	5	47	15	ROM	7	3	85	5
PRT	7	3	82	8	THA	3	1	88	7
SWE	35	6	37	18	TUN	11	3	78	8
UK	32	6	31	29	TUR	22	7	60	10
USA	22	5	51	21	ZAF	14	10	62	12

6 Reverse Causality

It is of interest to ascertain the effects of the climate change particularly for large economies. In fact, the identification of the macroeconomic effects of climate change could be altered by the reverse causality between the two variables as economic activity leads to emissions and changes in temperature, at least in the case of large greenhouse gas emitters. This selection criteria results in the following 10 countries: Australia, Brazil, Canada, China, Germany, India, Japan, Korea, United Kingdom, and the United States.

6.1 Model specification and identification restrictions

A large economies block, Y_t, consists of 10 real GDP time series expressed in logarithms. In each country, we assume that output is cointegrated with a linear combination of a country-specific nonstationary shock, $\Psi^{y}_{i,t}$ (i = 1..., 10), and the nonstationary component of same country's temperature, $\Psi^{T}_{i,t}$. Formally, we define a 10-by-1 vector of deviations of output from trend, $\hat{Y}_t$, as follows:

$$\hat{Y}_t = \begin{bmatrix} \hat{Y}_t^1 \\ \hat{Y}_t^2 \\ \vdots \\ \hat{Y}_t^{10} \end{bmatrix} = \begin{bmatrix} Y_t^1 - \Psi^Y_{1,t} - \lambda^1 \Psi^T_{1,t} \\ Y_t^2 - \Psi^Y_{2,t} - \lambda^2 \Psi^T_{2,t} \\ \vdots \\ Y_t^{10} - \Psi^Y_{10,t} - \lambda^{10} \Psi^T_{10,t} \end{bmatrix}. \tag{7}$$

We introduce a new variable in the model to capture deviations of global emissions from its long term trend, denoted as $\hat{E}_t$, is defined as deviations of global emissions from a long-term trend that could be attributed to economic activity. Then,

$$\hat{E}_t = E_t - \Psi^E_t. \tag{8}$$

The trend of global emissions are assumed to be cointegrated with all countries' output trends:

$$\Psi^E_t = \sum_{i=1}^{10} \delta^i \Psi^Y_{i,t}, \tag{9}$$

where δ^i (for$i = 1, \ldots, 10$) correspond to the cointegration between global emissions and output of the 10 considered countries.

Next, we define the vector of country-specific temperature deviation from trend, $\hat{T}_t$, as follows

$$\hat{T}_t = \begin{bmatrix} \hat{T}_t^1 \\ \hat{T}_t^2 \\ \vdots \\ \hat{T}_t^{10} \end{bmatrix} = \begin{bmatrix} T_t^1 - \Psi^T_{1,t} - \zeta^1 \Psi^E_t \\ T_t^2 - \Psi^T_{2,t} - \zeta^2 \Psi^E_t \\ \vdots \\ T_t^{10} - \Psi^T_{10,t} - \zeta^{10} \Psi^E_t \end{bmatrix}, \tag{10}$$

where ζ^i (for$i = 1, \ldots, 10$) correspond to the cointegration between temperature and emissions and global emissions.

The detrended global emission, temperatures, and real outputs evolve according to the following vector autoregressive processes of the stationarized variables:

$$\hat{E}_t = \sum_{i=1}^{p} B^i_{E,E}\hat{E}_{t-i} + \sum_{i=1}^{p} B^i_{E,Y}\hat{Y}_{t-i} + C_{E,Y}\Delta\Psi^Y_t + \phi^E_t, \tag{11}$$

$$\hat{T}_t = \sum_{i=1}^{p} B^i_{T,T}\hat{T}_{t-i} + \sum_{i=1}^{p} B^i_{T,E}\hat{E}_{t-i} + C_{T,T}\Delta\Psi^T_t + C_{T,E}\Delta\Psi^E_t + \phi^T_t, \tag{12}$$

and

$$\begin{aligned}\hat{Y}_t = &\sum_{i=1}^{p} B^i_{Y,Y}\hat{Y}_{t-i} + \sum_{i=1}^{p} B^i_{Y.T}\hat{T}_{t-i} + \sum_{i=1}^{p} B^i_{Y.E}\hat{E}_{t-i} + \\ &C_{Y,Y}\Delta\Psi^Y_t + C_{Y,T}\Delta\Psi^T_t + D_{Y,T}\phi^T_t + \phi^Y_t,\end{aligned} \tag{13}$$

where p is the number of lags, $\Delta\Psi^Y_t = [\Delta\Psi^Y_{1,t} \ldots \Delta\Psi^Y_{10,t}]'$, $\Delta\Psi^T_t = [\Delta\Psi^T_{1,t} \ldots \Delta\Psi^T_{10,t}]'$, $\phi^T_t = [\phi^T_{1,t} \ldots \phi^T_{10,t}]'$, and $\phi^Y_t = [\phi^Y_{1,t} \ldots \phi^Y_{10,t}]'$. Matrices of coefficients $B^i_{T,T}$, $B^i_{Y,Y}$, and $B^i_{Y,T}$ $(i = 1, \ldots, 10)$ are of orders 10-by-10; $B^i_{T,E}$ and $B^i_{Y,E}$ $(i = 1, \ldots, 10)$ are 10-by-1 matrices; while $B_{E,E}$ and $B_{E,Y}$ have orders of 1-by-10 and 1-by-10, respectively. Matrices embedding correlations of endogenous variables to permanent and transitory shocks, are $C_{T,T}$, $C_{Y,Y}$, $C_{Y,T}$, and $D_{Y,T}$ with the same order of 10-by-10, while $C_{E,Y}$ is a 1-by-10 matrix.

Let's define the vector of exogenous shocks $u_t = \left[\Delta\Psi^Y_t,\, \Delta\Psi^T_t,\, \Delta\Psi^E_t,\, \phi^Y,\, \phi^T,\, \phi^E\right]'$ and assume that it obeys the low of motion:

$$u_t = \Theta\, u_{t-1} + \Upsilon\, \epsilon_t, \tag{14}$$

where ϵ_t is a vector of 42 i.i.d. normally distributed disturbances. For simplicity, Θ and Υ are assumed to be diagonal implying that permanent and transitory country-specific shocks are uncorrelated with each other and with other country-specific shocks.

Assuming the observable variables are measured with error, and denoting the vector of observables as o_t, we have

$$o_t = \left[\Delta T^1_t,\, \ldots,\, \Delta T^{10}_t,\, \Delta E_t,\, \Delta Y^1_t,\, \ldots,\, \Delta Y^{10}_t\right]' + \Gamma\mu_t \tag{15}$$

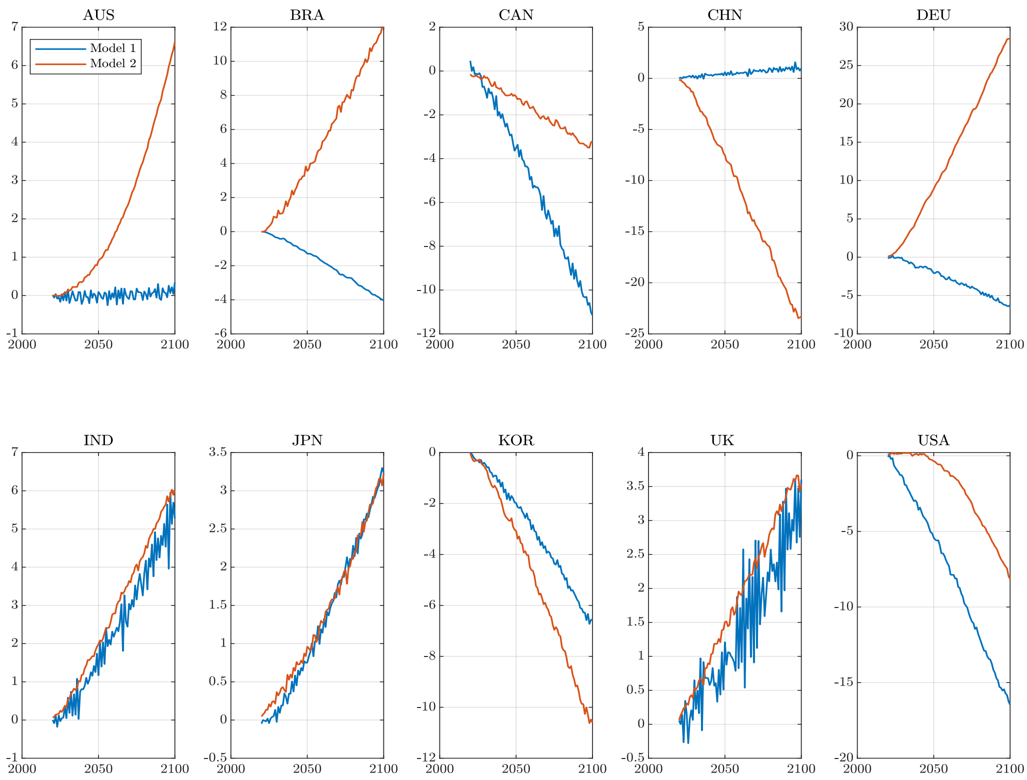
where μ_t is a 21-by-1 vector of i.i.d. normally distributed measurement errors and Γ is a diagonal matrix.

Combined together, Equations (7)–(15) can be written in a state-space format that can be estimated with Bayesian techniques while using the Kalman filter to evaluate the likelihood function. Further, we assume that the correlation of output across countries is entirely driven by global emission shocks through the channel of country-specific temperatures. Therefore, the matrices $B^i_{Y,Y}$ $(i = 1, \ldots, 10)$ and $C_{Y,Y}$ are constrained to be diagonal. Sign restrictions are imposed to be able to identify the structural shocks: (i) real output positively affects global emissions in the long-term—i.e., $\delta_i > 0$ for $i = 1, \ldots, 10$; and (ii) persistent shocks on emissions are positively correlated with temperature—i.e., $\zeta^i > 0$ for $i = 1, \ldots, 10$.[17]

6.2 Empirical results

Figure 9 presents the estimated effects of the sequence of permanent temperature shocks under the SSP5–8.5 scenarios, based on the alternative specifications. Models (1), in blue, and (2), in brown, refer to original version of the model and the one accounting for reverse causality, respectively.

Figure 9: Change in output 2020-2100



Model 1 (in blue): Without reverse causality. Model 2 (in brown): With reverse causality.

The impact of economic activity on temperature through global emissions chan-

[17] We assume Minnesota priors to the coefficients of $B^i_{E,E}$, $B^i_{E,Y}$, $B^i_{T,T}$, $B^i_{T,E}$, $B^i_{Y,Y}$, $B^i_{Y,T}$, and $B^i_{Y,E}$ for $i = 1, 2$. All estimated elements of the matrices $C_{E,Y}$, $C_{T,T}$, $C_{T,E}$, $C_{Y,Y}$, $C_{Y,T}$, and $D_{Y,T}$ are assumed to have normal prior distributions with mean zero and unit standard deviation. The diagonal elements of the matrix Υ, representing the standard deviations of the innovations in the exogenous shocks are all assigned Inv-Gamma prior distributions with mean and standard deviations equal to one and 2, respectively.

nels appears significant in Brazil, China, and Germany. In the simple model, output shows a mild response to permanent temperature disturbances. However, accounting for reverse causality reveals significant output losses in Brazil and Germany, while China is estimated to experience substantial growth gains. In contrast, the estimated long-term effects of climate change on the remaining seven large economies are virtually unaffected by the reverse causality assumption. Finally, we argue that for the remaining countries not included in this regression, the results should remain unchanged as global emissions are exogenous to their economic performances.

7 Conclusion

In this paper, we develop an empirical model to evaluate the impact of climate change, identified as permanent temperature shocks, on economic activity. Additionally, country-specific estimates enable us to reexamine the widely held belief that cooler or wealthier economies will remain unaffected or may even benefit from rising temperatures, while hotter and poorer countries will suffer the adverse effects of climate change.

The econometric contribution of the paper is twofold. First, we allow temperature shocks to materialize in the form of non-persistent and persistent disturbances to temperature, aligning naturally with the definition of climate change. Second, we use Bayesian estimation with the Kalman filter to identify country-specific shocks and their effects on real GDP in cold advanced economies along with warm emerging markets and developing economies.

Our results underscore the importance of considering the degree of persistence of temperature shocks. While cold and wealthy nations experience smaller output losses than warm and poor countries in response to temporary temperature increases, the situation reverses with the permanent temperature rises associated with climate change. In this scenario, cold and rich countries suffer greater economic damage than their warmer and poor counterparts. The rationale behind this result is that, according to country-specific estimates, the magnitude of permanent temperature shocks is greater in both absolute and relative terms in colder regions. Additionally, in recent decades, these countries have faced a notorious increase in the frequency and intensity of climate-related disasters, namely storms and wildfires.

To address the potential problem of reverse causality, we introduce a model that links output of the world's ten largest polluters, thereby influencing climate change. Our conclusions are robust, suggesting that discrepancies observed in previous studies may stem from limitations in effectively separating the enduring patterns of climate change from short-term weather fluctuations.

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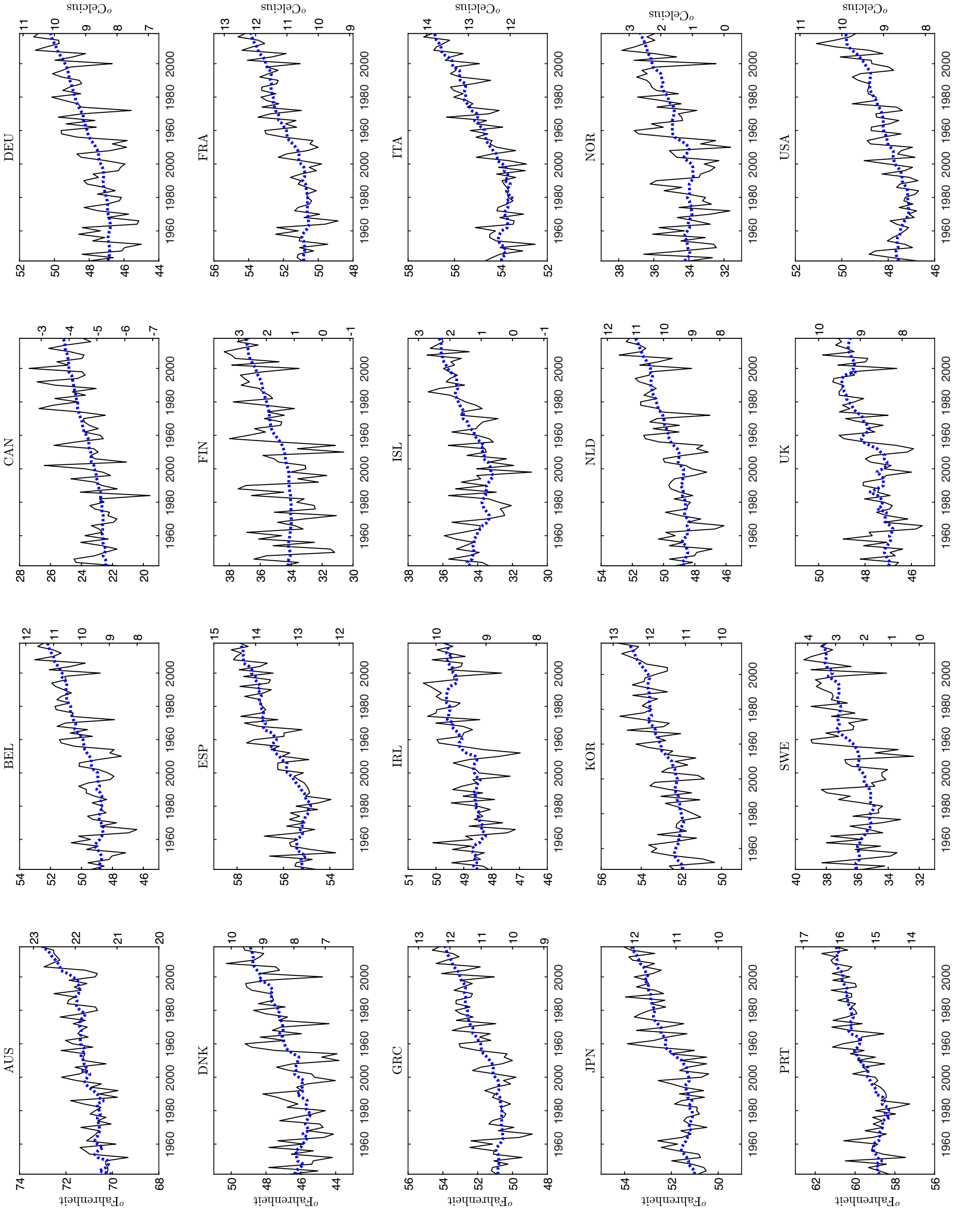
A Appendices

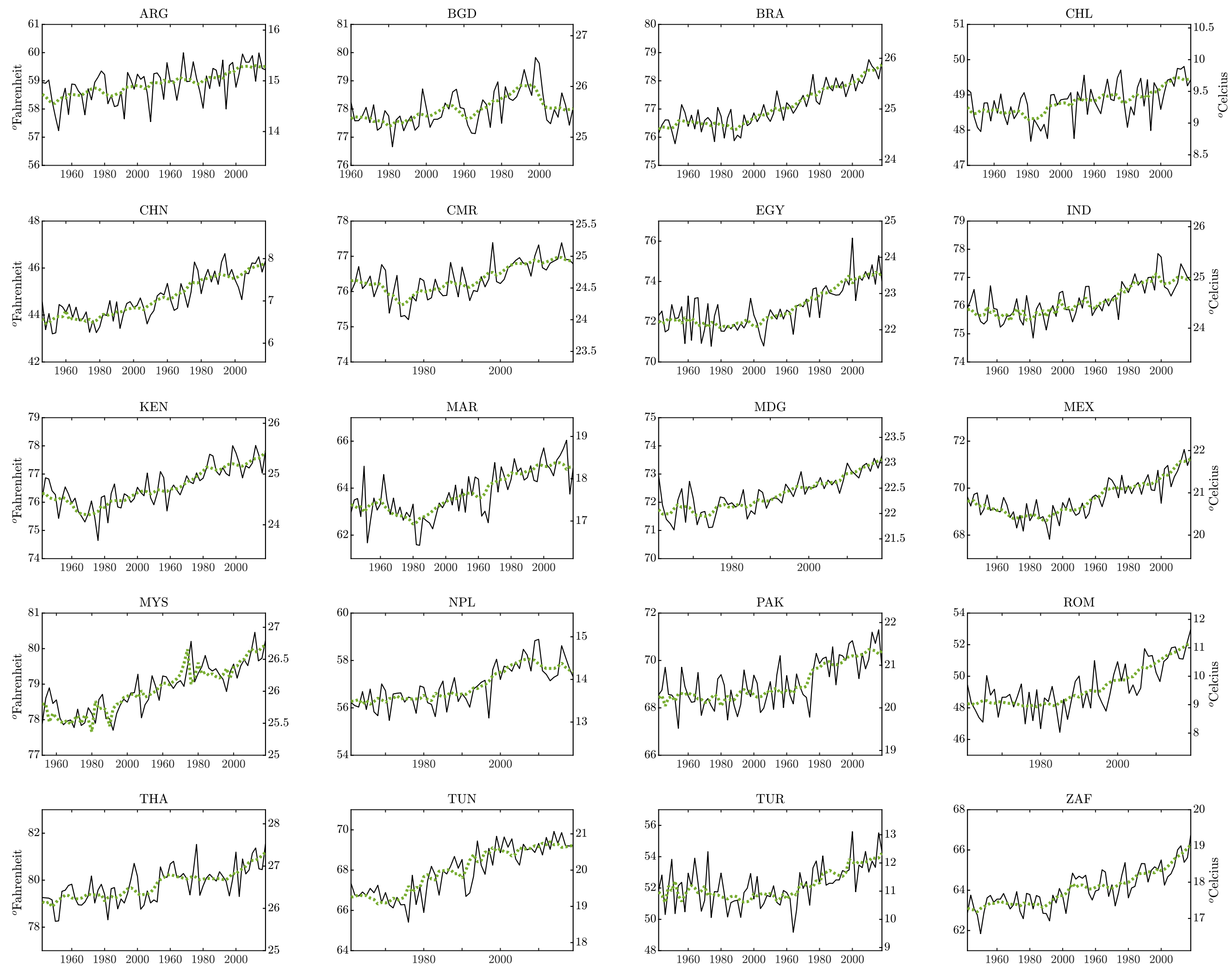
A.1 Stochastic Trends

Figure A.1.1: Average Temperature and Stochastic Trend: AEs



Note: Solid black lines illustrate the observed annual average temperatures. Dotted blue lines correspond to estimated stochastic trends.

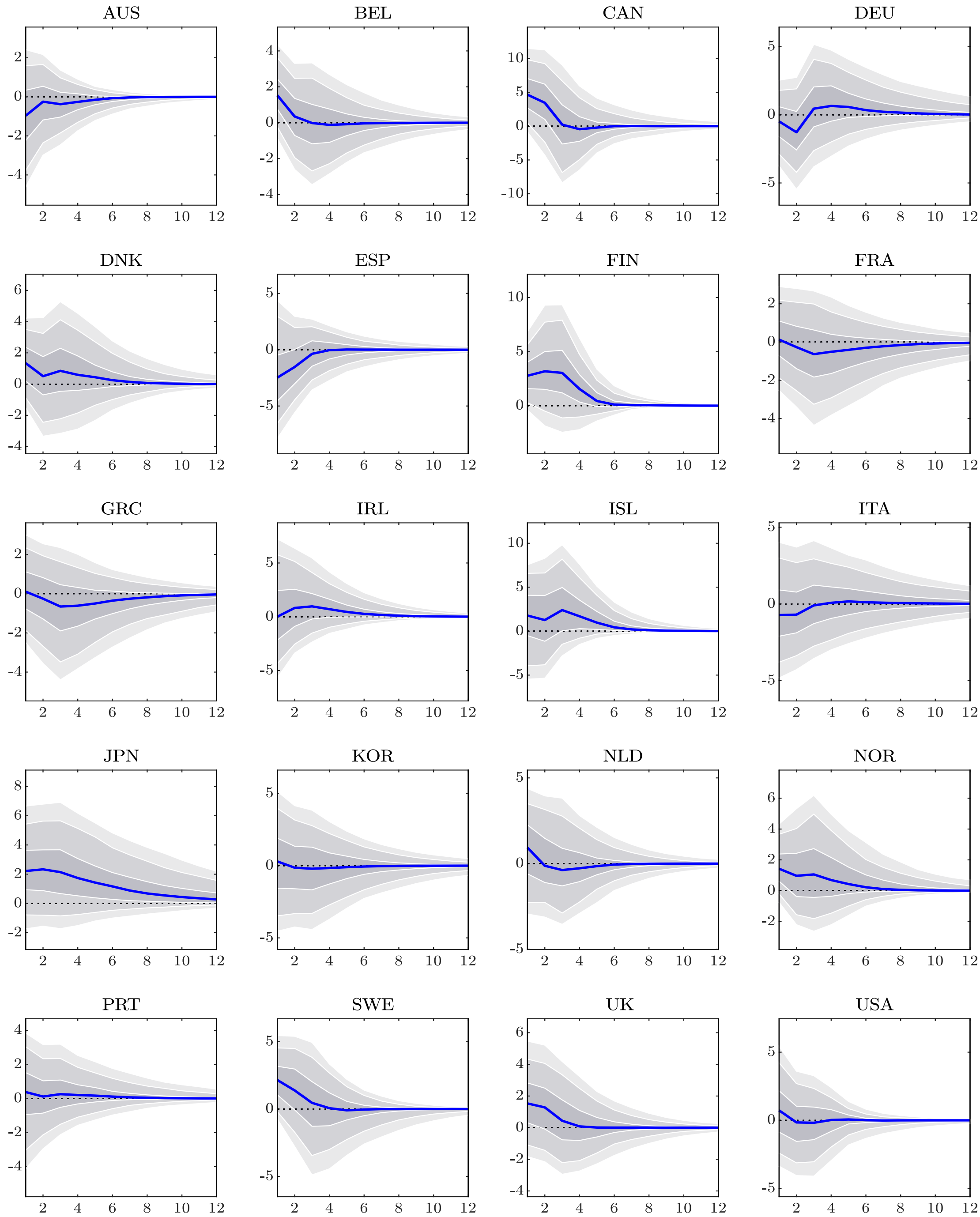
Figure A.1.2: Average Temperature and Stochastic Trend: EMDEs



Note: Solid black lines illustrate the observed annual average temperatures. Dotted green lines correspond to estimated stochastic trends.

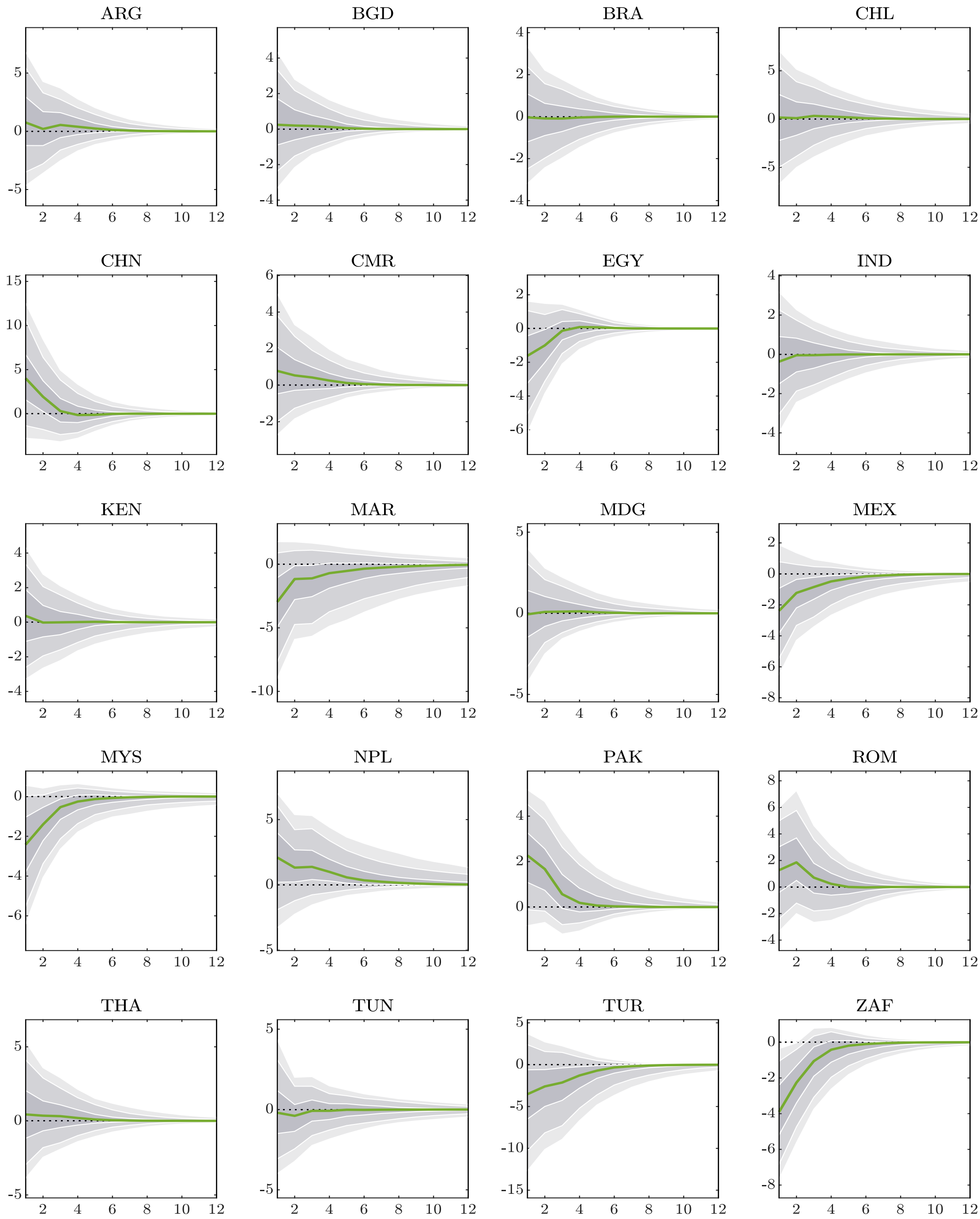
A.2 Impulse-Response Functions (Transitory Shock)

Figure A.2.1: Output Response to a +1^{o}C Transitory Shock: AEs



Notes: Blue solid lines correspond to the posterior median impulse responses in the model. Shaded areas correspond to the 90, 84, and 68 percent confidence intervals.

Figure A.2.2: Output Response to a +1^{o}C Transitory Shock: EMDEs



Notes: Green solid lines correspond to the posterior median impulse responses in the model. Shaded areas correspond to the 90, 84, and 68 percent confidence intervals.

A.3 Real Output under SSP5-8.5 Scenarios

Figure A.3.1: SSP5-8.5 Scenario Impact on Output: AEs

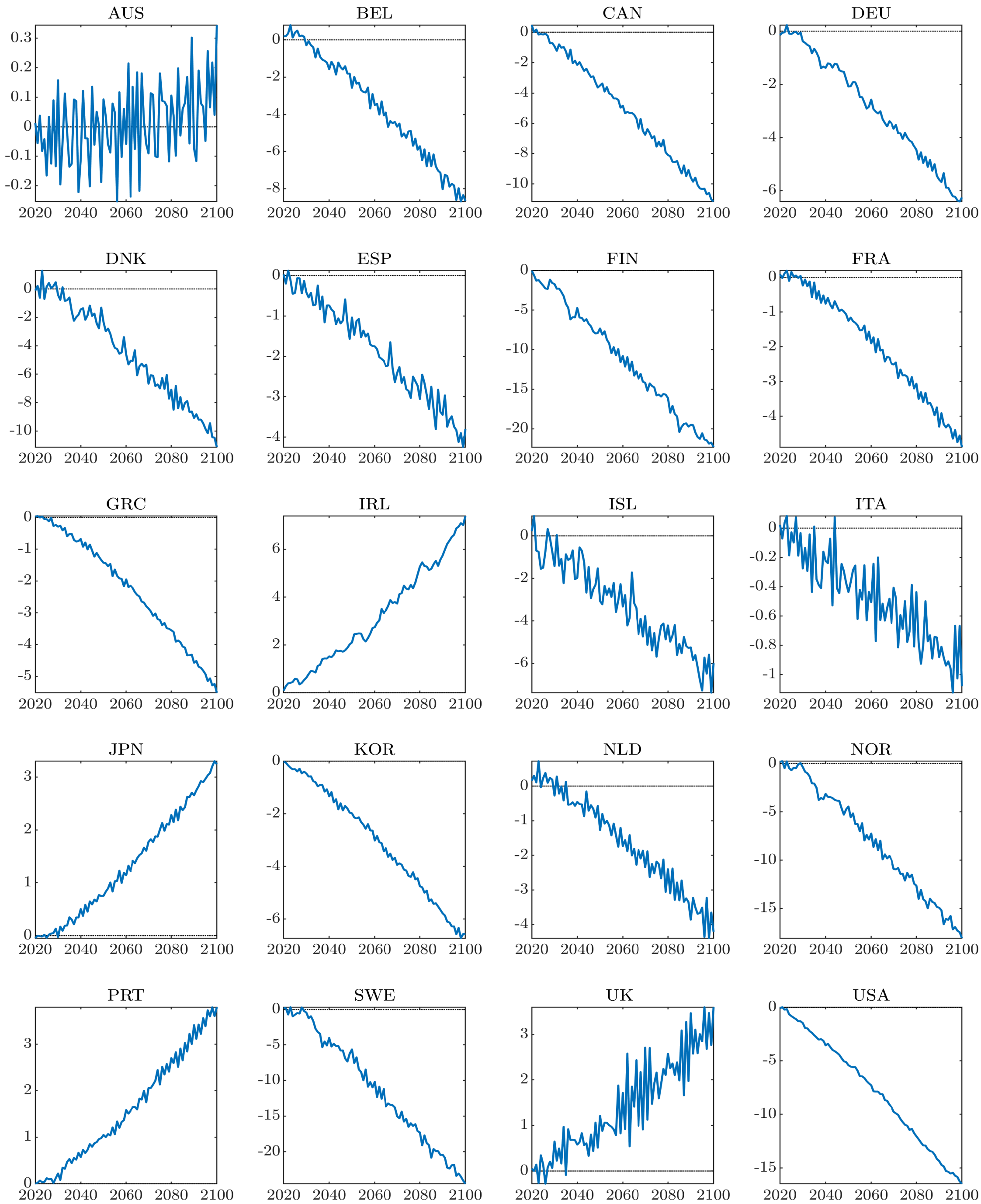
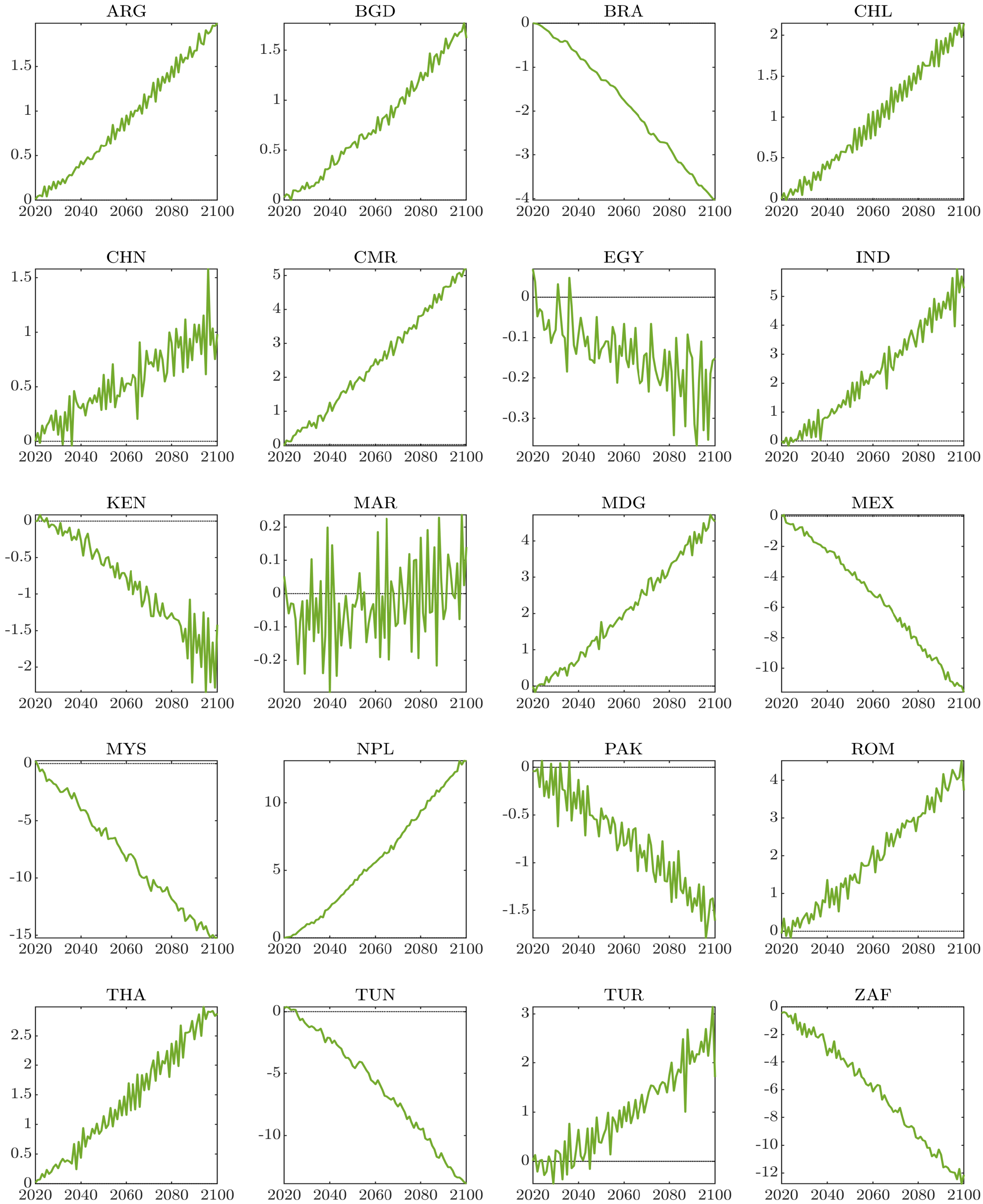


Figure A.3.2: SSP5-8.5 Scenario Impact on Output: EMDEs



PUBLICATIONS

A New Perspective on Temperature Shocks

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