Global Climate Change and the Long-Run Level of Output

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Abstract

This paper shows that separating persistent climate change from transitory weather fluctuations fundamentally changes our understanding of the macroeconomic costs of warming. It decomposes temperature into a global climate trend, heterogeneous country-level exposures, and short-run weather shocks, and links these components to trend output using a panel cointegration and error-correction framework. It documents large long-run level effects of climate change: a one-degree Celsius increase in the permanent climate component is associated with a 22 percent reduction in permanent real GDP in the long run within countries. Error-correction estimates indicate that this adjustment is extremely gradual, with convergence to the long-run output level taking many decades. These losses are driven primarily by exposure to the global climate rather than local climate, while transitory weather shocks mainly generate short-run volatility around the climate-dependent output path. The finding is robust across a wide range of robustness checks and is most pronounced for capital-intensive countries.

Keywords: Climate change; weather shocks; cointegration; long-run growth
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1 Introduction

Climate change is among the most profound economic challenges of the twenty-first century. While there is now broad consensus that higher temperatures depress short-run output growth, far less is known about how climate change affects economic activity over longer horizons. This distinction matters. Most of the empirical literature uses realized temperature variation as the treatment variable, implicitly combining persistent climate dynamics with transitory weather fluctuations (see for example, Dell et al. (2012); Burke et al. (2015); Colacito et al. (2019); Kahn et al. (2021); Nguyen (2024)). If warming primarily induces temporary fluctuations, economies can eventually revert to their potential paths. If, however, climate change permanently alters growth trajectories, the welfare and policy implications can be much larger.

This paper develops a new empirical framework to separate climate change from weather shocks and to quantify their distinct macroeconomic effects. The central idea is that observed global temperature evolves as the sum of a persistent climate component, characterized by a gradually adjusting warming rate, and transitory weather fluctuations. A climate shock is defined as an innovation that permanently shifts the trajectory of the warming rate, thereby altering long-run climate dynamics, while a weather shock reflects short-term deviations that eventually dissipate. By disentangling these components, the paper isolates climate change as a structural force and traces its impact on real GDP.

The paper makes three contributions. First, conceptually, it shifts the focus from short-run responses to weather shocks toward the long-run effects of persistent climate change on economic activity. Second, methodologically, it models the global climate trend as a stochastic process with shocks to the warming rate itself. This formulation allows climate change to operate through persistent changes in the trajectory of temperature rather than through one-time level shifts. This decomposition is implemented by Kalman filter in the spirit of standard unobserved-components models. Building on this structure, the paper develops a panel Kalman filter that decomposes country-level temperature into exposure to a common global climate trend, a country-specific climate deviation, and transitory local weather shocks. Third, with a panel cointegration framework[1], it links these decomposed climate and weather components to output, itself modeled with permanent and transitory components, enabling direct estimation of how global and local climate forces anchor long-

[1]Panel cointegration provides a natural framework for studying the macroeconomic effects of climate change because both temperature and output are highly persistent and evolve primarily at low frequencies. In contrast to standard growth regressions that emphasize short-run weather responses, a cointegrated system models long-run equilibrium relationships in levels while allowing for gradual adjustment through error-correction dynamics. To our knowledge, this paper is the first to apply a panel cointegration and error-correction framework to quantify the long-run macroeconomic effects of climate change.

run output levels while weather shocks generate cyclical fluctuations. In doing so, the paper connects three previously separate literatures: the macroeconomic effects of weather shocks identified from short-run temperature variation, the recent global-versus-local temperature literature emphasizing common climate forces, and new unobserved-components approaches that distinguish persistent climate dynamics from transitory fluctuations.

This work has conceptual implications concerning adaptation. Climate change is, by construction, persistent: trend shocks shift the baseline warming rate. Weather shocks, however, are transitory, fluctuating around the climate component, moving in both directions, and eventually dissipating. This difference matters for policy. Adaptation to weather shocks involves short-term measures to smooth fluctuations, whereas adaptation to climate change requires structural adjustments to reposition the economy on a new long-run path. Misclassifying climate change as weather shocks risks misdirecting adaptation resources toward transient variability rather than the persistent changes that shape long-run growth. By separating these components, this framework clarifies where scarce adaptation capacity should be concentrated.

This paper contributes to two emerging strands of research on the macroeconomic effects of temperature. The first strand emphasizes the global nature of climate risk. Bilal and Känzig (2025) show that global temperature shocks have substantially larger macroeconomic effects than local temperature shocks and derive a global damage function. Their identification strategy exploits global temperature variation, highlighting the importance of common climatic forces. However, their analysis is conducted using aggregate temperature realizations and does not distinguish between persistent climate change and transitory weather fluctuations.

The second strand explicitly separates persistent climate dynamics from short-run weather variation. In an early paper, Bloomfield (1992) extracts stochastic trends in global temperature. Rebei (2025) applies an unobserved-components model to national temperature and GDP series, decomposing both into permanent and transitory components and moving beyond reduced-form regressions on raw temperature realizations. In Rebei (2025), the model is estimated country by country and does not distinguish between global and local climate forces. The permanent climate component is specified as a local-level process, that is, a random walk in levels with i.i.d. innovations. While this framework captures persistence in temperature, it implies a zero expected rate of warming, so periods of accelerating or decelerating warming are interpreted as sequences of level innovations rather than as changes in the underlying warming trajectory. Closely related, Gospodinov et al. (2025) use frequency-domain methods to separate low-frequency temperature variation from high-frequency weather shocks and show that low-frequency temperature movements are as-

sociated with economically meaningful effects on output growth over medium horizons, while high-frequency weather shocks primarily affect short-run fluctuations.

This paper contributes to this literature in several dimensions. It models climate change as a stochastic trend with shocks to the warming rate itself, allowing climate change to operate through persistent changes in the trajectory of temperature rather than through one-time level shifts. This specification nests the local-level model as a special case and allows the data to determine whether persistence operates through levels or through the warming rate. In addition, it explicitly decomposes country-level temperature into exposure to a common global climate trend and country-specific local climate deviations, helping to distinguish the long-run effects of global climate change from those of residual local climate dynamics. These climate components are then linked to output within a unified panel framework. Rather than estimating country-by-country relationships, this paper estimates the long-run climate-output relationship using panel cointegration with country and year fixed effects.

To clarify the source of identification underlying this framework, the empirical strategy exploits persistent cross-country differences in climate dynamics. Permanent temperature reflects both exposure to a common global climate trend and country-specific local climate evolution driven by geography and physical characteristics. As a result, even after controlling for country fixed effects, global time effects, and transitory weather shocks, countries exhibit distinct low-frequency climate paths. Identification therefore arises from sustained within-country variation in permanent temperature, stemming from heterogeneous exposure to global warming as well as local climate dynamics.

Applying this framework to a global panel of 192 countries yields three main findings. First, persistent climate change is associated with a large long-run reduction in productive capacity: a one-degree Celsius increase in the permanent climate component is associated with roughly a 22 percent lower level of trend real GDP in the long run within countries.[2,3]This effect reflects a gradual adjustment of output toward a lower climate-constrained path rather than a short-run growth response. By contrast, transitory weather fluctuations have no statistically significant effect on trend output once persistent climate dynamics are accounted

[2]Our estimated long-run output losses are of similar magnitude to those reported by Bilal and Känzig (2025), despite differences in empirical objects and identification. While Bilal and Känzig (2025) infer the effect of a permanent temperature increase from the ratio of cumulative impulse responses to identified global temperature shocks, our estimates are based on a direct decomposition of output and temperature into permanent and transitory components.

[3]In the data, the standard deviation of annual changes in the estimated global climate component is approximately 0.04°C. Scaling the estimates by this variation implies that a one-standard-deviation increase in annual global climate change is associated with about a 1 percent reduction in the long-run level of output once adjustment is complete.

for and primarily generate short-run cyclical variation. The baseline result is robust across a wide range of robustness specifications and is qualitatively unchanged across alternative filtering choices.

Second, the estimated error-correction dynamics imply that adjustment to this lower climate-consistent output path is very slow. A one-degree permanent increase in temperature closes only about 2.3 percent of the remaining output gap per year. As a result, it takes roughly 30 years for half of the long-run output loss to materialize and close to a century for about 90 percent of the loss to be realized. In the years immediately following a climate shift, this adjustment operates through modest but persistent reductions in trend growth, on the order of about 0.6 percentage points initially, with the growth effect declining over time as the output gap narrows. Climate change therefore acts as a slow-moving constraint rather than as a sharp short-run growth shock.[4]

Third, long-run climate damages are highly heterogeneous across countries and driven primarily by global rather than local climate forces. Once climate zone is accounted for, income status alone does not significantly amplify long-run climate damages. Instead, persistent output losses are concentrated in cold-climate countries, among both advanced economies and EMDEs, while estimated effects in moderate and hot climates are small and statistically insignificant. Decomposing climate further, I find that these long-run losses are driven mainly by exposure to the global climate trend, with persistent country-specific local climate deviations playing little role in anchoring output. Short-run dynamics paint a complementary picture: transitory global weather shocks generate sizable but temporary fluctuations in output growth, whereas local weather shocks have relatively small effects, consistent with the evidence in Bilal and Känzig (2025).

Our decomposition of temperature into permanent and transitory components follows a large and well-established literature in macroeconometrics that uses state-space models and Kalman filtering to separate stochastic trends from cyclical fluctuations. These methods have long been applied to output and productivity, beginning with early unobserved-components models of GDP (Clark, 1987) and formalized in the structural time-series framework of Harvey (1989). Subsequent work emphasizes the economic interpretation of permanent versus transitory shocks and the sensitivity of decompositions to modeling assumptions (Morley et al., 2003). Closely related approaches have been used to model drifting trends and time-varying volatilities in inflation and other macroeconomic aggregates (Cogley and Sargent, 2005). Similar state-space techniques have also been applied outside macroeconomics, includ-

[4]The estimated magnitude indicates a very slow transition path. Since climate change proceeds incrementally, most current economies remain far from their climate-consistent steady state, implying that only a limited share of the eventual long-run loss has materialized to date.

ing to environmental and climate data, where Bloomfield (1992) extracts stochastic trends in global temperature, and to commodity markets, where permanent and transitory shocks are identified in oil prices using Kalman filtering (Rebei and Sbia, 2021). In this sense, our approach applies standard signal-extraction tools to temperature data rather than introducing an ad hoc decomposition.

The remainder of the paper is organized as follows. Section 2 introduces the state-space framework used to decompose global and country-level temperature into persistent climate components and transitory weather shocks, and to extract trend and cyclical components of real GDP. Section 3 presents the estimated temperature and output decompositions and documents the key properties of global climate dynamics, country-specific climate exposure, and short-run weather fluctuations. Section 4 estimates the long-run relationship between persistent climate change and trend output using a panel cointegration and error-correction framework, and characterizes the slow adjustment dynamics toward the climate-consistent output path. Section 4 also provides robustness checks to the baseline results. Section 5 examines heterogeneity in long-run climate effects across income groups and climate zones and explores capital intensity as a potential mechanism. Section 6 disentangles the roles of global and local climate forces, showing that long-run output losses are driven primarily by exposure to the global climate trend. Section 7 studies short-run macroeconomic responses to global and local weather shocks around the climate-anchored output path. Section 8 concludes.

2 Methodology

2.1 Global temperature

The observed global temperature at time t, denoted T_t^G, is decomposed into a smooth climate trend component μ_t^G and a short-run weather component w_t^G:

$$T_t^G = \mu_t^G + w_t^G \tag{1}$$

The global climate trend follows a damped local linear trend with a mean-reverting slope:

$$\mu_t^G = \mu_{t-1}^G + \beta_t^G, \tag{2}$$

$$\beta_t^G = c^G + \psi^G \beta_{t-1}^G + e_t^G, \qquad e_t^G \sim \mathcal{N}(0, \sigma_{e,G}^2),\ |\psi^G| < 1. \tag{3}$$

Here, β_t^G is the global warming rate, c^G is the slope drift, and ψ^G governs the persistence of deviations from the long-run warming rate $\beta_G^* = c^G/(1-\psi^G)$. The shocks e_t^G represent

innovations to the global warming rate.[5]

The global weather component follows an AR(1) process:

$$w_t^G = \phi^G w_{t-1}^G + \varepsilon_t^G, \qquad \varepsilon_t^G \sim \mathcal{N}(0, \sigma_{\varepsilon,G}^2) \tag{4}$$

2.2 Country-level temperature model

For each country c, the observed temperature $T_{c,t}$ is modeled as a combination of the global climate signal, a country-specific (filtered) climate deviation, and short-run local weather:

$$T_{c,t} = \alpha_c + \lambda_c \mu_t^G + \mu_{c,t}^{\text{loc}} + w_{c,t} \tag{5}$$

Here, α_c is a country fixed effect and λ_c is the loading of the country on the global climate level μ_t^G. The residual filtered component $\mu_{c,t}^{\text{loc}}$ captures persistent local deviations from the global baseline, evolving as

$$\mu_{c,t}^{\text{loc}} = \mu_{c,t-1}^{\text{loc}} + \beta_{c,t}^{\text{loc}}, \tag{6}$$

$$\beta_{c,t}^{\text{loc}} = \psi_c^{\text{loc}}\, \beta_{c,t-1}^{\text{loc}} + e_{c,t}^{\text{loc}}, \qquad e_{c,t}^{\text{loc}} \sim \mathcal{N}(0, \sigma_{e,c}^2),\ |\psi_c^{\text{loc}}| < 1. \tag{7}$$

The local warming rate $\beta_{c,t}^{\text{loc}}$ follows a stationary AR(1) around zero, and $e_{c,t}^{\text{loc}}$ are local slope innovations. Local weather is represented as

$$w_{c,t} = \phi_c w_{c,t-1} + \varepsilon_{c,t}, \qquad \varepsilon_{c,t} \sim \mathcal{N}(0, \sigma_{\varepsilon,c}^2) \tag{8}$$

2.3 Country GDP decomposition

For each country c, observed real GDP (in logs), $y_{c,t}$, is decomposed into a long-term trend component $\mu_{c,t}^y$ and a short-run transitory component $w_{c,t}^y$:

$$y_{c,t} = \mu_{c,t}^y + w_{c,t}^y \tag{9}$$

The GDP trend $\mu_{c,t}^y$ evolves as a damped local–linear trend:

$$\mu_{c,t}^y = \mu_{c,t-1}^y + \beta_{c,t}^y \tag{10}$$

$$\beta_{c,t}^y = c_c^y + \psi_c^y \beta_{c,t-1}^y + e_{c,t}^y, \qquad e_{c,t}^y \sim \mathcal{N}(0, \sigma_{e,y,c}^2),\ |\psi_c^y| < 1 \tag{11}$$

[5] In a special case where $c_G = 0$ and $\psi^G = 0$, the global temperature setup would be equivalent to Rebei (2025).

where $\mu^y_{c,t}$ is the filtered GDP trend (log level); $\beta^y_{c,t}$ is the filtered GDP growth rate (trend slope); c^y_c determines the long-run mean growth rate; $\beta^{*y}_c = c^y_c/(1-\psi^y_c)$; $e^y_{c,t}$ are structural growth shocks.

The short-run transitory component $w^y_{c,t}$ captures cyclical fluctuations around the trend and is modeled as an AR(1) process:

$$w^y_{c,t} = \phi^y_c w^y_{c,t-1} + \varepsilon^y_{c,t}, \qquad \varepsilon^y_{c,t} \sim \mathcal{N}(0, \sigma^2_{\varepsilon,y,c}),\ |\phi^y_c| < 1 \tag{12}$$

This structure provides filtered estimates of the GDP trend ($\mu^y_{c,t}$), trend growth rate ($\beta^y_{c,t}$), and cyclical component ($w^y_{c,t}$). Using superscripts for GDP variables ensures full distinction from the temperature trends μ^G_t and $\mu^{\text{loc}}_{c,t}$ defined earlier.

3 Temperature Decomposition

3.1 Data

The analysis combines long-span temperature and macroeconomic data designed to distinguish persistent climate dynamics from transitory weather fluctuations. Global temperature data (land and ocean surface) are obtained from the National Oceanic and Atmospheric Administration (NOAA) and span the period 1960 - 2022. Country-level temperature series are constructed from the ERA5 reanalysis dataset and aggregated to the national level using 2015 population weights. This approach ensures that measured temperature variation reflects conditions experienced by economic agents rather than sparsely populated regions, which is particularly important when linking climate dynamics to aggregate economic outcomes. The sample begins in 1960, corresponding to the onset of sustained global warming and the availability of reliable, internationally comparable national accounts data. Earlier decades exhibit weaker low-frequency temperature movements, providing limited identifying variation for persistent climate dynamics, while pre-1960 GDP data are much less consistent across countries.

Macroeconomic outcomes are measured using annual real GDP series from the Global Macroeconomic Database (GMD), which provides harmonized national accounts with broad postwar coverage. The combined dataset covers 192 countries over the period 1960-2022. Appendix Table A1 lists countries by income group and climate zone, while Appendix Table A2 summarizes data coverage across countries.

Observed temperatures and GDP are used only as inputs into the state-space model; all climate, weather, trend GDP, and cyclical GDP variables used in the regressions are filtered outputs from the estimated system rather than transformed versions of the raw

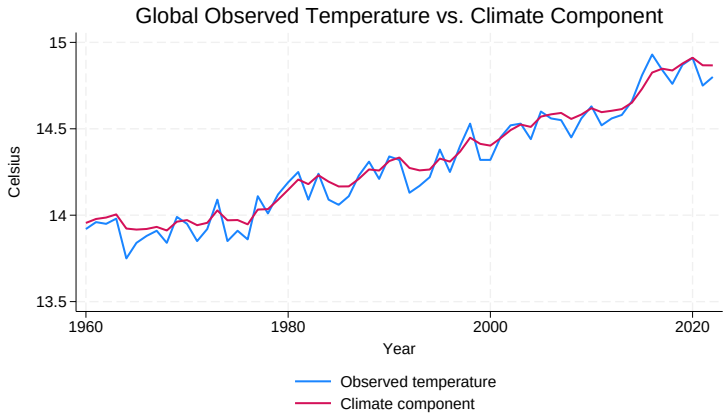
series. No smoothing, demeaning, or detrending is applied to either temperature or GDP prior to estimation. All trend-cycle decompositions are generated internally by the state-space model, allowing the data to determine the degree of persistence and volatility in both climate and economic variables.

The regression analysis begins in 1970 to mitigate sensitivity to initial conditions in the Kalman filter. Although the panel is unbalanced due to unavailable GDP data, coverage is extensive: more than the 90 percent of countries have the full 53 annual observations from 1970-2022, and results are robust to restricting the sample to countries with near-complete coverage. When real GDP growth is used, it is winsorized at the 1st and 99th percentiles to reduce the influence of extreme observations that are unlikely to reflect weather- or climate-related fluctuations. Appendix Table A3 reports summary statistics for the 1970-2022 sample.

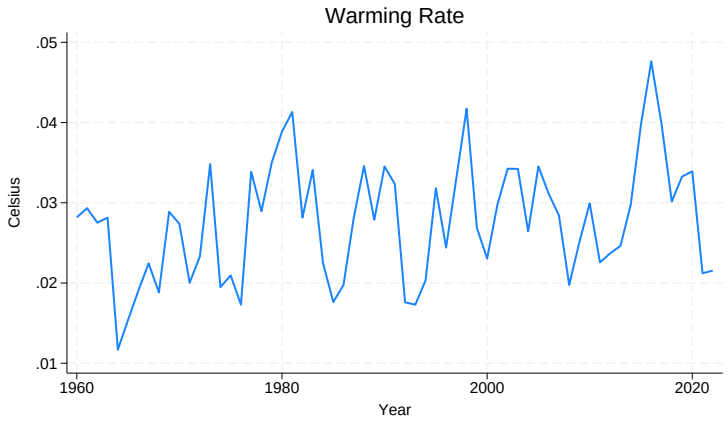
3.2 Global temperature

Figure 1 presents the decomposition of global observed temperature into its underlying climate component, the estimated warming rate, and the warming shocks. Panel (a) shows that the observed global temperature has closely tracked the estimated climate component since the 1960s, with both series trending upward by about 1°C over the sample period. Panel (b) presents the estimated warming rate, which exhibits considerable variability but generally trended upward from the 1970s through the 1990s before stabilizing at roughly 0.02 to 0.03°C per year in the 2000s and 2010s. This pattern highlights that the pace of warming has not been constant, instead alternating between acceleration phases and periods of stabilization. ψ^G is estimated equal 0.716298, implying that global climate change operates through gradual shifts in the trajectory of temperature rather than through one-time level jumps. Panel (c) displays the estimated warming shocks, which fluctuate around zero with no apparent persistence, consistent with the econometric assumption that innovations to the warming rate follow a white-noise process.

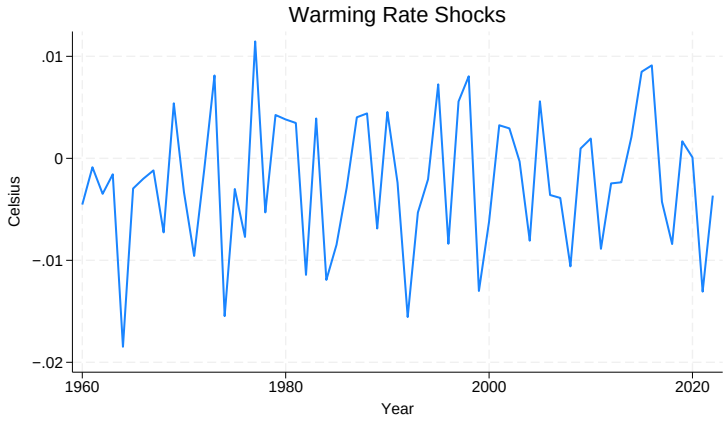
Figure 2 shows the estimated global weather component w_t^G (blue) together with its associated shocks ε_t (red). The shocks represent unpredictable innovations that directly drive the short-term fluctuations in global temperature. As expected from an AR(1) process, ε_t and w_t^G move closely together: shocks generate contemporaneous jumps in the weather series, which then decay gradually according to the estimated autoregressive parameter.



(a) Observed global temperature (T_t^G) and estimated climate component μ_t^G



(b) Estimated warming rate (β_t^G)



(c) Estimated warming shock (e_t^G)

Figure 1: Global Climate Trend

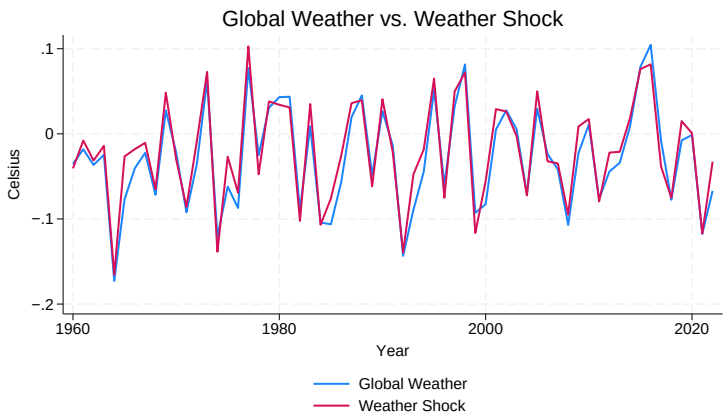


Figure 2: Global weather (w_t^G) and weather shocks (ε_t^G)

3.3 Country temperature decomposition

Figure 3 presents temperature decomposition observed across nine selected countries representing different climate: USA, Finland, Brazil, Germany, India, Japan, South Africa, Vietnam, and Barbados over the period from 1965 to 2022. The first five years of the estimation window (1960-1965) are dropped because the filtered components are less stable at the beginning of the sample. Each depicts two key metrics: the observed temperature, represented by a fluctuating blue line, and a climate component produced by the model, illustrated by a smoother red line. The climate model includes both global and local climate components. Most countries exhibit a noticeable upward trajectory in both observed temperatures and the climate component, suggesting a general warming trend over the seven-decade span, and some countries have sharper rises in temperature. For instance, the USA and Finland show increases from around 19°C and 6°C to approximately 20.5°C and 9°C, respectively, by 2020s. Similarly, Brazil and Japan display rises from 26.5°C to 28°C and 17°C to 19°C, respectively.

Figure 4 illustrates the estimated weather component $w_{c,t}$ for the same set of representative countries. For each country, the blue line represents the weather component $w_{c,t}$ and the red line represents the weather shocks. The blue line highlights the short-run fluctuations in annual temperature (i.e. the weather). It reflects the difference between the two lines in Figure 3. The magnitude of these shocks varies substantially across countries: for example, Finland and Japan's temperatures exhibit relatively large swings. Overall, the weather component captures the noisy, transitory shocks that can temporarily obscure longer-run climate signals in the observed temperature record. The magnitude of the year-to-year weather fluctuations is large compared to the slow change in climate.

Figure 5 displays the estimated country loadings on the global climate trend (λ_c). These

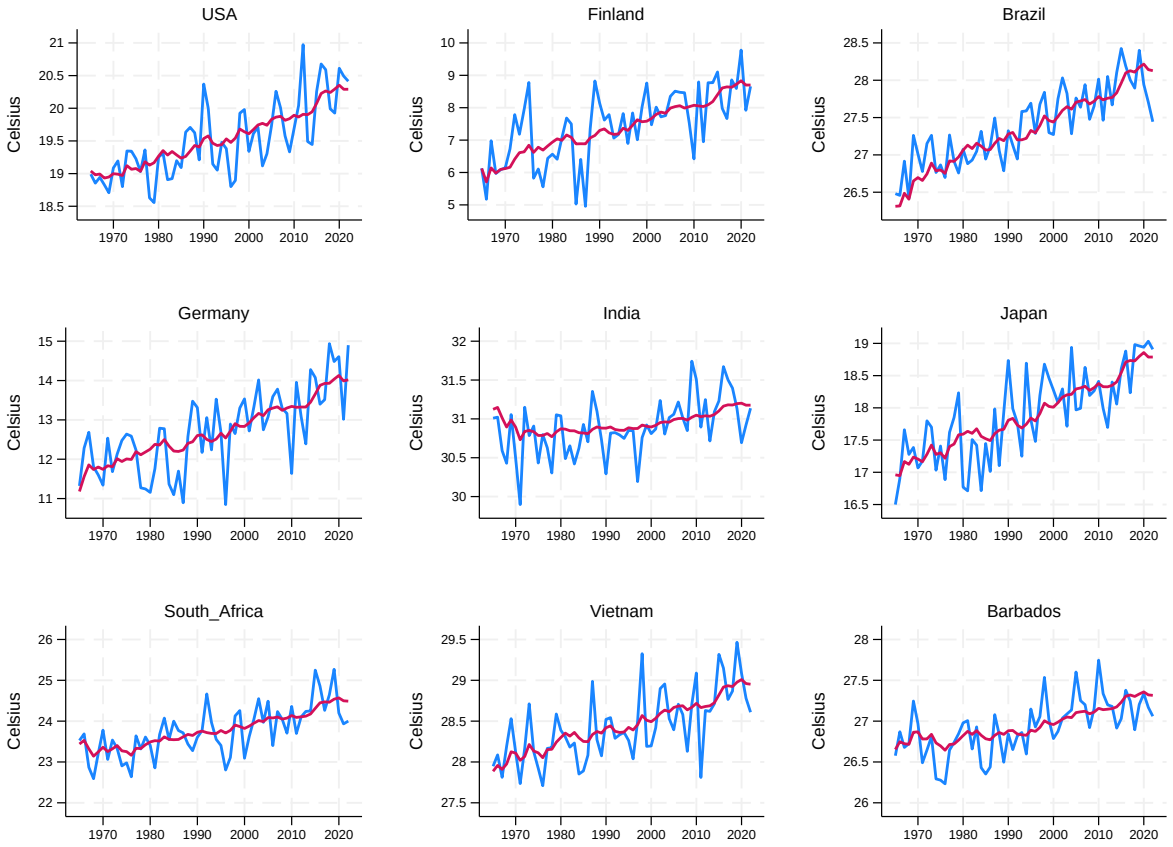


Figure 3: Country temperature ($T_{c,t}$) and country climate ($\alpha_c + \lambda_c \mu_t^G + \mu_{c,t}^{\text{loc}}$)

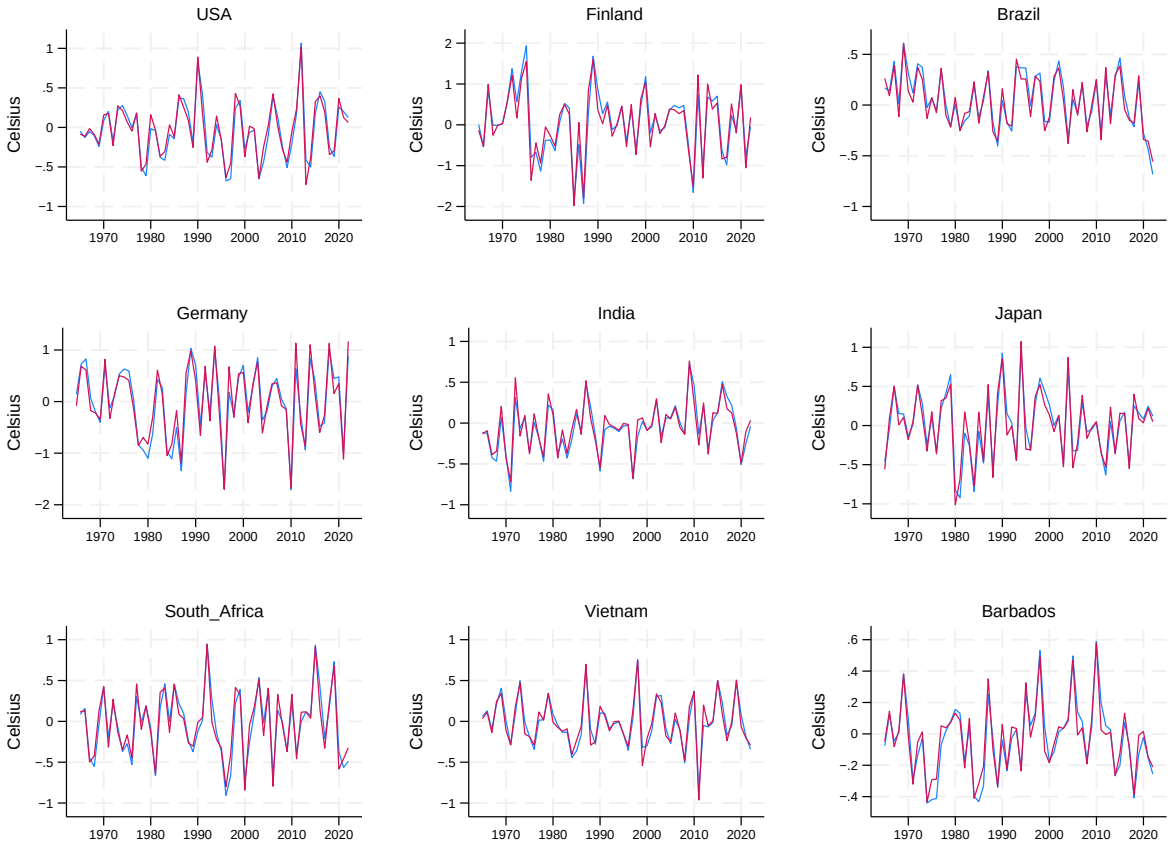


Figure 4: Country weather ($w_{c,t}$, in blue) and weather shocks ($\varepsilon_{c,t}$, in red)

loadings quantify how strongly each country's temperature responds to changes in the global warming trend. The spatial pattern reveals clear heterogeneity: polar and high-latitude regions often exhibit values well above one, consistent with polar amplification, while many coastal or maritime countries load less heavily on the global trend, reflecting oceanic buffering. These differences are not surprising: climate science has long emphasized polar amplification and maritime moderation. Their magnitude highlights the importance of allowing country-specific responses rather than imposing a one-size-fits-all global temperature measure. This heterogeneity strengthens identification in the panel regressions and underscores that the global warming signal translates unevenly across geographies.

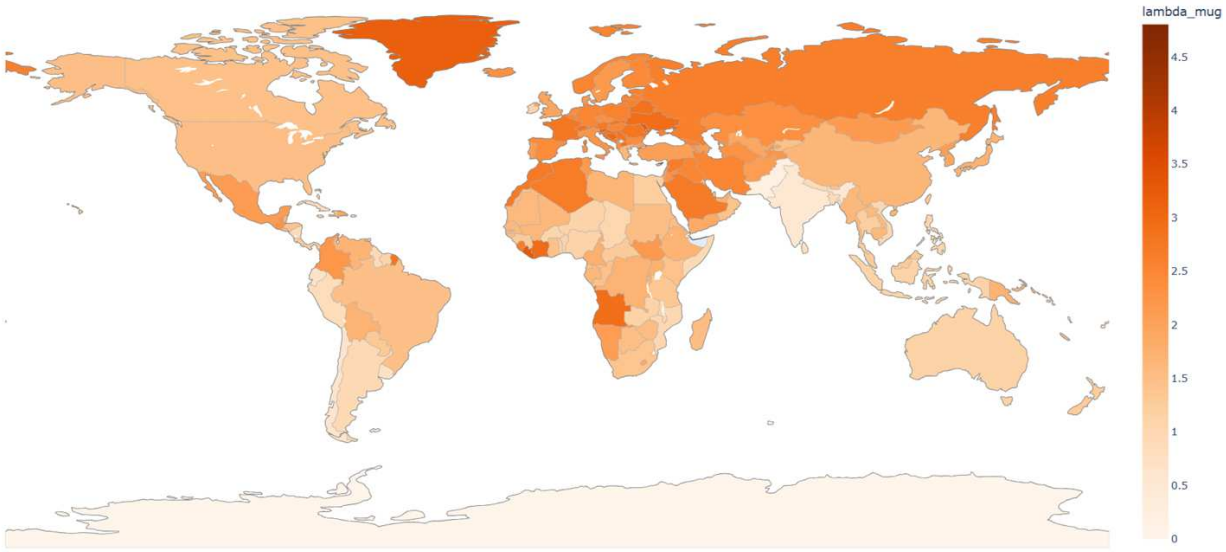


Figure 5: Country loading of global temperature (λ_c)

Figure 6 illustrates country climate decomposition from 1965 to 2022 across the nine countries: global climate loading (blue), country fixed effects (green), and country varying local climate (red). Across all countries, the blue line shows a clear upward trend, indicating that global climate forces are the primary driver of rising temperatures. In contrast, both the green and red lines remain flat, suggesting that country aggregate climate conditions are generally connected to global warming

3.4 GDP composition

Figures 7 and 8 present the decomposition of real GDP into permanent (trend) and transitory components for a representative set of countries. For most cases, including the United States, Finland, Brazil, India, and Vietnam, observed log real GDP almost visibly overlaps with

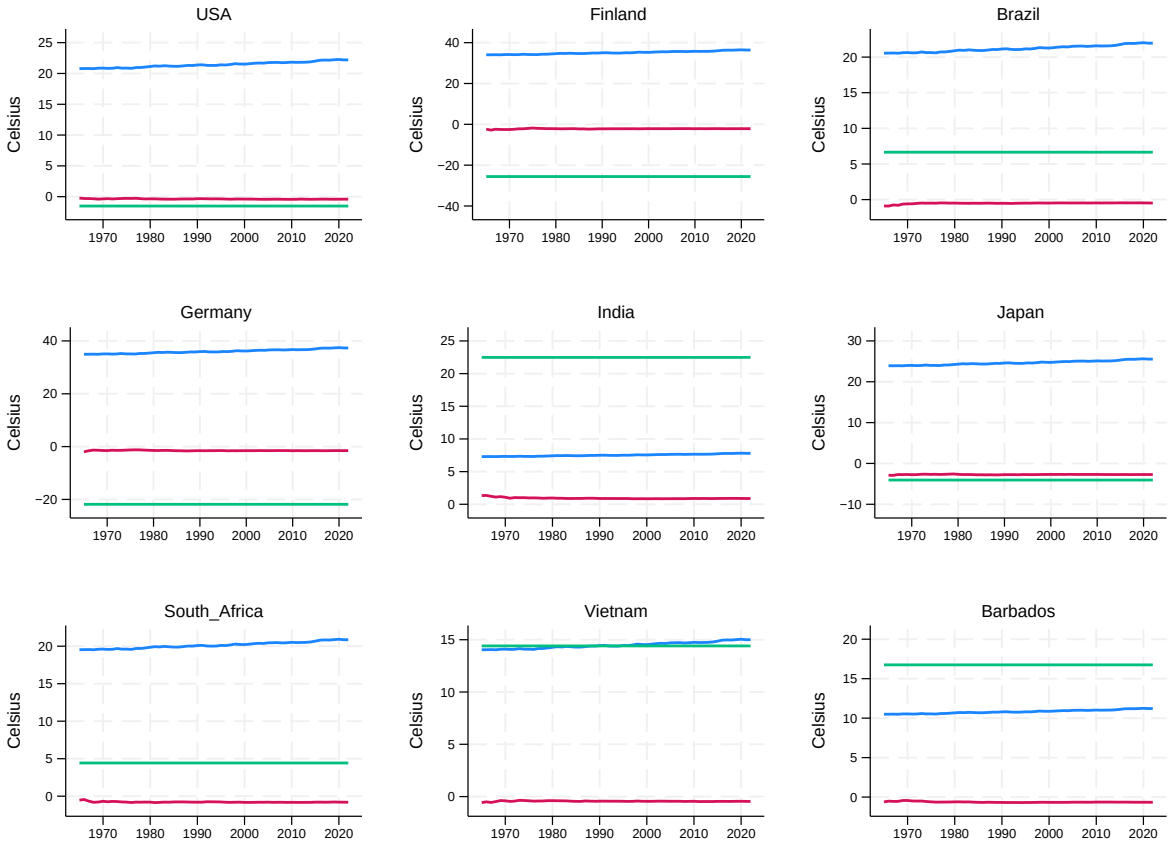


Figure 6: Global loading (blue, $\lambda_c \mu_t^G$), country fixed effects (green, α_c) and country local climate (red, $\mu_{c,t}^{\text{loc}}$)

the estimated trend component throughout the sample period, indicating that output is driven primarily by persistent shifts in the underlying growth path rather than by short-lived fluctuations. In a smaller number of cases, most notably Germany, Japan, and South Africa, deviations between observed GDP and its trend are more visible, reflecting larger cyclical episodes or prolonged periods of adjustment. The close alignment between observed and trend GDP in most countries reflects the dominance of low-frequency output movements rather than mechanical overfitting, as evidenced by the presence of meaningful yet mean-reverting transitory components in countries with larger cyclical fluctuations (see Figure 8)

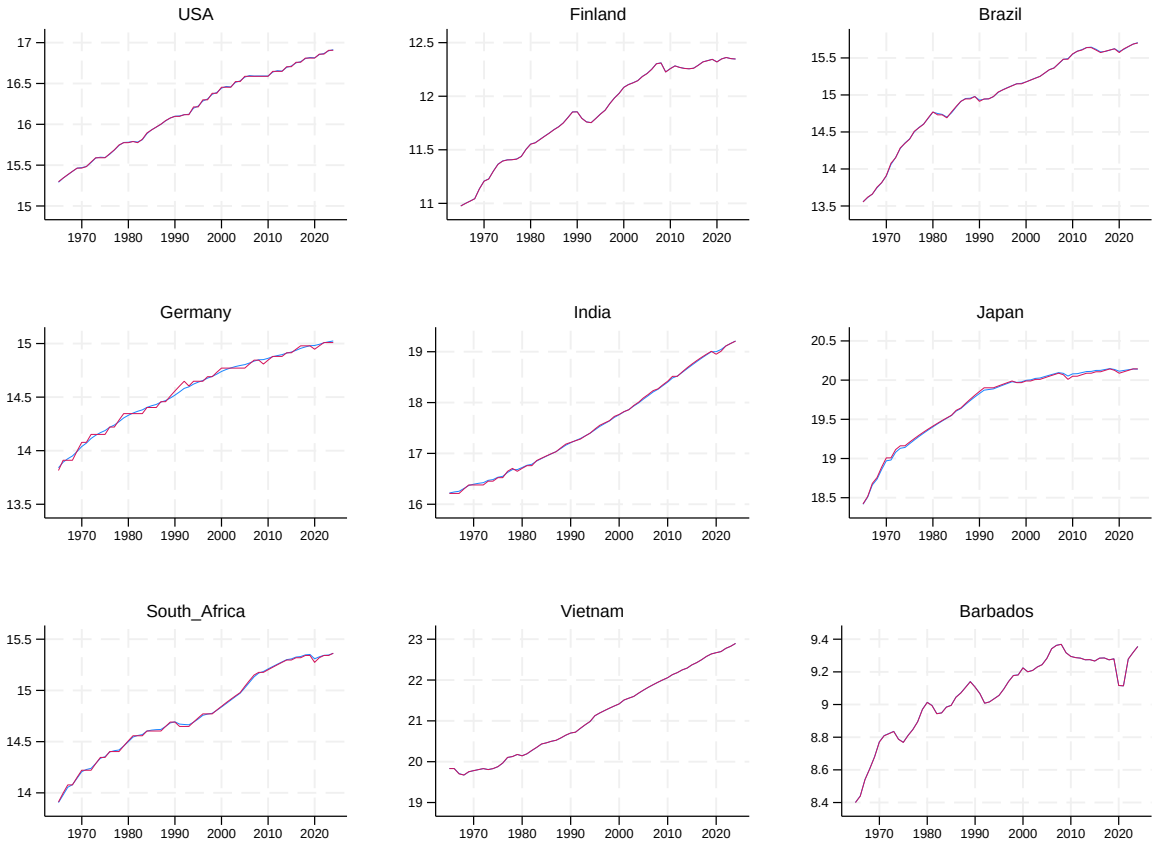


Figure 7: Log of Real GDP ($y_{c,t}$) in blue and Log of Real Trend GDP ($\mu^{y}_{c,t}$) in red

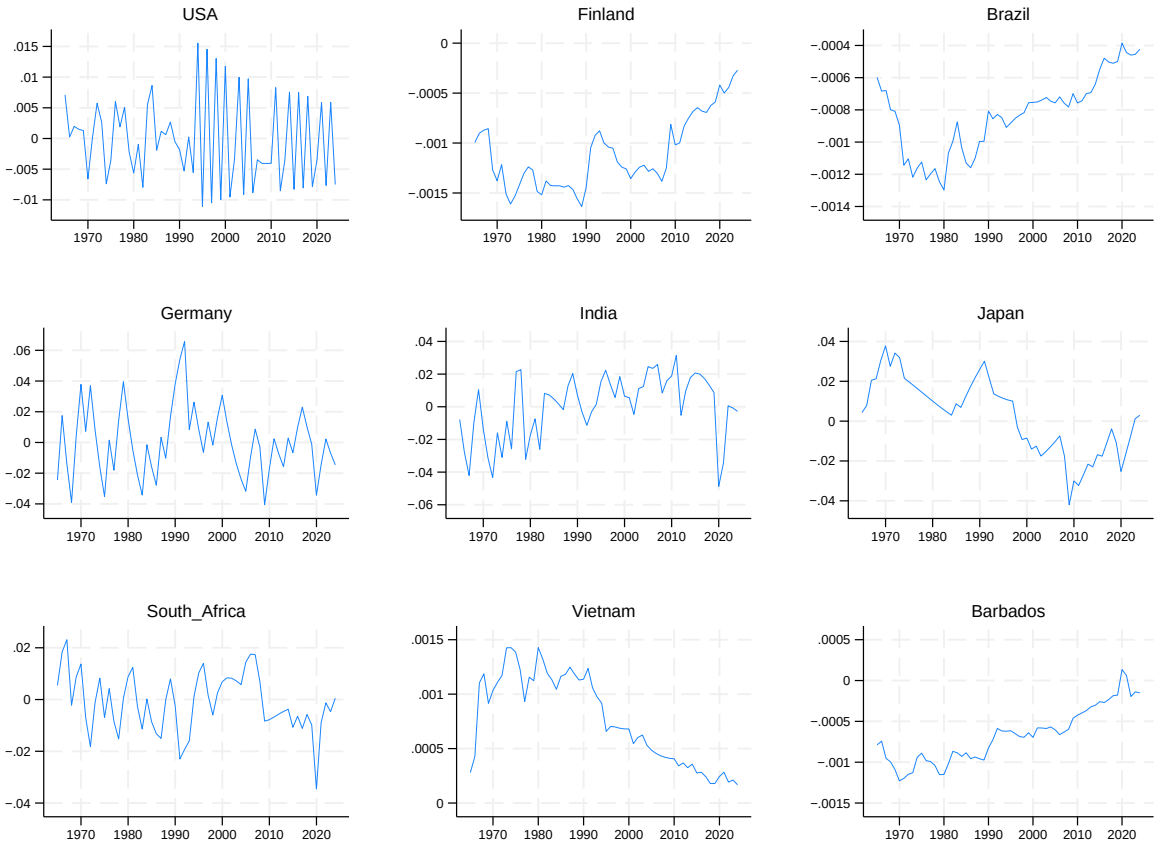


Figure 8: Log of Real Transitory GDP ($w_{c,t}^{y}$)

4 Long-run Impacts of Climate: an Panel Cointegration Approach

To estimate the long-run impacts of climate change on economic activity, this section estimates the long-run relationship between the permanent (climate) component of temperature and the long-run (trend) component of real GDP, and then characterizes the adjustment dynamics toward that long-run relationship. The key motivation is that both climate and potential output are slow-moving objects that exhibit strong persistence and are unlikely to be stationary in levels. Regressions that treat these processes as stationary shocks may have low power at annual frequencies and can yield unstable short-run estimates. An error-correction model (ECM) provides a disciplined way to combine (i) a long-run equilibrium relationship in levels with (ii) short-run dynamics in growth rates, while allowing temporary deviations from the long-run relationship to be gradually corrected over time.

4.1 Constructing the permanent climate component

Let μ_t^G denote the estimated global climate trend from Section 2.1 and $\mu_{c,t}^{loc}$ the country-specific climate deviation from Section 2.2. Country c loads on the global climate trend with loading λ_c. Define the permanent climate component for country c as

$$\mu_{c,t}^T \equiv \alpha_c + \lambda_c \mu_t^G + \mu_{c,t}^{loc}, \tag{13}$$

which captures the slow-moving, non-stationary component of local temperature that arises from (i) global warming transmitted differentially across countries and (ii) persistent local deviations from the global baseline.

I measure the long-run component of output using the filtered GDP trend $\mu_{c,t}^y$ (log level) from the GDP decomposition in Section 2.3. The empirical analysis focuses on the post-1970 sample to ensure broad country coverage and stable measurement.

4.2 Step 1: the long-run (cointegrating) relationship in levels

I first estimate the long-run equilibrium relationship between trend log real GDP and the permanent climate component using a two-way fixed-effects panel specification:

$$\mu_{c,t}^y = \alpha_c + \tau_t + \beta\, \mu_{c,t}^T + u_{c,t}, \tag{14}$$

where α_c are country fixed effects and τ_t are year fixed effects. Country fixed effects absorb time-invariant differences in levels of output and climate across countries, while year fixed effects absorb global macroeconomic shocks common to all countries. Importantly, identification of the long-run relationship does not rely on common global variation alone. Because countries differ systematically in their exposure to global climate change and has their own local climate, permanent temperature retains substantial low-frequency within-country variation even after demeaning by year fixed effects. As a result, equation (14) captures a long-run relationship between permanent output and temperature driven by differential exposure to global climate, and own local climate.

Estimated long-run semi-elasticity. Table 1 reports the estimated β from (14). The coefficient is negative and statistically significant. Since $\mu^y_{c,t}$ is in logs and $\mu^T_{c,t}$ is measured in degrees Celsius, β can be interpreted as a semi-elasticity: a one-degree (permanent) increase in the climate component is associated with an approximately $100 \times \beta$ percent lower level of trend GDP in the long run, within country (for small β).

Table 1: Long-run relationship between trend GDP and the permanent climate component

Dependent variable	$\mu^y_{c,t}$ (trend log real GDP)
$\mu^T_{c,t}$ (permanent climate component, °C)	-0.2542^{***}
	(0.0713)
Country fixed effects	Yes
Year fixed effects	Yes
Observations	9,943
Countries	192
Within R^2	0.707

Notes: The table reports estimates of the long-run relationship between trend log real GDP and the permanent climate component. The sample includes only countries classified as advanced economies or emerging market and developing economies (EMDEs) according to the IMF World Economic Outlook (WEO). Robust standard errors clustered by country are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

The estimated coefficient on the permanent climate component is negative and statistically significant. The high within-country R-squared indicates that the permanent climate component and common time effects jointly explain a substantial share of within-country variation in trend GDP. At the same time, the near-zero between-country R-squared (not shown) reflects the fact that cross-country level differences are absorbed by fixed effects, reinforcing that the estimate relies on time-series rather than cross-sectional variation. The point estimate implies that a one-degree Celsius increase in the permanent climate component is associated with approximately a 22 percent lower level of trend GDP in the long run,

within country ($exp(-0.254) = 0.776$). To assess whether the estimated long-run effect is driven by outliers, Appendix Figure A2 presents the partial regression plot corresponding to the specification in Table 1. The negative relationship between trend output and the permanent climate component is visible across the distribution of the data after removing country and year fixed effects, indicating that the estimated effect is not likely driven by outliers.[6]

This estimate reflects the cumulative impact of persistent climate change. The magnitude of the estimated coefficient should be interpreted as the long-run anchoring effect of climate on economic activity. A permanent increase in climate temperature does not imply an immediate collapse in output; instead, it lowers the level around which the economy operates in the long run. This distinction is crucial. The estimate does not imply that GDP falls by about 22 percent in the year of warming. Rather, it indicates that, once adjustment is complete, the economy converges to a persistently lower output path consistent with climate-constrained productive capacity. Climate change affects output primarily through slow-moving channels such as capital depreciation, infrastructure durability, labor productivity, health, and sectoral reallocation. As a result, the long-run level effect of climate change can be economically large even when short-run growth responses are modest or difficult to detect at annual frequency. In addition, this pooled estimate masks substantial heterogeneity across climate zones. As shown in the next section, long-run climate damages are concentrated in cold-climate countries, while estimated effects in moderate and hot climates are small and statistically insignificant. The coefficient in Table 1 should therefore be interpreted as a weighted average of highly heterogeneous country-level responses rather than as a uniform global effect.

Finally, it is useful to note that the estimated long-run climate effect reflects equilibrium output outcomes conditional on all endogenous responses, including technological progress and adaptation. To the extent that these forces mitigate climate damages, the estimated coefficient represents a *lower bound* on the structural impact of climate change on long-run output.

[6]Our approach is closely related to recent work that infers the long-run impact of climate change from short-run temperature shocks using local projections or VARs, following the logic of Sims (1986), including Kahn et al. (2021) and Bilal and Känzig (2025). While these studies recover the permanent effect as the ratio of cumulative impulse responses of output and temperature, I estimate the same long-run object directly by linking trend output to the permanent component of temperature in a state-space framework. My contribution is to estimate the permanent climate–output relationship transparently and directly, without relying on the extrapolation of short-run dynamics.

4.3 Step 2: Error-correction dynamics

The regression in (14) provides an estimate of the long-run relationship, but it does not by itself establish that the relationship is an equilibrium anchor to which the economy returns after shocks. To test for equilibrium adjustment, I construct the error-correction term (ECT) as the residual from the long-run relationship:

$$\widehat{ECT}_{c,t} \equiv \mu^{y}_{c,t} - \widehat{\alpha}_c - \widehat{\tau}_t - \widehat{\beta}\,\mu^{T}_{c,t}. \tag{15}$$

If trend output and climate are linked by a stable long-run relationship, then deviations from that relationship should predict subsequent adjustments in trend GDP growth.

I estimate the ECM in (trend) growth rates:

$$\Delta\mu^{y}_{c,t} = \phi\,\widehat{ECT}_{c,t-1} + \gamma\,\Delta\mu^{T}_{c,t} + \sum_{j=1}^{2}\rho_j\Delta\mu^{y}_{c,t-j} + \theta_0\Delta w_{c,t} + \theta_1\Delta w_{c,t-1} + \gamma_c + \tau_t + \eta_{c,t}, \tag{16}$$

where $\Delta\mu^{y}_{c,t}$ is trend GDP growth, $\Delta\mu^{T}_{c,t}$ is the change in the permanent climate component and $\Delta w_{c,t}$ is the change in the country-specific weather component. γ_c and τ_t are country and year fixed effects. Standard errors are clustered by country.

The coefficient ϕ governs error correction. A negative and statistically significant ϕ implies that when trend GDP is above the level implied by climate (a positive $\widehat{ECT}_{c,t-1}$), subsequent trend GDP growth is lower, bringing output back toward the long-run path. The term γ captures whether changes in the permanent climate component have an immediate effect on trend growth. In a climate context, a natural benchmark is that permanent climate change shifts the long-run level of output, while short-run growth fluctuations are dominated by transitory weather and global cyclical forces. In that case, ϕ is expected to be negative, while γ may be small at annual frequencies.

The ECM in Table 2 provides direct evidence of error correction. The estimated coefficient on the lagged error-correction term is $\widehat{\phi} \approx -0.0232$, indicating that deviations of trend GDP from the climate-consistent long-run path are gradually corrected over time. The statistically significant error-correction term is consistent with gradual adjustment toward a stable long-run relationship between $\mu^{y}_{c,t}$ and $\mu^{T}_{c,t}$. The magnitude implies very slow adjustment: roughly 2.3 percent of the remaining deviation is eliminated each year. In practical terms, following a one-degree permanent increase in temperature that lowers long-run trend GDP by about 22 percent, it takes approximately 30 years to close half of the resulting output gap and close to a century (around 95–100 years) to eliminate 90 percent of the gap toward the lower climate-consistent path. This adjustment initially manifests as a modest

Table 2: Error-correction model for trend GDP growth

Dependent variable	$\Delta\mu^{y}_{c,t}$ (trend GDP growth)
$\widehat{ECT}_{c,t-1}$ (error-correction term)	-0.0232^{***}
	(0.0028)
$\Delta\mu^{T}_{c,t}$ (permanent climate change)	-0.0036
	(0.0120)
$\Delta\mu^{y}_{c,t-1}$	0.4423^{***}
	(0.0291)
$\Delta\mu^{y}_{c,t-2}$	0.0598^{***}
	(0.0169)
$\Delta w_{c,t}$ (local weather)	-0.0006
	(0.0013)
$\Delta w_{c,t-1}$ (local weather)	-0.0012
	(0.0009)
Country fixed effects	Yes
Year fixed effects	Yes
Observations	9,367
Countries	192
Within R^2	0.294

Notes: The table reports estimates of an error-correction model for trend GDP growth. The error-correction term $\widehat{ECT}_{c,t-1}$ is constructed as the lagged residual from the long-run relationship between trend GDP and the permanent climate component reported in Table 1. The sample includes only countries classified as advanced economies or emerging market and developing economies (EMDEs) according to the IMF World Economic Outlook (WEO). Robust standard errors clustered by country are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

but persistent drag on trend growth, on the order of about 0.6 percentage points in the first few years (given by $0.0232 \times 0.254 \approx 0.006$), and then declines mechanically over time as the gap narrows. In the climate context, these dynamics reflect the gradual erosion of productive capacity through channels such as capital depreciation, rising maintenance costs, reduced labor productivity, and slow sectoral reallocation. Because these forces operate through long-lived stocks, adjustment unfolds over decades rather than through abrupt contractions.

In contrast, contemporaneous changes in the permanent climate component $\Delta\mu_{c,t}^{T}$ have a limited short-run association with trend growth at annual frequency. This is consistent with the view that climate change does not operate as a conventional macroeconomic shock, but rather as a slow-moving structural force whose effects accumulate over time. At annual horizons, incremental changes in the climate trend are small relative to weather shocks and cyclical fluctuations, so their economic consequences emerge primarily through gradual adjustment in levels rather than through immediate changes in growth rates.

Local weather shocks have no statistically significant effect on trend GDP growth once long-run climate conditions and error-correction dynamics are controlled for, indicating that idiosyncratic weather fluctuations mainly influence short-run economic volatility rather than the long-run path of output.

Panel cointegration diagnostics: Because permanent output and temperature components are highly persistent, we complement the error-correction analysis with formal panel cointegration diagnostics. We employ the error-correctionbased tests of Westerlund (2007), which assess whether deviations from a candidate long-run relationship are corrected over time. This approach allows for heterogeneous adjustment dynamics across countries and accounts for cross-sectional dependence through bootstrap inference.

Appendix Table A4 reports the results. In the full sample of 192 countries, the panel statistic (Pt) rejects the null hypothesis of no cointegration at the 10% level using dependence-robust bootstrap p-values, while group-mean statistics provide weaker evidence (Panel A). This pattern is consistent with heterogeneous long-run adjustment and the presence of global shocks, which are known to reduce the power of cointegration tests in finite samples.

As a robustness check, we re-estimate the tests excluding countries that experience prolonged episodes of exceptional growth, which are likely to reflect idiosyncratic structural breaks unrelated to climate. In this restricted sample of 179 countries, the panel statistic rejects the null of no cointegration at the 5% level (Panel B). The strengthening of the diagnostics is consistent with structural breaks weakening cointegration tests in the full sample. In this restricted sample, the estimated long-run coefficient on permanent temperature is slightly larger in magnitude and more precisely estimated, with an estimate of -0.265.

Overall, we interpret these results as suggestive evidence of long-run adjustment between

permanent temperature and output components. Given the presence of global shocks, heterogeneous climate exposure, and generated permanent states, we view cointegration tests as complementary diagnostics that support the error-correction dynamics discussed above.

4.4 Robustness checks

To further assess the robustness of the long-run climate-output relationship and clarify the role of filtering and dynamic specification, results in Appendix Table A5 complement the error-correction results with simple first-difference and long-difference benchmarks. These exercises deliberately abstract from the cointegration structure and serve as transparent checks that rely only on changes in output and changes in the permanent climate component.

First differences: First, I estimate a panel regression of annual real GDP growth on annual changes in the permanent climate component, including country and year fixed effects. Consistent with the slow-moving nature of climate change, the estimated coefficient is imprecise and statistically insignificant at annual frequency. This lack of power is expected: incremental changes in the climate trend are small from year to year, while output growth is dominated by short-run cyclical variation, making it difficult to detect level effects using first differences alone.

Long differences: Second, I estimate long-difference regressions that relate changes in output between 1970 and 2022 to the corresponding change in the permanent climate component over the same period. In contrast to the annual first-difference specification, the long-difference estimates are large, negative, and highly statistically significant, whether output is measured using filtered trend GDP or observed GDP levels. These long-difference results closely mirror the magnitude of the long-run coefficient obtained from the cointegration specification, indicating that the estimated climate damages are not an artifact of the state-space filtering or the ECM structure. These benchmarks reinforce the interpretation that climate change primarily operates through gradual level effects that accumulate over decades, rather than through detectable contemporaneous effects on annual growth rates. The ECM framework is therefore well suited to the data: it reconciles weak short-run growth responses with strong long-run anchoring of output to persistent climate dynamics.

Hodrick-Prescott (HP)-filtered GDP: As a further robustness check, I assess whether the long-run climate-output relationship depends on the specific trend extraction method used for output. In the baseline analysis, trend output is obtained from a state-space decomposition that allows for stochastic trend growth. To provide a more well-known benchmark, I replace this measure with alternative low-frequency representations of output based on the HP filter applied to log real GDP, using annual smoothing parameters of $\lambda = 100$

and $\lambda = 6.25$, and also consider specifications using log GDP levels without statistical filtering (see Appendix Table A6). Re-estimating the long-run fixed-effects regression with these alternative measures yields remarkably similar results: the estimated coefficient on the permanent climate component remains negative, highly statistically significant, and quantitatively close to the baseline estimates across all specifications. This stability indicates that the main findings are not an artifact of the state-space trend specification or of a particular filtering choice, but instead reflect a robust low-frequency relationship between persistent climate change and the level of output.

HP-filtered country temperature: Finally, I assess robustness to the construction of the climate variable itself by replacing the state-space permanent climate component with a purely statistical low-frequency temperature trend. Specifically, I apply the HP filter to observed country-level temperature, extracting a smooth temperature trend separately for each country using annual smoothing parameters of $\lambda = 100$ and $\lambda = 6.25$. Appendix Table A7 reports the corresponding long-run fixed-effects regressions of trend output on these HP-filtered temperature measures. Across both specifications, the estimated coefficients remain negative and statistically significant, confirming that the long-run climate-output relationship does not hinge on the state-space decomposition of temperature. The magnitudes are modestly attenuated relative to the baseline estimates, which is expected given that HP filtering is a coarse statistical procedure that mixes medium-frequency variation with persistent climate dynamics. Nevertheless, the stability of the sign and statistical significance provides strong evidence that the main results reflect a robust low-frequency relationship between warming and output levels rather than an artifact of the particular climate filtering approach.

Potential reverse causations: An important concern is reverse causation from economic activity to temperature, whereby higher output raises greenhouse gas emissions and could affect local temperature. Climate science, however, indicates that changes in surface temperature are driven by the accumulation of global emissions rather than contemporaneous national emissions. As a result, fluctuations in a country's output and emissions are unlikely to generate meaningful variation in its local temperature trend. Another related concern is that reductions in aerosol emissions, which exert a cooling effect, may raise temperature while coinciding with economic transitions that affect GDP. Such aerosol clean-up has been more pronounced in advanced economies, reflecting earlier environmental regulation and structural change. However, the estimated climate effects are identified from within-country variation over time and remain strong when the analysis is restricted to advanced economies (see Table 3). To the extent that advanced economies experienced broadly similar air-quality improvements, these common trends are absorbed by year fixed effects. For aerosol clean-

up to explain the results, it would need to vary across advanced economies in a way that is systematically correlated with the permanent climate component, $\mu_{c,t}^{T}$. Empirically, this channel does not appear to drive the results: when controlling for SO_2 emissions, a key aerosol gas, the estimated long-run impact of climate change on advanced economies' output remains strong (results not shown).[7]

4.5 Comparison with conventional raw temperature regressions

For comparison, this section reports conventional panel regressions that relate output directly to raw observed temperature, following the dominant approach in the climate–macro literature. In contrast to our baseline framework, these specifications do not distinguish between persistent climate change and transitory weather fluctuations. The purpose of this exercise is not to provide alternative estimates of long-run climate damages, but rather to illustrate how standard temperature regressions behave when applied to output levels and growth.

Appendix Table A8 reports fixed-effects regressions of output on observed temperature, controlling for country and year fixed effects and clustering standard errors at the country level. Columns (1) and (2) use trend output and log real GDP, respectively, as dependent variables. In both cases, the estimated temperature coefficient is negative, statistically significant, and is much smaller in magnitude compared to our baseline result. However, the economic interpretation of these coefficients is unclear as the raw temperature combines persistent climate change with high-frequency weather variation.

Column (3) of Table A8 reports a regression of output growth (winsorized at p1 and p99 levels) on observed temperature, which is the specification most commonly used in the existing literature. Consistent with prior findings, the estimated effect is smaller and less significant, reflecting short-run weather responses rather than persistent climate change. These benchmark results highlight the limitations of conventional temperature regressions for assessing long-run macroeconomic impacts of climate change and motivate our decomposition-based approach, which isolates the persistent climate component and links it explicitly to trend output in a panel cointegration framework.

[7] SO_2 emissions are included solely as a robustness check and should not be interpreted as a preferred control. SO_2 emissions are closely correlated with economic activity and industrial structure. Conditioning on them may absorb part of the endogenous output responses.

5 Heterogeneity in Long-Run Climate Effects

This section examines how the long-run impact of climate change varies across countries. Unlike much of the existing literature, which documents heterogeneous responses to short-run weather shocks, my focus is on persistent shifts in the climate mean. This distinction is important because the channels through which transitory temperature fluctuations affect output may differ fundamentally from those associated with long-run climate change. As a result, heterogeneity patterns commonly identified in weather-based studies need not carry over to the long-run climate dimension studied here.

5.1 Benchmark: Heterogeneity by income group

I begin by examining whether the long-run effect of climate change differs systematically between emerging market and developing economies (EMDEs) and advanced economies (AEs). This distinction is widely used in the climate–macro literature, reflecting differences in income levels, sectoral composition, capital intensity, and adaptive capacity.

Specifically, I estimate equation (2) separately for EMDEs and AEs, maintaining country fixed effects and year fixed effects in both subsamples. The dependent variable is trend output, $\mu^y_{c,t}$ while $\mu^T_{c,t}$ captures the permanent component of temperature. Standard errors are clustered at the country level.

Table 3: Long-run impact of climate by country group

	EMDEs	Advanced Economies
$\mu^T_{c,t}$ (permanent climate component, °C)	-0.190^{**}	-0.509^{**}
	(0.089)	(0.197)
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	8,020	1,923
Countries	155	37
Within R^2	0.693	0.819

Notes: The table reports estimates of the long-run relationship between trend log real GDP and the permanent climate component for emerging market and developing economies (EMDEs) and advanced economies (AEs), estimated separately using two-way fixed effects. Robust standard errors clustered by country are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 3 reports the results. The estimated long-run effect of climate change is negative and statistically significant for advanced economies, while the corresponding estimate for EMDEs is smaller in magnitude and statistically insignificant. Taken at face value, these

results suggest that long-run climate change has imposed larger output costs in advanced economies than in EMDEs.

However, income groups differ systematically in their long-run climate exposure. In particular, advanced economies are disproportionately located in colder climate zones, while hot climates are almost exclusively populated by EMDEs. As a result, the split-sample estimates may conflate development status with climate regime. I therefore next allow the long-run climate–output relationship to vary jointly by income group and climate zone.

5.2 Joint heterogeneity by income group and climate zone

To disentangle the roles of development status and climate exposure, I estimate a unified specification that allows the long-run effect of climate change to vary jointly by income group and climate zone. Countries are classified into cold, moderate, and hot climate zones based on the long-run distribution of average annual temperature, with moderate climates serving as the omitted category. Cold (hot) climates are defined as countries whose long-term average temperature falls below the 25th percentile (above the 75th percentile) of the cross-country distribution. Appendix Figure A1 shows the resulting climate-zone classification.

I interact the permanent climate component $\mu_{c,t}^{T}$ with the EMDE dummy variable and climate zones, as well as their double interactions. This fully saturated specification nests the income-group split as a special case while preserving a common identifying structure across countries. All regressions include country and year fixed effects, so identification comes from country-specific deviations from the global climate trajectory.

Table 4 reports the estimated coefficients, while Table 5 presents the implied long-run effects for each income–climate group combination. The implied effects reported in Table 5 are constructed as linear combinations of the estimated coefficients in Table 4. The omitted category is advanced economies located in moderate climate zones, so the coefficient on μ^{T} represents the long-run climate semi-elasticity for that group. Note that hot-climate countries in the sample are all EMDEs (see Appendix Table A1), so the effect of climate change in hot countries is identified by the sum of $\mu_{c,t}^{T}$, $\mu_{c,t}^{T} \times$ Hot, and $\mu_{c,t}^{T} \times$ EMDE. As a result, there is no separately identified effect for hot advanced economies.

Two results stand out from Tables 4 and 5. First, once climate zone is accounted for, EMDE status by itself does not significantly amplify long-run climate damages: the implied effects for EMDEs in moderate climates are close to zero, and the EMDE–AE differential within cold climates is not statistically large. This pattern suggests that cross-country differences in long-run climate impacts operate primarily through climate exposure rather than income level per se. Second, and more importantly, long-run climate damages are strongly neg-

Table 4: Long-Run Climate Effects: Income Group × Climate Zone

Variable	Coefficient
$\mu^T_{c,t}$	−0.049
	(0.144)
$\mu^T_{c,t}$× Hot	−0.029
	(0.114)
$\mu^T_{c,t}$× Cold	−0.193
	(0.135)
$\mu^T_{c,t}$× EMDE	0.059
	(0.151)
$\mu^T_{c,t}$× EMDE × Cold	−0.135
	(0.169)
Country fixed effects	Yes
Year fixed effects	Yes
Observations	9,943
Countries	192

Notes: The omitted category is advanced economies in moderate climates. Climate-zone indicators are time-invariant and enter only through interactions with $\mu^T_{c,t}$. Robust standard errors clustered at the country level are reported in parentheses.

Table 5: Implied Long-Run Effects of Climate Change by Group

Income group	Climate zone	Implied effect
Advanced economy	Moderate	−0.050
Advanced economy	Cold	−0.243***
EMDE	Moderate	0.009
EMDE	Hot	−0.020
EMDE	Cold	−0.319***

Notes: Implied effects are linear combinations of coefficients from Table 4. Statistical significance is based on delta-method standard errors. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. The omitted category is advanced economies located in moderate climate zones, so the coefficient on $\mu^T_{c,t}$ represents the long-run climate semi-elasticity for that group. The implied effect for cold-climate advanced economies adds the interaction term $\mu^T \times$ Cold, while the implied effect for EMDEs in moderate climates adds $\mu^T_{c,t} \times$ EMDE. For cold-climate EMDEs, the implied effect combines $\mu^T_{c,t}$, $\mu^T_{c,t} \times$ Cold, $\mu^T_{c,t} \times$ EMDE, and $\mu^T_{c,t} \times$ EMDE $\times$ Cold. Hot-climate countries in the sample are all EMDEs, so the effect of climate change in hot regions is identified by the sum of μ^T, $\mu^T_{c,t} \times$ Hot, and $\mu^T_{c,t} \times$ EMDE. As a result, there is no separately identified effect for hot-climate advanced economies.

ative and statistically significant in cold-climate countries, both among advanced economies and EMDEs, while estimated effects are small and statistically insignificant in moderate and hot climates. This pattern contrasts sharply with the short-run weather-shock literature, which typically finds larger adverse effects of high temperatures in hot countries and in EMDEs (e.g., Dell et al. (2012), Burke et al. (2015)). It is consistent to Rebei (2025), who shows that richer and colder economies are more resilient to transitory temperature fluctuations but experience larger output losses in response to permanent temperature shifts.

The difference reflects the nature of the shock under consideration. Transitory weather fluctuations primarily affect output through short-run labor productivity and agricultural channels, whereas persistent shifts in the climate mean operate through slower-moving mechanisms that shape productive capacity. In historically cold climates, economic structures and capital stocks have evolved in close alignment with prevailing temperature norms, so persistent warming can generate sizable adjustment costs even when short-run temperature deviations appear neutral or beneficial.

5.3 On the potential mechanisms

A potentially key mechanism underlying the heterogeneous long-run effects is systematic variation in capital intensity across climate zones. Figure 9 shows that cold-climate economies are substantially more capital intensive than economies in moderate or hot climates. This pattern provides an interpretation for why long-run climate damages are concentrated in colder regions. Capital stocks, infrastructure, and the built environment are inherently climate specific, having been designed for historical temperature distributions. Persistent warming can therefore raise depreciation rates, increase maintenance costs, and shorten asset lifespans, gradually reducing the effective services generated by a given stock of capital.[8]

Capital intensity also amplifies climate damages through reallocation frictions. In economies with large stocks of climate-adapted capital, relative productivity shifts induced by climate change are costly to accommodate, as capital is often sector- and location-specific and cannot be redeployed quickly. Persistent climate change can thus induce prolonged periods of inefficient allocation, manifesting as sustained level losses rather than short-run growth effects. This interpretation aligns closely with the slow error-correction dynamics estimated in Section 4.

Table 6 provides complementary regression evidence consistent with this mechanism. Column (1) interacts the permanent climate component with an indicator for high capital

[8]See for example Mulholland and Feyen (2021), who show that global warming significantly raises the risk of heat-related damage to European road and rail infrastructure, reflecting the vulnerability of capital-intensive countries with capital assets designed for historically cooler temperatures.

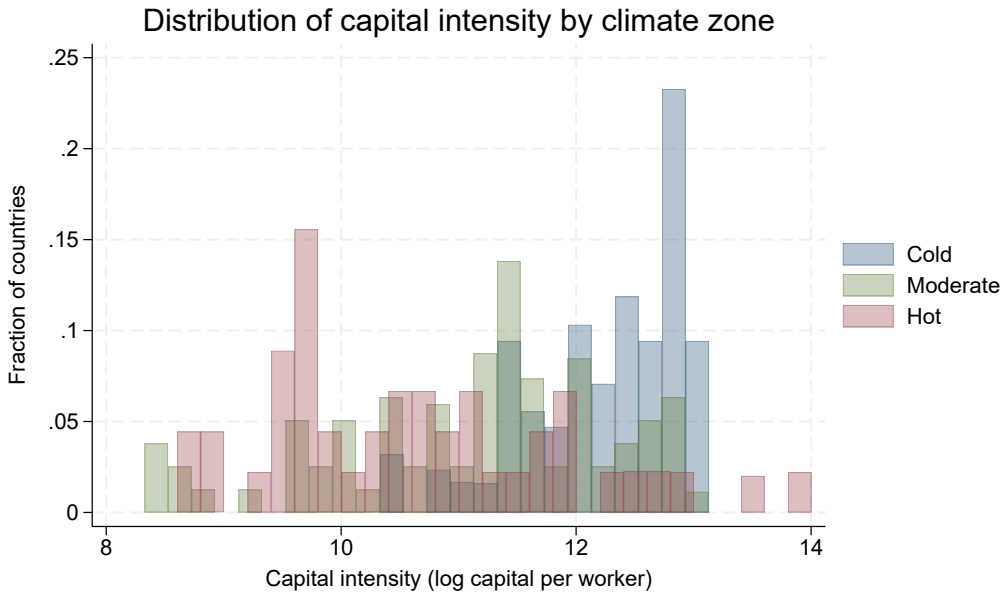


Figure 9: Distribution of capital intensity by climate zone

Note: The figure overlays histograms of capital intensity (log capital per worker) for cold, moderate, and hot climate zones. The vertical axis reports the fraction of countries in each bin within a given climate zone, so each histogram integrates to one. Capital intensity is constructed from Penn World Table capital stock and employment (average between 1970-2023).

intensity, defined as countries whose average capital over labor ratio exceeds the sample median. Capital and labor data are drawn from Penn World Table 11.0 and averaged over all available years. The interaction term is negative and statistically significant, indicating that long-run climate damages are concentrated in more capital-intensive economies. Column (2) further decomposes this heterogeneity by allowing the climate's impacts to vary across climate zones. The estimated effects are largest and statistically significant in cold-climate countries, while effects in hot climates are small and statistically insignificant. Conditional on climate zone, the interaction with capital intensity remains negative and statistically significant, though attenuated, reflecting the close empirical association between cold climates and high capital intensity. Put differently, within a given climate zone, more capital-intensive economies experience larger long-run climate damages.

6 Global or Local Climate as a Main Driver?

A new literature emphasizes that climate change should be understood as a global phenomenon rather than as a collection of independent local shocks. Bilal and Känzig (2025)

Table 6: Capital Intensity, Climate Zone, and Long-Run Climate Effects

	(1) High Capital Intensity	(2) Climate Zone Interactions
Permanent climate component ($\mu_{c,t}^T$)	−0.055	0.091
	(0.104)	(0.109)
$\mu_{c,t}^T\times$ High capital intensity	−0.224***	−0.154*
	(0.078)	(0.085)
$\mu_{c,t}^T\times$ Cold climate		−0.229***
		(0.081)
$\mu_{c,t}^T\times$ Hot climate		−0.044
		(0.106)
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	9,943	9,943
Countries	192	192
Within R^2	0.714	0.719

Notes: The table reports fixed-effects regressions of trend output ($\mu_{c,t}^y$) on the permanent climate component and its interactions with baseline country characteristics. High capital intensity is equal 1 if a country's average capital over employment exceeds the sample median. Capital and labor data are drawn from Penn World Table 11.0 and averaged over all available years. Climate zones are classified using long-run average temperature. All specifications include country and year fixed effects. Standard errors are clustered at the country level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

show that global temperature fluctuations have substantially larger and more persistent macroeconomic effects than country-level temperature variation. They argue that this difference arises because global temperature captures the evolution of the climate system itself and is closely linked to the incidence of extreme climatic events such as heatwaves, droughts, and storms. By contrast, local temperature variation used in conventional panel regressions is weakly correlated with these extremes and therefore understates the macroeconomic costs of climate change.

Motivated by this global–local distinction, this section examines whether a similar asymmetry emerges when climate dynamics are decomposed directly at the country level. Rather than contrasting global temperature with local temperature measures, as in the existing literature, I decompose country-level climate into exposure to a common global climate factor and a residual local climate component. This approach allows us to isolate the macroeconomic effects of globally-driven climate change from those of country-specific climate deviations within a unified panel framework, and to assess whether global climate forces embedded in local temperature dynamics serve as the primary long-run anchor for output.

Formally, I estimate the following specification:

$$\mu_{c,t}^{T} \;=\; \alpha_c + \tau_t \;+\; \beta_1 \left(\lambda_c \mu_t^{G}\right) \;+\; \beta_2 \, \mu_{c,t}^{\text{loc}} \;+\; u_{c,t}, \tag{17}$$

where $\mu_{c,t}^{T}$ denotes the climate-driven component of temperature for country c at time t. The term μ_t^{G} represents the common global climate factor, capturing the evolution of the global climate system over time. The country-specific loading λ_c measures each country's exposure to this global factor, allowing the impact of global climate change to vary across countries.[9] It is useful to emphasize that λ_c is estimated entirely from temperature dynamics. The component $\mu_{c,t}^{\text{loc}}$ captures local climate deviations that are orthogonal to the global factor. The specification includes country fixed effects α_c and year fixed effects τ_t, so identification comes from differential exposure to the global climate factor across countries and from within-country variation in local climate deviations over time.

To assess the relative importance of global and local climate forces, I decompose the within-country variance of the permanent climate component, $\mu_{c,t}^{T} = \lambda_c \mu_t^{G} + \mu_{c,t}^{\text{loc}}$, into the contributions of each component. The decomposition shows that low-frequency climate variation within countries is overwhelmingly driven by exposure to the global climate factor. The global-exposure term $\lambda_c \mu_t^{G}$ accounts for essentially most (about 117%) of the within-country variance of $\mu_{c,t}^{T}$, while the local component $\mu_{c,t}^{\text{loc}}$ accounts for about 10%. The shares

[9] Countries differ systematically in their exposure λ_c (see Figure 5), reflecting geographic and physical climate characteristics. This heterogeneity implies that a common global warming trajectory maps into distinct country-specific permanent climate paths $\mu_{c,t}^{T}$ over time.

sum to 100% once the negative covariance term is included, with $2\,\mathrm{Cov}(\lambda_c \mu_t^G, \mu_{c,t}^{\mathrm{loc}})$ contributing about -27%. This negative covariance indicates that local climate deviations tend to partially offset globally-driven climate movements.

Table 7: Global versus Local Climate Components

	(1) $\mu_{c,t}^Y$	(2) $\mu_{c,t}^Y$
$\lambda_c \mu_t^G$	-0.3236^{***}	-0.1927^{**}
	(0.0786)	(0.0912)
$\mu_{c,t}^{\mathrm{loc}}$	-0.0114	
	(0.1274)	
Country fixed effects	Yes	Yes
Year fixed effects	Yes	No
Climate-zone × year FE	No	Yes
Observations	9,943	9,943
Countries	192	192
Within R^2	0.712	0.725

Notes: This table reports fixed-effects estimates of equation (17). The term $\lambda_c \mu_t^G$ captures each country's exposure to the common global climate factor, where μ_t^G denotes the global climate component and λ_c measures country-specific exposure. The variable $\mu_{c,t}^{\mathrm{loc}}$ captures country-specific local climate deviations from the global component. Column (1) includes country and year fixed effects. Column (2) replaces global year fixed effects with climate-zone-by-year fixed effects, absorbing any global shocks or secular trends common to countries within the same climate regime. The local climate component is excluded in column (2) to isolate identification from within-zone heterogeneity in exposure to the global climate trend. Standard errors are clustered at the country level and reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 7 reports the corresponding fixed-effects estimates with trend (permanent) output $\mu_{c,t}^Y$ as the dependent variable. Column (1) shows a sharp contrast between global and local climate components. Exposure to the global climate factor, $\lambda_c \mu_t^G$, is associated with a large, negative, and statistically significant effect on output, while the coefficient on the local climate component $\mu_{c,t}^{\mathrm{loc}}$ is small and statistically indistinguishable from zero. In other words, long-run climate damage to trend output is driven primarily by exposure to the global warming trend rather than by persistent country-specific local climate drift. Countries that are more exposed to global climate change experience systematically larger output losses, even after controlling for common global shocks through year fixed effects and for time-invariant country characteristics through country fixed effects. This finding indicates that global climate change operates as a binding long-run force on aggregate economic performance.

The insignificance of the local climate component is economically intuitive and informative. Local climate deviations net of global warming are comparatively small and more likely to be partially offset through adaptation, migration, or changes in production patterns. As

a result, local climate variation does not appear to anchor the long-run level of aggregate output once exposure to the global climate factor is accounted for.

A potential concern with this specification is that countries with higher exposure to the global climate trend, λ_c, are disproportionately located in colder regions, so that $\lambda_c \mu_t^G$ could partly correlate with other time-varying forces that differentially affect cold-climate economies. To address this concern, Column (2) replaces global year fixed effects with climate-zone-by-year fixed effects, which absorb any global shocks or secular trends common to countries within the same climate regime. Identification in this specification therefore comes exclusively from within-zone heterogeneity in exposure to global warming. The estimated effect of $\lambda_c \mu_t^G$ remains negative and statistically significant, indicating that long-run output losses are not driven by generic cold-region trends but by differential exposure to the global climate factor itself.

7 Short-Run Dynamics of Global and Local Weather Shocks

While previous Sections focus on long-run climate anchoring, much of the existing literature studies short-run macroeconomic responses to weather shocks. This section reconciles these perspectives by examining the dynamic responses to global and local weather fluctuations around the long-run climate path.

7.1 Conceptual distinction between climate and weather

Sections 4 through 6 focus on the long-run relationship between climate and aggregate output, emphasizing how exposure to global climate change anchors the level of economic activity over time. Much of the existing empirical literature, however, studies a different object: short-run macroeconomic responses to weather fluctuations. These studies typically exploit high-frequency variation in temperature, precipitation, or extreme events, either at the local level or at the global scale, and document economically meaningful effects on output growth, productivity, and sectoral activity over horizons ranging from one to several years.

The distinction between climate and weather is primarily one of persistence. Climate reflects slow-moving, persistent shifts in the underlying state of the climate system, while weather captures transitory deviations around that state. As a result, climate change is naturally associated with long-run level effects on output, whereas weather shocks are more likely to generate short-run fluctuations and adjustment dynamics. Importantly, these two dimensions are not substitutes but complements. Short-run weather shocks occur around a

climate-dependent baseline, and their economic impact may depend on the prevailing climate conditions.

A similar distinction applies to the global versus local dimension. Global weather phenomena, such as El Nio events or synchronized heat anomalies, generate correlated shocks across countries and have been shown to affect global economic activity in the short to medium run. Local weather shocks, by contrast, are more idiosyncratic and primarily influence domestic economic outcomes. While both types of weather variation matter for short-run dynamics, neither necessarily determines the long-run level of output once persistent global climate exposure is taken into account.

This section complements the long-run framework developed earlier by examining short-run dynamics around the climate-driven output path. I show how short-run responses to weather shocks can coexist with the finding that long-run output levels are primarily anchored by exposure to global climate change.

7.2 Econometric specification for short-run weather dynamics

I use weather shocks extracted from the state-space decomposition of temperature discussed in Sections 2 and 3. Global weather shocks are defined as innovations to the global weather component,

$$w_t^G = T_t^G - \mu_t^G,$$

where ε_t^G denotes the corresponding innovation to the AR(1) process governing w_t^G. Local weather shocks are defined analogously as innovations to the country-specific weather component,

$$w_{c,t} = T_{c,t} - (\alpha_c + \lambda_c \mu_t^G + \mu_{c,t}^{\text{loc}}),$$

with $\varepsilon_{c,t}^{\ell}$ denoting the innovation to local weather in country c at time t. By construction, both shocks are orthogonal to persistent climate dynamics and capture unpredictable, transitory fluctuations in temperature.

To estimate short-run responses, I follow the global temperature literature and employ panel local projections. For each horizon $h = 0, 1, \ldots, H$, I estimate the following local projection, following Jordà (2005):

$$\Delta y_{c,t+h} = \alpha_c^{(h)} + \theta_h^G \, \varepsilon_t^G + \theta_h^{\ell} \, \varepsilon_{c,t}^{\ell} + \sum_{j=1}^{2} \rho_j^{(h)} \Delta y_{c,t-j} + u_{c,t+h}^{(h)}, \tag{18}$$

where $\Delta y_{c,t}$ is year-on-year change in log real GDP (and not trend GDP), ε_t^G is the global weather shock, $\varepsilon_{c,t}^{\ell}$ is the local weather shock, $\alpha_c^{(h)}$ are horizon-specific country fixed ef-

fects, and $u_{c,t+h}^{(h)}$ is the horizon-specific error term. The coefficients θ_h^G, θ_h^l trace the impulse responses of output growth to global and local weather shocks.

I do not include year fixed effects in equation (18). The reason is that the global weather shock ε_t^G is identical across countries by construction, so time fixed effects would mechanically absorb it. This choice follows directly from the logic in Bilal and Känzig (2025), who emphasize that global weather shocks must be identified from common time-series variation rather than cross-sectional differences. Identification of local weather effects, by contrast, relies on cross-country heterogeneity in $\varepsilon_{c,t}^{\ell}$.

7.3 Short-run responses to global and local weather shocks

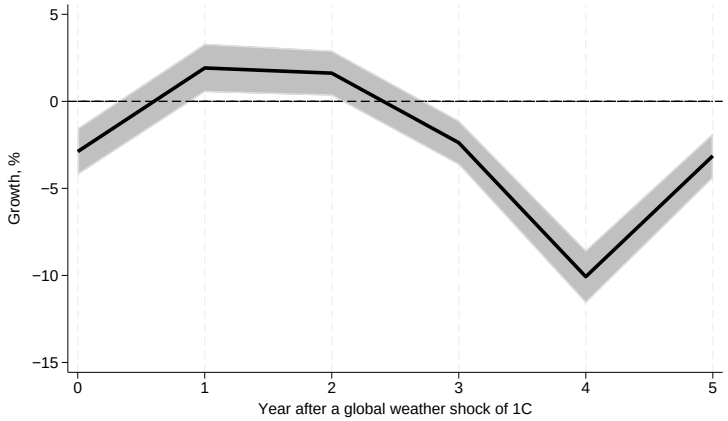
Panel A of Figure 10 reports the impulse response of output growth to a one degree Celsius global weather shock, defined as an innovation to the transitory global weather component orthogonal to the global climate trend. The response is economically large and transitory. Output growth declines on impact, turns positive in the first two years following the shock, and then reverses sharply several years later before gradually converging back toward zero. The non monotonic profile indicates delayed propagation (such as natural disasters or reconstruction). These dynamics relate closely to the mechanism emphasized by Bilal and Känzig (2025). In their framework, global temperature shocks generate large macroeconomic effects because they are associated with extreme climate events such as natural disasters. Although disasters materialize as discrete local events, their economic impact reflects exposure to common global climatic forces that simultaneously strain adjustment capacity across countries. My results complement this insight by showing that innovations to global weather around the climate path induce substantial short-run macroeconomic fluctuations.

Panel B of Figure 10 presents the corresponding impulse response to a local weather shock. In contrast, the response is small, statistically weak, and short lived. The wide confidence bands indicate substantial heterogeneity across countries, consistent with local weather shocks being absorbed through short-run adaptation, spatial reallocation, and sectoral adjustment.

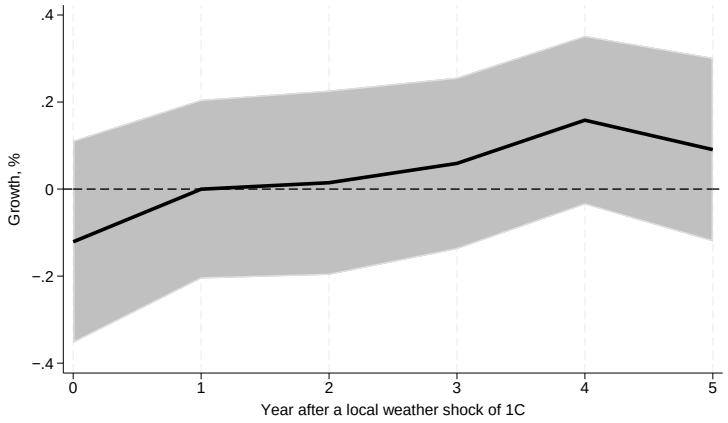
The contrast between global and local weather responses reinforces the distinction highlighted by Bilal and Känzig (2025). Shocks that are driven by global climatic forces, whether observed through disaster realizations or through synchronized weather anomalies, generate larger and more systematic macroeconomic effects than shocks that are purely local in nature. Local weather variation, while relevant for short-run volatility, does not give rise to sustained aggregate responses once global climate exposure is accounted for.

In summary, the impulse responses reconcile short-run weather-based evidence with the

long-run climate results in this paper. Persistent global climate change anchors long-run output levels, as shown in Section 6. Global weather shocks, which are larger in magnitude, generate sizable short-run dynamics around that path. Local weather shocks primarily affect transitory volatility without shaping aggregate growth trajectories.



(a) Global weather shock



(b) Local weather shock

Figure 10: Impulse responses of output growth to global and local weather shocks

Again, it is useful to clarify how this framework differs from Bilal and Känzig (2025), who study the macroeconomic effects of temperature shocks without explicitly separating persistent climate dynamics from transitory weather fluctuations. In this paradigm, global temperature realizations are a combination of both climate and weather components. Global temperature shocks can can materialize through extreme events such as natural disasters.[10] Natural disasters can be interpreted as manifestations of global temperature shocks, which

[10]There is a large literature on the short-run macroeconomic impacts of natural disasters, see Noy (2009), Loayza et al. (2012), Felbermayr and Gröschl (2014), Nguyen et al. (2025)...

include both global climate and weather. My approach adopts a different but complementary paradigm. I decompose temperature into a persistent climate component and a transitory weather component using a state-space framework. As a result, the shocks analyzed in Section 7 are explicitly weather shocks, defined as innovations orthogonal to the underlying climate path. This allows me to study short-run macroeconomic dynamics around a climate-dependent baseline, while keeping long-run climate anchoring, the focus of this study, analytically separate.

8 Conclusions

This paper shows that distinguishing persistent climate change from transitory weather fluctuations is essential for understanding the macroeconomic consequences of warming. By decomposing temperature into a global climate trend, heterogeneous country-level exposures, and short-run weather shocks, and linking these components to trend output within a panel cointegration framework, I uncover large and economically meaningful long-run level effects of climate change. A permanent increase in the climate component leads economies to converge gradually to a lower output path, with an estimated reduction in trend GDP of roughly 22 percent following a one-degree Celsius increase, but the process takes an extremely long time. These long-run losses are driven primarily by exposure to the global climate trend rather than by persistent local climate deviations, while weather shocks mainly generate short-run volatility around the climate-dependent output path. The results reconcile evidence of sizable short-run weather effects with slow-moving but substantial long-run climate damages.

The findings have clear policy implications. Because climate change operates as a persistent constraint on productive capacity rather than as a sequence of temporary shocks, effective adaptation requires structural and forward-looking responses. Policies that focus narrowly on smoothing short-run weather fluctuations risk understating the scale of adjustment needed when climate change permanently lowers potential output. Instead, adaptation and macro-fiscal planning should prioritize investments in climate-resilient capital, infrastructure durability, and sectoral reallocation, particularly in countries with high exposure to the global climate trend. Recognizing climate change as a long-run level shock, rather than a transitory disturbance, is therefore central to designing credible growth strategies, fiscal frameworks, and climate-resilient development paths.

The analysis in this paper points to important directions for future research. First, the estimates are based on historical data and reflect past patterns of adaptation, technology, and economic structure; the magnitude of future climate damages may differ as economies adjust, innovate, or implement new climate policies. As the empirical literature on climate change

(as opposed to weather shocks) is new, future research should aim to uncover the mechanisms and vulnerabilities underlying long-run climate damages. In particular, the finding that long-run losses are concentrated in cold-climate and capital-intensive countries raises important questions about the role of capital vintage, infrastructure design, and sectoral specialization, which warrant deeper investigation using micro-level data and structural approaches.

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A Appendix

	Cold	Moderate	Hot
Advanced Economies (AEs)	Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Slovak Republic, Slovenia, Sweden, Switzerland, United Kingdom, United States	Australia, Cyprus, Greece, Israel, Japan, Malta, New Zealand, Portugal, Puerto Rico, Singapore, Spain, Taiwan Province of China	
Emerging Market and Developing Economies (EMDEs)	Albania, Andorra, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Chile, Croatia, Georgia, Hungary, Kazakhstan, Kyrgyz Republic, Moldova, Mongolia, Montenegro, North Macedonia, Romania, Russian Federation, Serbia, Tajikistan, Uzbekistan	Afghanistan, Algeria, Angola, Antigua and Barbuda, Argentina, Aruba, Bahrain, Barbados, Belize, Bhutan, Bolivia, Brazil, Cabo Verde, China, Colombia, Comoros, Costa Rica, Cuba, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eswatini, Fiji, Gabon, Grenada, Guatemala, Honduras, India, Iran, Iraq, Jamaica, Jordan, Kuwait, Lebanon, Lesotho, Libya, Malaysia, Mauritius, Mexico, Morocco, Namibia, Nepal, Nicaragua, North Korea, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Qatar, Saudi Arabia, Seychelles, South Africa, Sri Lanka, St. Lucia, St. Vincent and the Grenadines, Syria, Thailand, Tonga, Tunisia, Turkiye, Ukraine, United Arab Emirates, Uruguay, Venezuela, Yemen	Bangladesh, Benin, Brunei Darussalam, Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Congo, Cote d'Ivoire, Democratic Republic of the Congo, Dominica, Eritrea, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Guyana, Haiti, Indonesia, Kenya, Laos, Liberia, Madagascar, Malawi, Maldives, Mali, Mauritania, Mozambique, Myanmar, Niger, Nigeria, Papua New Guinea, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, South Sudan, Sudan, Suriname, Tanzania, Timor-Leste, Togo, Uganda, Vanuatu, Vietnam, Zambia, Zimbabwe

Table A1: Country groups by income classification and climate zone.

Note: The sample includes 192 countries. Climate zones are defined using each country's average annual temperature over 1960-2022. Hot countries are above the 75th percentile of the temperature distribution, cold countries are the 25th percentile, and moderate countries are between the 25th and 75th percentiles.

	Number of temperature observations	Number of GDP observations
Number of countries	192	192
Mean	51.79	51.79
Minimum	15	15
1st percentile	33	33
10th percentile	53	53
25th percentile	53	53
Median	53	53
75th percentile	53	53
90th percentile	53	53
99th percentile	53	53
Maximum	53	53

Table A2: Country-level data coverage for temperature and GDP

Note: The table reports the distribution of the number of annual observations per country in the regression sample (1970-2022). Temperature and GDP coverage are identical by construction. South Sudan has the least coverage, only from 2008 to 2022

Variable	N	Mean	Min	p1	p10	p25	p50	p75	p90	p99	Max
Observed temperature (C)	9,943	23.62	2.74	6.40	12.38	18.01	26.27	28.62	31.14	35.02	36.33
Log real GDP	9,943	12.68	1.16	3.71	7.81	10.20	12.95	15.20	17.15	22.00	23.43
GDP growth (%)	9,943	3.54	−15.98	−15.98	−2.65	0.00	3.76	6.52	9.52	22.85	22.85

Table A3: Summary statistics

Note: The table reports summary statistics for annual country-level observations used in the regression sample. Observed temperature is measured in degrees Celsius, log real GDP is in natural logarithms, and GDP growth is expressed in percent. Real GDP growth is winsorized at p1 and p99

Table A4: Panel cointegration tests: Westerlund (2007)

Statistic	Value	Z-statistic	p-value	Robust p-value
Panel A: Full sample (192 countries)				
Gt	-1.292	-4.201	0.000	0.090
Ga	-3.066	2.242	0.988	0.180
Pt	-16.417	-8.005	0.000	0.055
Pa	-1.934	-4.342	0.000	0.120
Panel B: Excluding growth-spurt countries (179 countries)				
Gt	-1.294	-4.092	0.000	0.070
Ga	-3.128	1.983	0.976	0.130
Pt	-16.417	-8.213	0.000	0.040
Pa	-2.145	-5.170	0.000	0.070

Notes: The table reports error-correctionbased panel cointegration tests following Westerlund (2007). Robust p-values are obtained using dependence-robust bootstrap procedures. The null hypothesis is no cointegration. In Panel B, the sample excludes countries that experience prolonged episodes of exceptional growth, defined as at least five consecutive years of real GDP growth above 10 percent. The excluded countries are Armenia (ARM), Bosnia and Herzegovina (BIH), Botswana (BWA), China (CHN), Cabo Verde (CPV), Djibouti (DJI), Ethiopia (ETH), Equatorial Guinea (GNQ), Liberia (LBR), Maldives (MDV), Myanmar (MMR), Oman (OMN), and Qatar (QAT). These episodes largely reflect idiosyncratic structural changes such as post-conflict recoveries, commodity booms, large-scale investment surges, or economic transitions, rather than gradual climate dynamics. Excluding these countries improves the power of cointegration diagnostics without materially affecting the estimated long-run climate relationship.

Table A5: Robustness: First-Difference and Long-Difference Benchmarks

	(1) First diff. GDP growth	(2) Long diff. Trend GDP	(3) Long diff. GDP level
Change in permanent climate ($\Delta\mu^T$)	-0.290	-0.222^{***}	-0.222^{***}
	(1.283)	(0.067)	(0.067)
Country fixed effects	Yes	No	No
Year fixed effects	Yes	No	No
Observations	9,751	175	175
Countries	192	175	175
R^2	0.090	0.034	0.033

Notes: Column (1) reports a first-difference panel regression of annual real GDP growth on annual changes in the permanent climate component, including country and year fixed effects. Columns (2) and (3) report long-difference regressions relating changes in output between 1970 and 2022 to changes in the permanent climate component over the same period, using trend output and observed output, respectively. Long-difference specifications are estimated in the cross section with heteroskedasticity-robust standard errors. First-difference regressions are expected to be underpowered at annual frequency because persistent climate change evolves gradually and affects output primarily through slow-moving adjustment in levels rather than short-run growth.

Table A6: Robustness to Alternative Trend Extraction: HP-Filtered GDP

	(1) HP trend $\lambda = 100$	(2) HP trend $\lambda = 6.25$	(3) Log GDP (levels)
Permanent climate component (μ^T)	-0.254^{***}	-0.252^{***}	-0.251^{***}
	(0.071)	(0.072)	(0.071)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	9,943	9,943	9,943
Countries	192	192	192
Within R^2	0.716	0.706	0.700

Notes: This table reports long-run fixed-effects regressions of output on the permanent climate component using alternative measures of low-frequency output. Columns (1) and (2) use HodrickPrescott filtered trends of log real GDP with annual smoothing parameters $\lambda = 100$ and $\lambda = 6.25$, respectively. Column (3) uses log real GDP levels without statistical filtering. All specifications include country and year fixed effects and are estimated on the post-1970 sample. Standard errors are clustered at the country level. Across all specifications, the estimated coefficient on the permanent climate component remains negative, highly statistically significant, and quantitatively similar to the baseline results, indicating that the long-run climateoutput relationship is not sensitive to the choice of trend extraction method.

Table A7: Robustness to Temperature Trend Extraction: HP-Filtered Country Temperature

	(1) HP temp trend $\lambda = 100$	(2) HP temp trend $\lambda = 6.25$
HP-filtered temperature trend ($\widehat{T}^{HP}$, °C)	-0.207^{***}	-0.151^{***}
	(0.058)	(0.043)
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	9,943	9,943
Countries	192	192
Within R^2	0.706	0.704

Notes: This table reports long-run fixed-effects regressions of trend log output on a purely statistical low-frequency component of country-level temperature. The regressor is the Hodrick–Prescott filtered trend of annual country temperature (in degrees Celsius), constructed from observed temperature and filtered separately within each country. Column (1) uses an annual smoothing parameter $\lambda = 100$ and column (2) uses $\lambda = 6.25$. Both specifications include country and year fixed effects and are estimated on the post-1970 sample. Standard errors are clustered at the country level and reported in parentheses. The negative and statistically significant coefficients indicate that the main long-run relationship is robust to replacing the state-space permanent climate component with a transparent HP-based temperature trend.

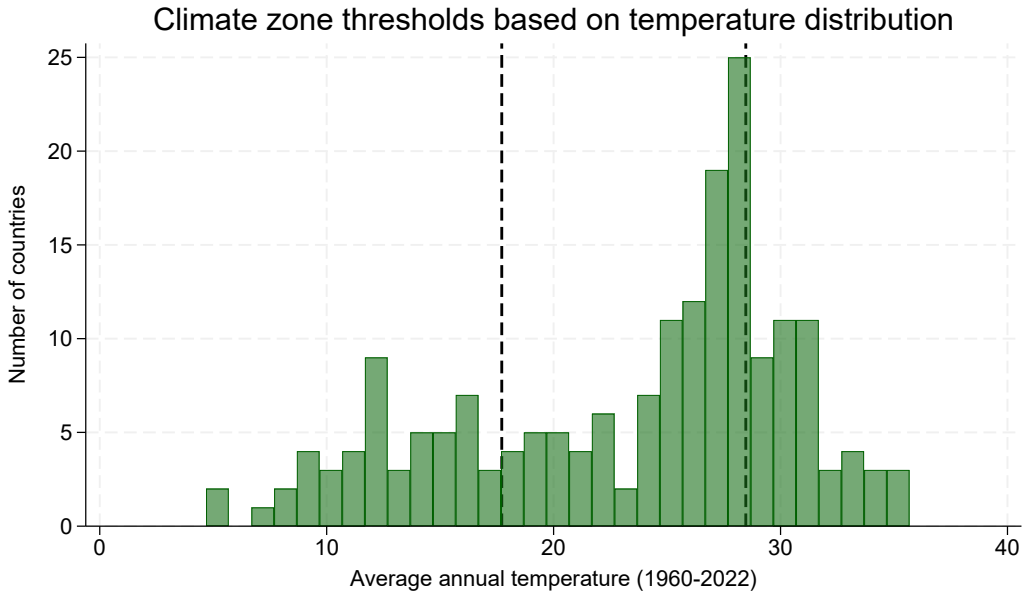


Figure A1: Distribution of countries across climate zones

Note: The figure plots the distribution of countries by average annual temperature over 1970-2022. Vertical dashed lines indicate the 25th and 75th percentiles of the country-level temperature distribution, which are used to define cold, moderate, and hot climate zones.

Table A8: Benchmark Regressions Using Raw Temperature

	(1) Trend Output μ_{it}^{Y}	(2) Log Output $\log Y_{it}$	(3) Output Growth ΔY_{it} (%)
Observed temperature	-0.052^{***}	-0.051^{***}	-0.163
	(0.015)	(0.015)	(0.139)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	9,943	9,943	9,943
Countries	192	192	192
Within R^2	0.700	0.694	0.092

Notes: This table reports conventional panel regressions relating output to raw observed temperature, following the standard approach in the climate–macro literature. Column (1) uses trend log output, Column (2) uses log real GDP, and Column (3) uses output growth in percent. All specifications include country and year fixed effects, and standard errors clustered at the country level are reported in parentheses.

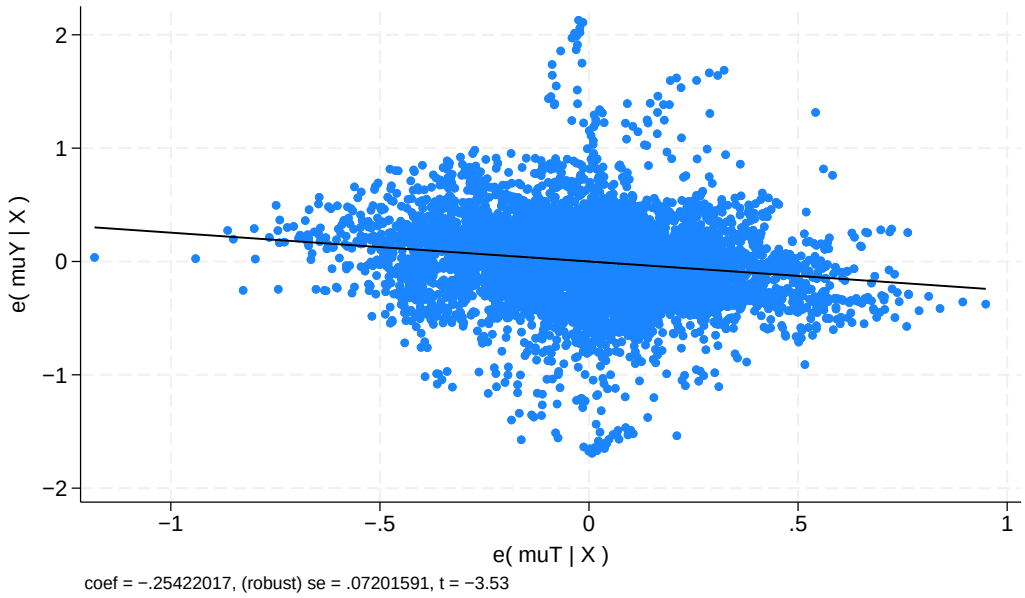


Figure A2: Partial scatterplot

Note: This figure presents the partial regression plot corresponding to the long-run specification in Table 1. Both trend real GDP $\mu^{y}_{c,t}$ and the permanent climate component $\mu^{T}_{c,t}$ are residuals after removing country and year fixed effects. The fitted line corresponds to the estimated coefficient in Table 1 ($\beta = -0.252$). The negative relationship is supported across the distribution of the data and is not driven by a small number of extreme observations. The upper outliers are driven by episodes of exceptionally rapid, largely resource-based growth in Equatorial Guinea, Liberia, and Nauru.