CLIMATE SHOCKS AND THE DISTRIBUTION OF INCOME AND WEALTH: EVIDENCE FROM 159 COUNTRIES, 1980-2023

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Climate Shocks and the Distribution of Income and Wealth: Evidence from 159 Countries, 1980–2023

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Abstract

We study the effects of temperature shocks on the distribution of income and wealth across 159 countries over the period 1980–2023. Combining distributional data from the World Inequality Database with disaggregated daily climate records, we construct temperature bins that capture the frequency of temperature extremes at the country-year level. Panel regressions with country and year fixed effects reveal a nonlinear, inverted-U-shaped relationship between temperature and income growth: moderate temperatures have negligible effects, while extreme heat (days above 30°C) significantly reduces income growth by approximately 0.06 to 0.07 percentage points per additional day. Local projection estimates show significant contemporaneous income losses that dissipate within one to two years. The damage pattern is remarkably uniform across the income distribution, with no statistically distinguishable differences between deciles. Similarly, we find no significant effect of temperature shocks on wealth accumulation, which may reflect either slower portfolio adjustment dynamics or limitations in the available data. Future research should exploit subnational and household-level income and wealth data to better capture within-country heterogeneity that may be attenuated in country-level analyses.

1   Introduction

The intensity and frequency of climate shocks have increased markedly in recent decades. A growing literature documents the macroeconomic costs of these changes (Burke et al., 2015; Dell et al., 2014), establishing that temperature shocks reduce output and productivity while increasing mortality. Recent work has substantially revised upward the estimated aggregate damages: Bilal and Känzig (2026) show that a 1°C increase in global temperature reduces world GDP by approximately 12% after six years, while Nath et al. (2025) estimate that 3.7°C of warming would reduce global GDP by 7–12% by the end of the century, with persistent but not permanent growth effects. Yet relatively few studies examine how climate variability reshapes

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the *distribution* of income and wealth within and across countries. This gap has potentially meaningful implications for the aggregate welfare effects of climate shocks: if temperature shocks affect different parts of the distribution differently, aggregate damage estimates may obscure the full welfare cost of climate change and mislead the design of compensatory policies.

A first strand of the literature focuses on between-country inequality. Diffenbaugh and Burke (2019) demonstrate that warming driven primarily by wealthy nations' cumulative emissions has widened the gap between rich and poor countries, reducing per capita GDP in the poorest nations by 17–30% relative to a world without anthropogenic warming. Dell et al. (2012) show that higher temperatures substantially reduce economic growth in developing countries, with consequences extending beyond agriculture to industrial output and political stability. These findings suggest that climate change acts as a regressive global redistribution mechanism, disproportionately burdening the regions least responsible for emissions and least equipped to adapt.

A second strand examines within-country distributional effects. At the global level, Davis (2025) estimates that warming between 1980 and 2016 increased global income inequality by approximately 4%, disproportionately reducing income growth for the lowest earners. Gilli et al. (2024) project that climate change will widen within-country income distributions through both direct exposure and general-equilibrium channels. Dang et al. (2026) provide subnational estimates showing that a 1°C temperature increase raises poverty by 0.6–1.2 percentage points and the Gini coefficient by 1.3–1.9%, with subnational effects substantially larger than what country-level analyses capture. Household-level studies from developing countries confirm that poorer households bear the brunt of climate shocks (Bangalore et al., 2016). Hsiang et al. (2017) provide spatially explicit estimates for the United States showing that economic damages from climate change increase quadratically with global mean temperature, and that the poorest counties face damages of 2–20% of county income under business-as-usual emissions. Coronese et al. (2025) document that hurricanes in the United States reduce both income and wages, with wages exhibiting a more persistent decline and the poorest counties suffering disproportionately. Palagi et al. (2022) find that precipitation anomalies have nonlinear effects on income inequality in a global panel, with the poorest quintile suffering disproportionately.

Despite this progress, most cross-country studies rely on aggregate inequality measures such as Gini coefficients or income shares (Hong and Kim, 2024; Otrachshenko and Popova, 2021), which compress the rich information contained in the full income distribution into a single statistic. A few studies examine distributional climate effects within specific countries (e.g. Aggarwal (2021) for India) but wealth inequality remains almost entirely unexplored in the climate literature. This omission is significant: wealth determines households' capacity to self-insure against income shocks, and the interplay between income losses and asset destruction may exacerbate vulnerabilities.

This paper addresses these gaps along three dimensions. First, we exploit the full distributional detail of the World Inequality Database (WID), which provides harmonized pre-tax and post-tax income distributions as well as wealth distributions for 159 countries from 1980 to 2023. Rather than collapsing distributional information into summary indices, we estimate separate effects for

each income decile and for the bottom and top halves of the wealth distribution. Second, we integrate these distributional data with high-frequency daily climate records, constructing temperature bins that capture the number of days each country-year experiences in nine temperature intervals. This bin-based approach allows us to identify the nonlinear dose–response relationship between temperature exposure and economic outcomes without imposing a parametric functional form. Third, we combine panel regressions with fixed effects, local projections following Nath et al. (2025), and long-difference regressions following Burke and Emerick (2016) to characterize both the contemporaneous and dynamic effects of temperature on income and wealth.

Our main findings are as follows. Panel regressions reveal a pronounced inverted-U-shaped relationship between temperature and aggregate income growth: moderate days around the reference bin (18–22°C) are associated with no significant effect, while each additional day above 30°C reduces income growth by approximately 0.06 to 0.07 percentage points. This nonlinear pattern is remarkably consistent across income deciles, with no statistically distinguishable differences between them. Local projections show that a contemporaneous temperature shock significantly depresses income, with the effect dissipating within one to two years. Heterogeneity analyses by country income level and climate zone yield qualitatively similar patterns but with wider confidence intervals, indicating that the aggregate relationship is robust but that subgroup-specific estimates lack precision. In contrast, we find no statistically significant effects of temperature on wealth growth, whether measured for the bottom 50% or the top 50% of the wealth distribution.

The remainder of the paper is organized as follows. Section 2 describes the data sources and variable construction. Section 3 presents the empirical strategy. Section 4 discusses the main findings, including heterogeneity analyses and dynamic responses. Section 5 concludes.

2   Data and Measurement

2.1   Income and Wealth Data

Income and wealth distributions come from the World Inequality Database (WID). The WID constructs Distributional National Accounts (DINA) following the methodology described in Chancel et al. (2025a). The central idea is to allocate the totals recorded in the System of National Accounts (SNA) to individual adults using the best available micro-data for each country-year. This framework has two advantages relative to stand-alone survey estimates which have been used in the climate impacts literature. First, the use of fiscal data, where available, corrects for the well-documented underrepresentation of top incomes in household surveys, which can severely bias measured inequality. Second, the macro-micro consistency constraint ensures that income shares across percentiles are anchored to independently measured national aggregates, rather than depending entirely on the accuracy of any single micro-data source.

Given that the scope of this paper is global and dates back in time, it is noteworthy that data quality varies across countries and over time. The WID assigns each country-year observation a

quality score from 0 (no distributional data; estimates rely on regional imputations or historical extrapolation) to 5 (high-quality fiscal micro-data with comprehensive coverage). In our sample of 159 countries over 1980–2023, high-income OECD countries typically score 3–5, while many developing countries score 1–2 and rely more heavily on survey-based estimates with parametric top-income corrections. We use the full sample to maximize geographic coverage but note that measurement error is likely larger for low-scoring countries, which could attenuate estimated climate effects precisely where they may be largest.

We draw on three sets of variables from the WID. First, *aggregate national income per adult* (WID code `anninc`). National income equals GDP minus capital depreciation plus net foreign income, making it a closer measure of the resources available to a country's residents than GDP. Second, *pre-tax income* (`aptinc`) by national–level decile, which distributes national income across ten population groups ranked by individual pre-tax income. Pre-tax income comprises labor income, capital income, and mixed income from self-employment; it is measured before personal income taxes but after the operation social insurance benefits. Third, *average net household wealth by wealth group* (`ahweal`), which measures net worth (financial plus non-financial assets minus liabilities) for the bottom 50% and top 50% of the wealth distribution. All monetary variables are expressed in 2023 purchasing power parity (PPP) euros using the WID's PPP conversion factors.

2.2 Climate Data

Daily temperature, precipitation, and wind speed data come from the gridded climate dataset constructed by Lamperti et al. (2024). These data provide daily weather observations on a global grid, which we aggregate to the country level using 2015 population weights. Population weighting ensures that our climate measures reflect the weather conditions experienced by the average person in each country rather than the average over uninhabited terrain, a distinction that matters for geographically large or climatically diverse countries.

From the daily temperature series, we compute three types of climate variables for each country-year. First, annual average temperature, precipitation, and wind speed serve as baseline controls. The sample-wide mean temperature is approximately 19.5°C, with a standard deviation of 7.4°C, reflecting the wide range of climatic conditions in our 159-country sample (Table 1). Second, following the temperature bin approach pioneered by Schlenker and Roberts (2009) and applied to health outcomes by Deschênes and Greenstone (2011) and Gould et al. (2024), we construct temperature bins by counting the number of days in each year that fall into nine temperature intervals: (< 6), $[6, 10)$, $[10, 14)$, $[14, 18)$, $[18, 22)$, $[22, 26)$, $[26, 30)$, $[30, 34)$, and (> 34)°C. The bin $[18, 22)$ serves as the omitted reference category. Third, for the dynamic specifications, we compute 10-year trailing moving averages of annual temperature and define temperature shocks as deviations from this moving average.

2.3 Temperature Bins: Motivation and Construction

The temperature bin approach, introduced by Schlenker and Roberts (2009) in the context of U.S. crop yields, offers several advantages over simpler alternatives such as annual mean temperature or quadratic temperature terms. A country's annual mean temperature may remain stable even as the distribution of daily temperatures shifts: warmer days may replace both cool and moderate days without changing the mean. Bins capture such shifts directly. Moreover, the bin specification imposes no parametric assumptions on the shape of the temperature–outcome relationship, allowing the data to reveal nonlinearities that a polynomial might miss or distort.

Figure 7 in the Appendix illustrates the distribution of days across temperature bins by world region for the year 2000. The variation is substantial: Sub-Saharan African and South Asian countries concentrate their exposure in the 22–34°C range, while European and East Asian countries cluster in the 6–18°C bins. This geographic heterogeneity in temperature exposure is central to identification, as it generates cross-country variation in the intensity of heat exposure conditional on fixed effects.

2.4 Control Variables and Country Classification

All specifications control for annual average precipitation and wind speed, following Auffhammer et al. (2013), who demonstrate that temperature and precipitation are historically correlated and must be jointly estimated to obtain unbiased temperature coefficients. We also include country-specific linear and quadratic time trends to absorb smooth, country-level changes in income or wealth that might correlate with gradual warming.

For the heterogeneity analysis, we classify countries along two dimensions. Countries whose time-averaged national income falls below the sample median are labeled "poor"; the remainder are "rich." Countries whose time-averaged temperature falls below the sample median are designated "cold"; the remainder, "hot." These median splits are deliberately simple. Their purpose is not to identify precise income or temperature thresholds but rather to test whether the aggregate temperature–income relationship differs qualitatively between broad country groups that face different baseline conditions and adaptive capacities.

Table 1. Summary Statistics

	N	Mean	St. Dev.	Min	Max
Panel A: Annual Averages					
Temperature (°C)	11,448	19.54	7.38	−7.72	29.87
Precipitation (mm/day)	11,448	3.35	2.22	0.02	14.09
Wind Speed (m/s)	11,448	9.42	1.34	6.48	15.72
Panel B: Temperature Bins (days/year)					
Days < 6°C	11,448	37.39	64.97	0	365
Days 6–10°C	11,448	20.59	30.40	0	177
Days 10–14°C	11,448	27.16	34.90	0	178
Days 14–18°C	11,448	34.33	43.35	0	366
Days 18–22°C	11,448	51.47	71.50	0	366
Days 22–26°C	11,448	99.69	94.62	0	366
Days 26–30°C	11,448	83.66	102.30	0	366
Days 30–34°C	11,448	8.60	26.77	0	213
Days > 34°C	11,448	2.35	12.46	0	127
Panel C: Extreme Temperature Days (days/year)					
Days > 90th percentile	11,448	36.39	10.34	3	99
Days > 95th percentile	11,448	18.19	6.93	0	63

Notes: National income is expressed in 2023 PPP euros. Temperature bins count the number of days per year within each temperature interval (in °C). Extreme days count days where temperature exceeds the 90th or 95th percentile threshold for that country after removing country and year fixed effects. Sample: 159 countries, 1980–2023.

3   Empirical Strategy

Our empirical approach combines three complementary strategies, each designed to address different aspects of the temperature–distribution relationship while mitigating distinct identification concerns.

3.1   Panel Regressions with Temperature Bins

Our baseline specification follows the panel approach of Dell et al. (2012) and Burke et al. (2015), adapted to exploit the temperature bin structure:

$$Y_{i,t} = \sum_{b \neq \text{ref}} \beta_b \, D_{i,t}^b + \mathbf{Z}_{i,t}' \boldsymbol{\gamma} + \alpha_i + \delta_t + \varepsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ denotes the outcome (income growth, wealth growth, or income share) for country i in year t; $D_{i,t}^b$ is the number of days in temperature bin b; and $\mathbf{Z}_{i,t}$ includes average precipitation, average wind speed, and country-specific linear and quadratic time trends. The country fixed effects α_i absorb all time-invariant differences between countries (geography, institutions, baseline

climate) that might confound the temperature–outcome relationship. The year fixed effects δ_t absorb global shocks common to all countries in a given year, such as global recessions or pandemic effects.

The coefficients of interest, β_b, measure the effect of one additional day in temperature bin b relative to one additional day in the reference bin $[18, 22]$°C. Identification comes from year-to-year variation in the distribution of daily temperatures within each country, after removing country means and global trends. The key identifying assumption is that, conditional on fixed effects, time trends, and weather controls, the realization of daily temperatures within a year is as good as random with respect to contemporaneous economic outcomes. This assumption would be violated if countries systematically altered their economic behavior in anticipation of temperature realizations, which is implausible at the daily frequency.

For the heterogeneity analysis, we interact the temperature bin variables with country-group indicators. Specifically, we estimate:

$$Y_{i,t} = \sum_{b \neq \text{ref}} \beta_b \, D_{i,t}^b \cdot G_i + \mathbf{Z}_{i,t}' \boldsymbol{\gamma} + \alpha_i + \delta_t + \varepsilon_{i,t}, \tag{2}$$

where G_i is a binary indicator for the country group of interest (poor, cold). The interaction coefficients β_b now measure the *differential* effect of temperature bin b for the indicated group relative to the omitted group.

3.2   Dynamic Local Projections

To trace the dynamic response of income to temperature shocks, we employ local projections following Davis (2025). Rather than using temperature bins, this specification exploits deviations from a country's recent temperature norm:

$$\Delta^h y_{i,t+h} = \beta_1^h \, \tau_{i,t} + \beta_2^h \, \overline{T}_{i,t} + \beta_3^h \left(\tau_{i,t} \cdot \overline{T}_{i,t} \right) + \mathbf{Z}_{i,t}' \boldsymbol{\gamma}^h + \mu_i + \eta_t + u_{i,t+h}, \tag{3}$$

where $\Delta^h y_{i,t+h} \equiv y_{i,t+h} - y_{i,t}$ denotes the cumulative change in the log or level of income from year t to year $t+h$; $\tau_{i,t} \equiv T_{i,t} - \overline{T}_{i,t}$ is the temperature shock, defined as the deviation of annual mean temperature from a 10-year trailing moving average $\overline{T}_{i,t}$; and $\mathbf{Z}_{i,t}$ includes lagged dependent variables and lagged shocks to control for serial correlation. The interaction term $\tau_{i,t} \cdot \overline{T}_{i,t}$ allows the marginal effect of a temperature shock to depend on the country's baseline climate, capturing the intuition that a 1°C shock may be more damaging in an already-hot country than in a temperate one.

We estimate equation (3) separately for each horizon $h = 0, 1, \ldots, 5$ and for each income decile, yielding a decile-by-horizon panel of impulse responses. The coefficient β_1^h traces out the dynamic effect of a contemporaneous temperature shock on income at horizon h, allowing us to distinguish between transitory shocks that dissipate quickly and persistent effects that accumulate over time.

3.3 Long-Difference Regressions

To assess whether the short-run panel results translate into long-run effects from sustained climate change, we follow the long-difference strategy of Burke and Emerick (2016). We compare two five-year windows (1996–2000 and 2018–2022) and estimate:

$$\overline{\Delta y_i} = \beta_1 \, \overline{\Delta T_i} + \beta_2 \, \overline{\Delta T_i}^2 + \beta_3 \, \overline{\Delta P_i} + \beta_4 \, \overline{\Delta P_i}^2 + \overline{\Delta \varepsilon_i}, \tag{4}$$

where $\overline{\Delta y_i}$ is the change in average growth between the two periods, and $\overline{\Delta T_i}$ and $\overline{\Delta P_i}$ are the corresponding changes in average temperature and precipitation. The quadratic terms allow for nonlinear effects of long-run climate change on growth. By differencing across periods separated by roughly two decades, this approach eliminates all time-invariant country characteristics and identifies the effect from the cross-country variation in the magnitude and direction of climate change experienced over this interval.

We extend the long-difference specification to include interactions with the cold-country indicator, allowing the long-run relationship between warming and economic outcomes to differ between countries that start from cooler versus warmer baseline climates. We estimate these regressions separately for the bottom 50% and top 50% of the wealth distribution to test whether long-run climate change has differential effects across the wealth distribution.

4 Results

4.1 Temperature Bins and Aggregate Income Growth

Figure 1 reports estimated coefficients from equation (1) with the annual growth rate of national income per adult as the dependent variable. The pattern is nonlinear. Days in the cooler bins (below 18°C) show small, imprecisely estimated effects that are statistically indistinguishable from the reference bin, with the exception of the coldest bin (< 6°C), which carries a marginally significant negative coefficient of -0.024 pp ($p = 0.08$). The warm-but-moderate bins (22–26°C and 26–30°C) show negative point estimates (-0.008 and -0.013 pp, respectively) but are not statistically significant. The relationship changes sharply in the 30–34°C bin, where each additional day reduces income growth by approximately 0.07 percentage points ($p < 0.001$). The coefficient for the hottest bin (> 34°C) is of similar magnitude (-0.06 pp) but imprecisely estimated due to the rarity of such extreme days in most countries.

To put these magnitudes in perspective, consider a country that experiences 10 additional days in the 30–34°C range in a given year relative to its historical norm, a shift well within observed interannual variability. Our estimates imply that this shift would reduce income growth by roughly 0.7 percentage points. For a country growing at 2% per year, such a shock would eliminate over a third of its annual income gains.

This inverted-U-shaped pattern is consistent with the established literature. Burke et al. (2015)

document a similar nonlinear relationship between annual mean temperature and GDP growth, with an optimum around 13°C. Our bin-based approach refines this finding by showing that the damage is concentrated in the right tail of the daily temperature distribution: it is the frequency of very hot days, not the annual mean per se, that drives the aggregate income losses.
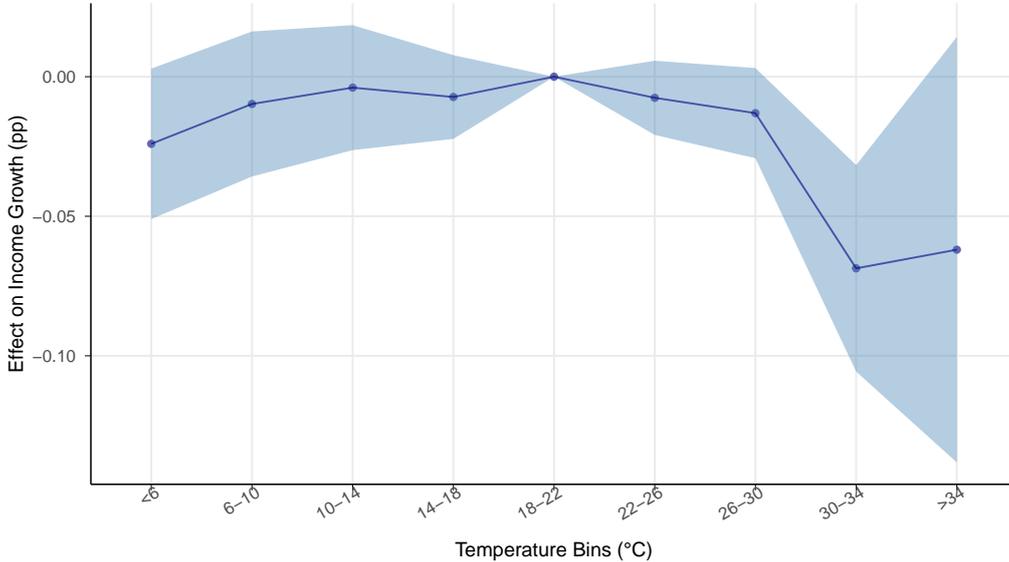

Figure 1. Effect of temperature bins on aggregate income growth (country and year FE). Each point represents the estimated effect of one additional day in the indicated temperature bin relative to the $[18, 22)$°C reference bin. Shaded area shows 95% confidence intervals.

4.2 Distributional Effects Across Income Deciles

A key question is whether the aggregate income losses documented above fall evenly across the income distribution or concentrate among particular groups. Figure 2 overlays the aggregate national income result with the estimated effect on the top income decile (90th–100th percentile of pre-tax income). The nonlinear pattern is strikingly similar: both series exhibit the inverted-U shape with significant negative effects above 30°C, and the confidence intervals overlap substantially across all temperature bins. We cannot reject the null hypothesis that the top decile and aggregate national income respond identically to temperature extremes.This uniformity across the distribution is itself a substantive finding.

Figure 8 in the Appendix presents the comparison between the bottom 50% and top 50% of the pre-tax income distribution, confirming the same pattern: the nonlinear relationship with temperature is present across both halves, with no statistically distinguishable difference between them.

This uniformity contrasts with much of the existing literature. Palagi et al. (2022) find that the poorest quintile suffers disproportionately from precipitation anomalies, Gilli et al. (2024) project widening within-country distributions under warming, and Coronese et al. (2025) document that the poorest U.S. counties bear the largest income losses from hurricanes. Our inability to

detect such heterogeneity likely reflects a limitation of the analysis rather than a genuine absence of distributional effects. Country-level income deciles aggregate over millions of individuals with very different occupations, locations, and exposures. This aggregation may wash out the within-country heterogeneity that finer-grained studies are able to detect. The local projections, which do show a gradient favoring upper deciles at $h = 0$, hint that distributional differences may exist but are difficult to isolate with the level of aggregation used here.
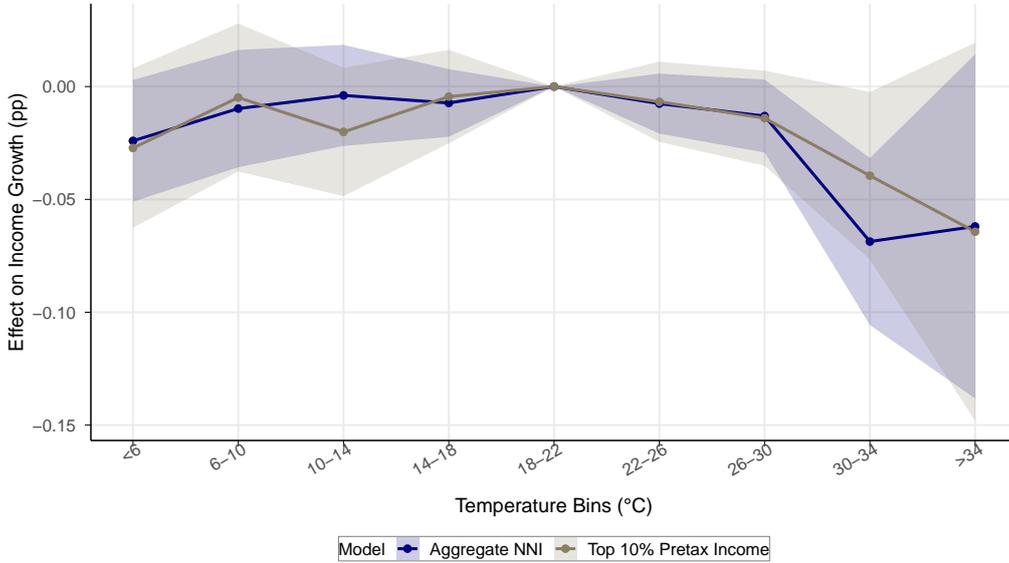

Figure 2. Effect of temperature bins on income growth: aggregate national income (blue) and top 10% pre-tax income (brown). Country and year fixed effects. Shaded areas show 95% confidence intervals.

4.3 Heterogeneity: Poor vs. Rich Countries

A central hypothesis in the climate–economy literature is that poor countries are more vulnerable to temperature shocks due to their greater dependence on agriculture and more limited adaptive capacity (Dell et al., 2012). To test this, we interact the temperature bin variables with our poor-country indicator, as in equation (2).

Figure 3 displays the estimated interaction coefficients. The inverted-U shape remains visually apparent: the point estimates suggest that extreme heat is more damaging for poor countries across most temperature bins. However, none of the interaction coefficients reaches conventional levels of statistical significance. The 95% confidence intervals are wide, reflecting the loss of statistical power inherent in splitting the sample and the considerable heterogeneity within each group.

This lack of significance should not be interpreted as evidence that poor and rich countries are equally affected. Rather, it reflects the well-known difficulty of detecting interaction effects in panel data with moderate sample sizes. The point estimates are economically meaningful and directionally consistent with the prior literature; what the data lack is the precision to

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distinguish the differential effect from zero at conventional confidence levels. A larger sample or more granular within-country data would likely sharpen these estimates.

Figure 3. Differential effect of temperature bins on income growth for poor countries (interaction term). Country and year fixed effects. The coefficients measure the *additional* effect for countries with below-median average income.

4.4 Heterogeneity: Cold vs. Hot Countries

The cold versus hot country analysis tests whether countries already adapted to warm climates exhibit different sensitivity to temperature extremes. One might expect cold countries to be more vulnerable to heat waves given their limited experience with extreme heat, or conversely that hot countries face larger absolute damages because they operate closer to physiological and agronomic temperature thresholds.

Figure 4 shows that the estimated interaction coefficients for the cold-country group are uniformly insignificant, with wide confidence intervals spanning zero across all bins. The absence of a detectable differential effect may reflect opposing forces: cold countries may be more sensitive to heat waves per se, but they also tend to be richer (higher latitudes correlate with higher income in our sample), which provides offsetting adaptive capacity. Alternatively, the temperature bins may not vary enough within the cold-country subsample to identify the effect precisely, since cold countries by construction have few days in the hottest bins.
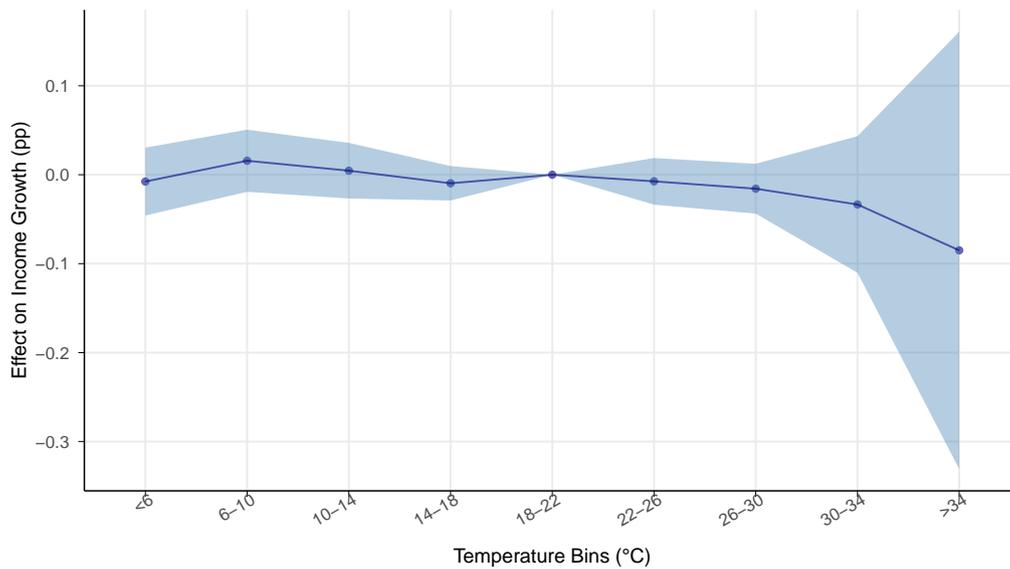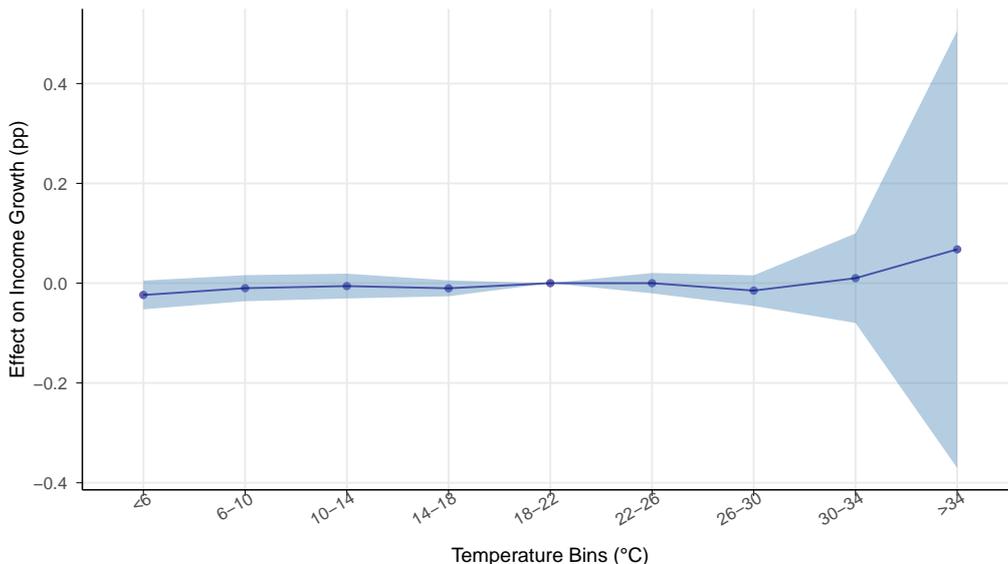
Figure 4. Differential effect of temperature bins on income growth for cold countries (interaction term). Country and year fixed effects. The coefficients measure the *additional* effect for countries with below-median average temperature.

4.5 Dynamic Responses to Temperature Shocks

The panel regressions in the preceding sections estimate the contemporaneous effect of temperature on income growth within a given year. But temperature shocks may have effects that persist, accumulate, or reverse over time. To characterize these dynamics, we turn to the local projection estimates from equation (3).

Figure 5 presents the estimated impulse responses for all ten income deciles. Panel (a) shows the log-difference specification, where the dependent variable is the change in log income between year t and year $t + h$. At horizon $h = 0$ (the contemporaneous effect), a positive temperature shock reduces income across all deciles, with point estimates ranging from -0.014 log points for the top decile to -0.056 log points for the bottom decile. The effect is statistically significant for the lower deciles (p0–p20), where the confidence intervals exclude zero, but not for the upper deciles. At $h = 1$, point estimates remain negative across all deciles (approximately -0.01 to -0.02 log points) but are no longer statistically significant. By $h = 2$, the estimates are close to zero and erratically signed, suggesting that the income effects of temperature shocks are concentrated in the contemporaneous year and dissipate within one to two years. Panel (b) shows the level-difference specification, which yields a qualitatively similar pattern.

Two features of the dynamic response merit discussion. First, the gradient across deciles at $h = 0$ is notable: the bottom decile suffers roughly four times the contemporaneous loss of the top decile. This contrasts with the bin regressions, which show uniform effects across deciles for aggregate income growth. The difference may reflect the distinct specifications: the local projections define shocks as deviations from a country's 10-year moving average temperature, while the bin

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regressions use year-to-year variation in the number of days falling in each temperature interval. Second, the rapid dissipation of effects (significant at $h = 0$ but not at $h = 1$) suggests that annual temperature shocks are transitory rather than persistent in their income effects, consistent with economies adjusting within a year or two. This pattern is broadly consistent with the framework of Davis (2025), whose local projection approach we adapt here, though the rapid dissipation contrasts with Nath et al. (2025), who find persistent but not permanent growth effects of warming.

The widening of confidence intervals at longer horizons reflects the compounding of estimation uncertainty as we project further into the future.

(a) Log-difference specification   (b) Level-difference specification
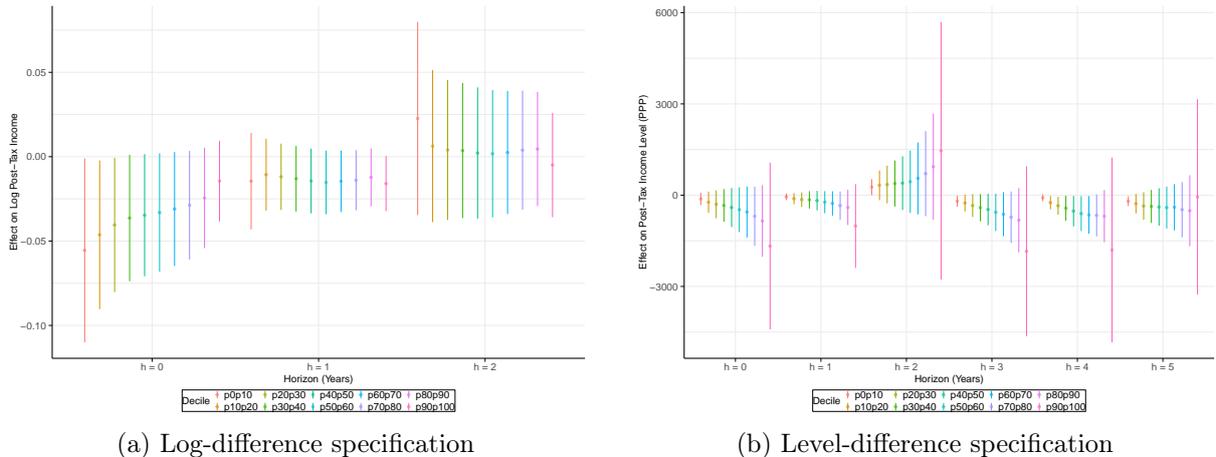
Figure 5. Dynamic response of income to a temperature shock, by income decile. Each point shows the estimated effect of a 1°C temperature shock on the change in income from year t to year $t + h$, with 95% confidence intervals. All deciles (p0p10 through p90p100) are shown simultaneously.

4.6 Effects on Wealth

A distinguishing contribution of this paper is the examination of wealth, not just income, in relation to temperature shocks. Figure 6 presents the estimated effects of temperature bins on wealth growth for the bottom 50% and top 50% of the wealth distribution.

The results are strikingly different from the income regressions: none of the temperature bin coefficients is statistically significant for either wealth group. The point estimates are small and erratically signed, with no discernible nonlinear pattern. The wide confidence intervals mean that we cannot distinguish between a true zero effect and effects that are real but too small to detect with our data.

Several explanations may account for this null result. First, wealth adjusts more slowly than income. National income reflects contemporaneous production and is directly tied to weather-sensitive sectors such as agriculture and outdoor labor. Wealth, by contrast, reflects the cumulative value of assets whose prices respond to many forces beyond local temperature. A heat wave that reduces a country's GDP growth in a given year may have little immediate effect on the market

value of its housing stock or the book value of its firms' assets.

Second, the WID wealth data, while the best available for cross-country analysis, are considerably noisier than the income data. Wealth is notoriously difficult to measure as most countries do not provide administrative data on the distribution of wealth. Moreover, it is subject to important fluctuations such as changes in asset valuation. This measurement error attenuates coefficient estimates toward zero and inflates standard errors, making it harder to detect genuine effects.

Third, it is possible that wealth responds to temperature through channels such as reduced investment or gradual capital depreciation that operate over decades rather than years, making them invisible in our annual panel framework (Chancel et al., 2025b).
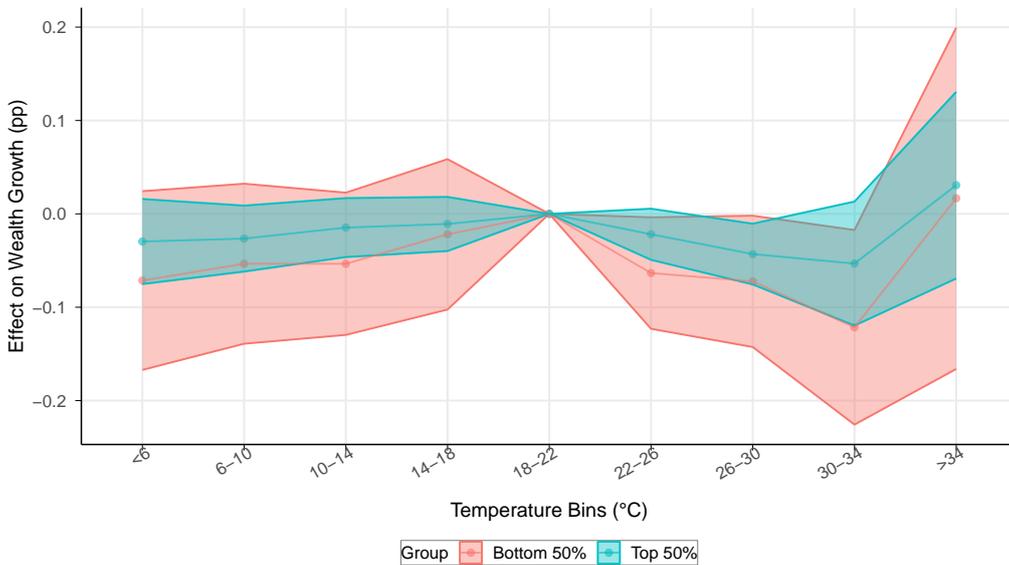
Figure 6. Effect of temperature bins on wealth growth: bottom 50% vs. top 50% of the wealth distribution (country and year FE). Shaded areas show 95% confidence intervals.

4.7 Long-Difference Estimates

The panel regressions exploit year-to-year variation in temperature to identify short-run effects, but they cannot directly tell us whether the cumulative effect of sustained warming over decades mirrors the annual estimates. To bridge this gap, Table 2 reports long-difference estimates from equation (4), which compare changes in average growth and average climate between 1996–2000 and 2018–2022.

The long-difference results are broadly consistent with the panel estimates in sign and magnitude, though they are less precisely estimated due to the smaller effective sample size (one observation per country rather than 40+). The quadratic temperature terms suggest a concave relationship between long-run warming and growth changes, consistent with the inverted-U pattern from the bin regressions. Complete results for specifications with poor/rich and cold/hot interactions, as well as separate estimates for the bottom and top halves of the wealth distribution, are reported

in Appendix D.

Table 2. Long-Difference Estimates: Aggregate Income and Wealth Growth

	Dependent variable:					
	Δ Rel. Income Growth			Δ Wealth Growth		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔT	0.202	0.046	1.051	1.876**	1.941**	1.775*
	(0.624)	(0.624)	(0.704)	(0.874)	(0.884)	(0.957)
ΔT^2	−0.006	−0.005	−0.021	−0.061**	−0.060*	−0.059*
	(0.016)	(0.017)	(0.017)	(0.030)	(0.031)	(0.032)
ΔP		1.433	1.472		−0.182	−0.146
		(1.329)	(1.311)		(1.517)	(1.529)
ΔP^2		−0.179*	−0.165*		0.038	0.038
		(0.093)	(0.091)		(0.109)	(0.109)
ΔW			−9.729			13.274
			(9.786)			(12.702)
ΔW^2			0.285			−0.641
			(0.500)			(0.651)
Constant	−2.191**	−1.899*	−2.331**	−0.892	−0.993	−0.913
	(0.987)	(1.005)	(1.001)	(0.830)	(0.857)	(0.894)
Observations	206	206	206	207	207	207
R^2	0.001	0.036	0.076	0.027	0.029	0.035
Adjusted R^2	−0.009	0.017	0.048	0.018	0.010	0.006
Residual Std. Error	4.530	4.472	4.401	4.713	4.732	4.742
F Statistic	0.083	1.861	2.711**	2.878*	1.525	1.212

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: ΔT, ΔP, and ΔW denote changes in temperature, precipitation, and wind speed between the two periods (1996–2000 vs. 2018–2022). Standard errors in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

5 Conclusion

This paper provides a comprehensive examination of how temperature shocks affect the distribution of income and wealth across 159 countries over four decades. Three main findings emerge.

First, the relationship between temperature and income growth is strongly nonlinear, with a sharp damage threshold at 30°C. Each additional day in the 30–34°C range reduces national income growth by approximately 0.07 percentage points, an effect that, accumulated over the

many additional extreme heat days projected under climate change, implies substantial long-run income losses.

Second, the bin regressions show no statistically distinguishable differences in the damage pattern across income deciles. This uniformity is at odds with much of the literature, which finds that poorer households and regions suffer disproportionately (Coronese et al., 2025; Gilli et al., 2024; Palagi et al., 2022). We interpret this as a limitation of the country-level analysis, which aggregates over individuals with very different exposures and likely masks the within-country heterogeneity that finer-grained studies detect. The local projections, which do show larger contemporaneous losses for lower deciles, offer some support for this interpretation. Those dynamic estimates also indicate that the income effects of temperature shocks are concentrated in the year of the shock and dissipate within one to two years.

Third, wealth accumulation appears insulated from temperature fluctuations in our data. Whether this reflects genuine resilience, measurement limitations, or the slow operation of wealth-relevant channels remains an open question that future research with better wealth data and longer time horizons should address.

Our results underscore the urgency of both mitigation and adaptation. The steep nonlinearity of the damage function means that every fraction of a degree of avoided warming prevents a disproportionate amount of economic harm. At the same time, for the warming already locked in, investments in heat-resilient infrastructure and social protection can significantly reduce the human cost. The fact that these costs are borne broadly across the income distribution, not only by the poorest, widens the constituency for action but also complicates the design of targeted compensation.

Several limitations qualify these findings. First, our country-level analysis cannot capture within-country heterogeneity in climate exposure and economic outcomes. Dang et al. (2026) demonstrate that subnational poverty and inequality effects of warming are substantially larger than country-level estimates, suggesting that spatial aggregation may attenuate our estimated distributional effects. Second, the temperature bin approach treats all days within a bin as equivalent, ignoring potentially important variation in humidity and the timing of heat events within the agricultural cycle. Third, our fixed-effects strategy identifies effects from weather shocks rather than from permanent climate change; extrapolating to long-run warming requires the assumption that the damage function is stable as economies adapt, which may not hold if adaptation investments or structural transformation alter the temperature–output relationship over time.

These limitations notwithstanding, the concentration of economic damage in the extreme heat bins implies that the marginal benefit of adaptation investments increases sharply with warming. Although the income effects dissipate within one to two years, the contemporaneous losses are large enough to warrant rapid intervention through social protection and fiscal stabilizers. Finally, the null wealth results argue for expanded investment in wealth measurement in the developing world. If climate change is eroding the asset bases of the poorest populations, detecting this erosion requires data that do not yet exist for most countries.

16

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A   Descriptive Figures
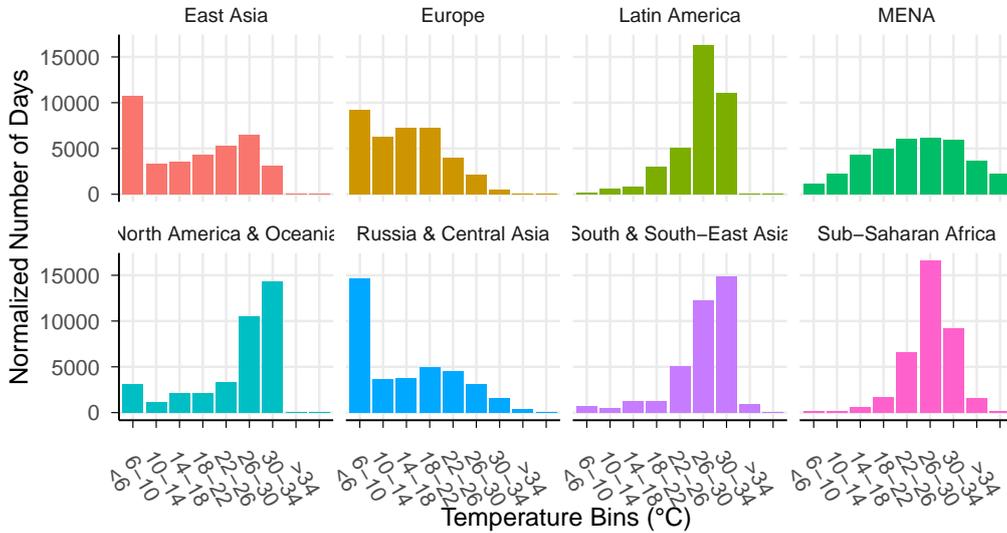
Figure 7. Distribution of days across temperature bins by region (year 2000). Each panel shows the average number of days per country in the region falling within each temperature interval, normalized by the number of countries to facilitate cross-region comparison.

B   Effects on Income and Wealth Inequality

In addition to the decile-level regressions reported in the main text, we estimated the effect of temperature bins on summary measures of income and wealth inequality directly. Specifically, we regressed the growth rate of the top-10% income share, the top-50% income share, and the top-50% wealth share on the full set of temperature bins, using the same specification as equation (1) with country and year fixed effects. None of these regressions yielded statistically significant coefficients on any temperature bin. This is consistent with the main finding that temperature shocks affect income levels across deciles in a roughly proportional manner, leaving distributional shares unchanged. As discussed in Section 4, this null result on inequality likely reflects the high level of aggregation in our data rather than a genuine absence of distributional effects.

C   Additional Coefficient Plots

C.1   Bottom 50% vs. Top 50% Income Growth
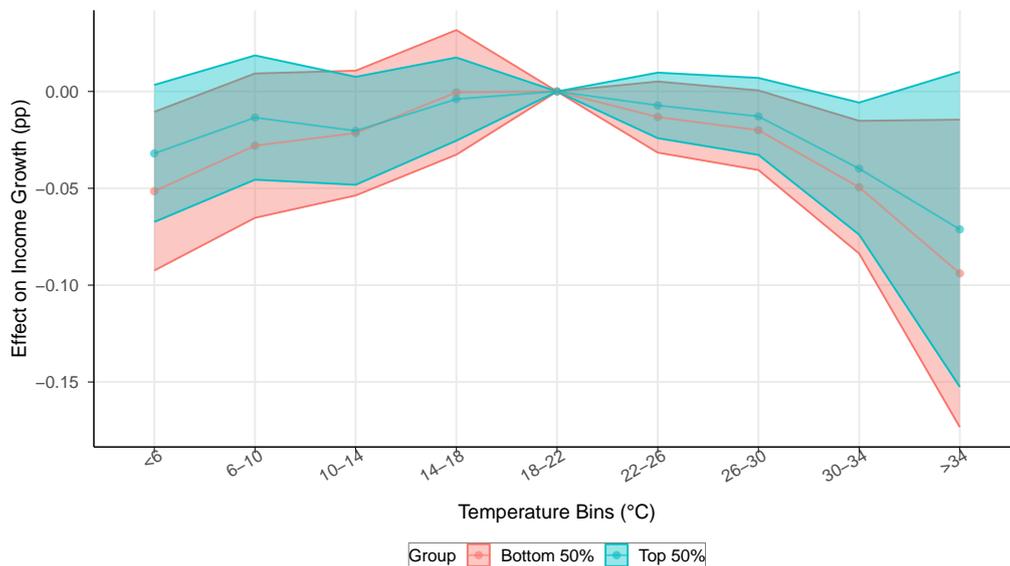
Figure 8. Effect of temperature bins on income growth: bottom 50% vs. top 50% of the pre-tax income distribution (country and year FE). Shaded areas show 95% confidence intervals.

C.2   Long-Difference Shock Visualization
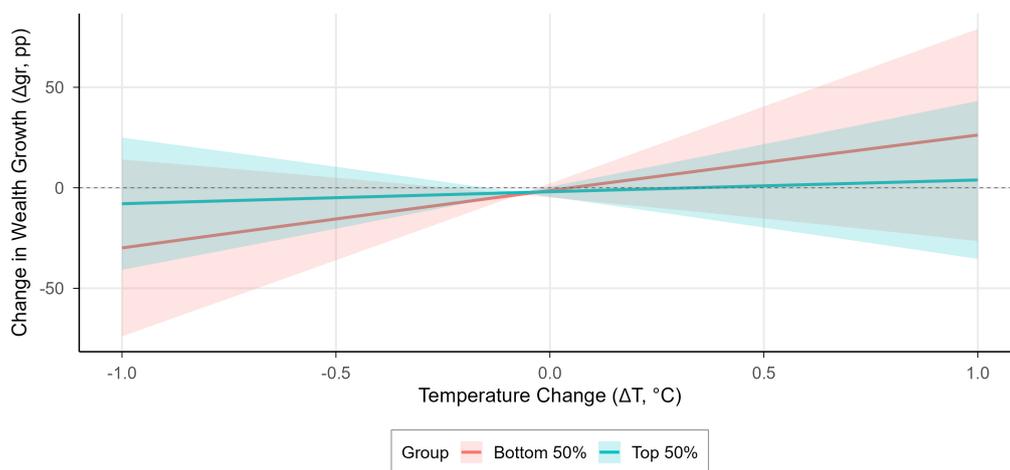
Figure 9. Long-difference model: predicted change in wealth growth as a function of temperature change (ΔT) for hot countries. The curves show the quadratic relationship estimated from equation (4) with cold-country interactions, evaluated at cold = 0. Bottom 50% and top 50% of the wealth distribution shown with 95% confidence intervals.

D   Regression Tables

D.1   Long-Difference Estimates: Poor vs. Rich

Table 3. Long-Difference Estimates: Poor vs. Rich Interaction

	Dependent variable:					
	Δ Rel. Income Growth			Δ Wealth Growth		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔT	−0.225	−0.214	0.878	3.593***	3.587***	3.500**
	(0.794)	(0.775)	(0.856)	(1.288)	(1.302)	(1.381)
ΔT^2	0.003	−0.007	−0.023	−0.100***	−0.098***	−0.099**
	(0.019)	(0.020)	(0.020)	(0.035)	(0.037)	(0.038)
ΔP		−1.789	−1.771		1.071	0.955
		(1.967)	(1.931)		(3.044)	(3.069)
ΔP^2		−0.022	−0.014		−0.155	−0.147
		(0.161)	(0.158)		(0.279)	(0.281)
ΔW			−13.583			23.057
			(16.353)			(19.985)
ΔW^2			0.446			−1.229
			(0.890)			(1.078)
$\Delta T\times$ Poor	0.913	0.876	1.058	−3.474**	−3.353*	−3.472*
	(1.043)	(1.015)	(1.181)	(1.727)	(1.747)	(1.845)
$\Delta T^2\times$ Poor	−0.023	−0.003	−0.012	0.114**	0.110**	0.110*
	(0.030)	(0.029)	(0.033)	(0.053)	(0.054)	(0.056)
$\Delta P\times$ Poor		7.153***	7.650***		−0.561	−0.599
		(2.671)	(2.638)		(3.619)	(3.661)
$\Delta P^2\times$ Poor		−0.362*	−0.373*		0.166	0.164
		(0.200)	(0.197)		(0.308)	(0.310)
$\Delta W\times$ Poor			16.080			−19.632
			(21.222)			(27.190)
$\Delta W^2\times$ Poor			−0.781			1.107
			(1.111)			(1.416)
Constant	−2.106**	−2.041**	−2.532**	−1.241	−1.303	−1.123
	(1.000)	(1.005)	(1.003)	(0.840)	(0.873)	(0.918)
Observations	206	206	206	207	207	207
R^2	0.005	0.085	0.137	0.050	0.056	0.063
Adjusted R^2	−0.015	0.048	0.083	0.031	0.018	0.005
Residual Std. Error	4.544	4.400	4.318	4.683	4.713	4.743
F Statistic	0.233	2.294**	2.552***	2.633**	1.476	1.094

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Poor is an indicator equal to 1 for countries with average income below the sample median. Periods compared: 1996–2000 vs. 2018–2022. Standard errors in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D.2 Long-Difference Estimates: Cold vs. Hot

Table 4. Long-Difference Estimates: Cold vs. Hot Interaction

	Dependent variable:					
	Δ Rel. Income Growth			Δ Wealth Growth		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔT	−8.718	−11.730*	−9.842	−0.864	1.075	1.869
	(6.067)	(6.030)	(6.046)	(11.977)	(12.150)	(12.220)
ΔT^2	0.180	0.235**	0.203*	−0.011	−0.044	−0.054
	(0.120)	(0.119)	(0.119)	(0.228)	(0.231)	(0.232)
ΔP		3.402**	2.308		0.962	1.128
		(1.700)	(1.760)		(1.916)	(1.929)
ΔP^2		−0.346***	−0.247*		−0.010	−0.019
		(0.122)	(0.129)		(0.143)	(0.144)
ΔW			3.617			23.492
			(13.492)			(17.129)
ΔW^2			−0.407			−1.210
			(0.701)			(0.883)
$\Delta T \times$ Cold	9.661	12.432**	11.258*	2.593	0.833	−0.077
	(6.115)	(6.060)	(6.085)	(11.990)	(12.153)	(12.221)
$\Delta T^2 \times$ Cold	−0.212*	−0.274**	−0.248**	−0.044	−0.021	−0.006
	(0.121)	(0.120)	(0.121)	(0.233)	(0.237)	(0.238)
$\Delta P \times$ Cold		−4.431	−3.412		−4.478	−4.864
		(2.706)	(2.976)		(3.249)	(3.293)
$\Delta P^2 \times$ Cold		0.361*	0.247		0.157	0.178
		(0.185)	(0.198)		(0.224)	(0.227)
$\Delta W \times$ Cold			−27.901			−29.929
			(20.137)			(26.474)
$\Delta W^2 \times$ Cold			1.553			1.615
			(1.036)			(1.348)
Constant	−2.552**	−1.951*	−2.583**	−0.859	−0.964	−1.084
	(0.998)	(1.017)	(1.038)	(0.841)	(0.868)	(0.919)
Observations	206	206	206	207	207	207
R^2	0.023	0.082	0.117	0.028	0.046	0.057
Adjusted R^2	0.004	0.045	0.062	0.009	0.008	−0.001
Residual Std. Error	4.502	4.407	4.367	4.736	4.738	4.758
F Statistic	1.180	2.208**	2.131**	1.448	1.202	0.984

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Cold is an indicator equal to 1 for countries with average temperature below the sample median. Periods compared: 1996–2000 vs. 2018–2022. Standard errors in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D.3 Long-Difference Estimates: Bottom 50% vs. Top 50%

Table 5. Long-Difference Estimates: Bottom 50% vs. Top 50%

	Dependent variable:											
	Δ Rel. Income Growth						Δ Wealth Growth					
	Bottom 50%			Top 50%			Bottom 50%			Top 50%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔT	−0.148	−0.320	−0.138	0.679	0.517	0.656	−0.193	−0.116	−0.128	0.472	0.545	0.718
	(0.651)	(0.648)	(0.647)	(0.594)	(0.595)	(0.596)	(1.991)	(2.000)	(2.043)	(1.483)	(1.485)	(1.512)
ΔT^2	0.019	0.019	0.018	0.023	0.023	0.023	0.022	0.026	0.023	0.043	0.044	0.045
	(0.019)	(0.019)	(0.019)	(0.017)	(0.017)	(0.017)	(0.062)	(0.062)	(0.063)	(0.046)	(0.046)	(0.047)
ΔP		−1.849	−1.142		−0.616	0.016		−3.427	−3.620		−3.096	−3.059
		(1.553)	(1.543)		(1.429)	(1.424)		(3.316)	(3.353)		(2.408)	(2.427)
ΔP^2		0.017	−0.011		−0.046	−0.072		0.329	0.345		0.294	0.286
		(0.112)	(0.111)		(0.103)	(0.102)		(0.244)	(0.248)		(0.181)	(0.183)
ΔW			34.279***			30.728***			16.067			−8.952
			(12.411)			(11.431)			(28.490)			(20.357)
ΔW^2			−1.929***			−1.713***			−0.889			0.380
			(0.657)			(0.605)			(1.505)			(1.071)
Constant	0.552	0.745	0.698	−1.155	−0.926	−0.965	−0.644	−0.878	−0.764	−1.580	−1.769	−1.864
	(0.821)	(0.829)	(0.814)	(0.750)	(0.762)	(0.750)	(1.708)	(1.731)	(1.758)	(1.221)	(1.233)	(1.248)
Observations	210	210	210	210	210	210	146	146	146	162	162	162
R^2	0.005	0.043	0.088	0.027	0.052	0.092	0.001	0.015	0.018	0.011	0.028	0.032
Adjusted R^2	−0.005	0.024	0.061	0.018	0.034	0.065	−0.013	−0.013	−0.025	−0.002	0.003	−0.006
Residual Std. Error	4.690	4.622	4.534	4.282	4.246	4.176	7.499	7.498	7.542	5.828	5.812	5.839
F Statistic	0.524	2.300*	3.270***	2.863*	2.826**	3.436***	0.068	0.543	0.421	0.845	1.133	0.843

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Bottom/Top 50% refers to the wealth distribution. Periods compared: 1996–2000 vs. 2018–2022. Standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D.4 Long-Difference Estimates: Bottom 50% vs. Top 50%, Poor vs. Rich

Table 6. Long-Difference Estimates: Bottom/Top 50%, Poor vs. Rich Interaction

	Dependent variable:											
	Δ Rel. Income Growth						Δ Wealth Growth					
	Bottom 50%			Top 50%			Bottom 50%			Top 50%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔT	−0.164	−0.208	−0.026	0.441	0.339	0.579	−0.800	−0.510	−0.370	−0.367	−0.188	−0.189
	(0.841)	(0.835)	(0.878)	(0.768)	(0.768)	(0.809)	(2.857)	(2.861)	(2.954)	(2.191)	(2.180)	(2.228)
ΔT^2	0.015	0.012	0.012	0.025	0.021	0.020	0.002	0.006	−0.0002	0.041	0.044	0.047
	(0.022)	(0.022)	(0.022)	(0.020)	(0.020)	(0.020)	(0.076)	(0.076)	(0.078)	(0.058)	(0.058)	(0.058)
ΔP		−3.179	−2.839		−1.624	−1.346		−4.992	−5.745		−3.426	−3.457
		(2.751)	(2.722)		(2.527)	(2.506)		(5.268)	(5.354)		(3.797)	(3.820)
ΔP^2		0.166	0.170		0.022	0.027		0.643	0.699		0.470	0.476
		(0.270)	(0.267)		(0.248)	(0.246)		(0.512)	(0.519)		(0.379)	(0.381)
ΔW			36.970**			32.334**			42.960			5.867
			(16.182)			(14.893)			(39.037)			(27.582)
ΔW^2			−2.060**			−1.829**			−2.303			−0.265
			(0.855)			(0.787)			(2.073)			(1.474)
$\Delta T \times$ Poor	−0.120	−0.464	−0.480	0.393	0.203	0.115	−0.644	−1.176	−1.312	0.477	−0.076	0.157
	(1.199)	(1.193)	(1.218)	(1.094)	(1.096)	(1.121)	(3.732)	(3.743)	(3.830)	(2.835)	(2.829)	(2.874)
$\Delta T^2 \times$ Poor	0.020	0.036	0.032	0.005	0.017	0.011	0.095	0.090	0.093	0.035	0.033	0.038
	(0.036)	(0.036)	(0.036)	(0.033)	(0.033)	(0.033)	(0.112)	(0.112)	(0.114)	(0.084)	(0.084)	(0.084)
$\Delta P \times$ Poor		1.518	2.137		2.306	2.821		−3.978	−3.589		−5.667	−5.626
		(3.599)	(3.611)		(3.311)	(3.328)		(8.397)	(8.515)		(5.996)	(6.019)
$\Delta P^2 \times$ Poor		−0.179	−0.222		−0.147	−0.188		−0.094	−0.157		0.086	0.047
		(0.305)	(0.303)		(0.280)	(0.279)		(0.637)	(0.644)		(0.468)	(0.470)
$\Delta W \times$ Poor			−11.864			−7.292			−76.421			−47.733
			(26.547)			(24.425)			(57.623)			(40.997)
$\Delta W^2 \times$ Poor			0.598			0.451			3.974			2.165
			(1.405)			(1.293)			(3.043)			(2.152)
Constant	0.417	0.487	0.536	−1.245	−1.022	−1.013	−0.433	−0.746	−0.529	−1.468	−1.671	−1.771
	(0.836)	(0.855)	(0.849)	(0.763)	(0.786)	(0.783)	(1.715)	(1.738)	(1.774)	(1.228)	(1.234)	(1.248)
Observations	210	210	210	210	210	210	146	146	146	162	162	162
R²	0.010	0.055	0.097	0.033	0.064	0.102	0.020	0.049	0.063	0.023	0.061	0.082
Adjusted R²	−0.009	0.017	0.042	0.014	0.027	0.047	−0.007	−0.006	−0.022	−0.002	0.012	0.008
Residual Std. Error	4.700	4.638	4.581	4.289	4.261	4.216	7.479	7.474	7.532	5.828	5.787	5.799
F Statistic	0.537	1.460	1.755*	1.745	1.720*	1.867**	0.731	0.886	0.741	0.916	1.242	1.108

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Bottom/Top 50% refers to the wealth distribution. Poor is an indicator equal to 1 for countries with average income below the sample median. Periods compared: 1996–2000 vs. 2018–2022. Standard errors in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D.5 Long-Difference Estimates: Bottom 50% vs. Top 50%, Cold vs. Hot

Table 7. Long-Difference Estimates: Bottom/Top 50%, Cold vs. Hot Interaction

	Dependent variable:											
	Δ Rel. Income Growth						Δ Wealth Growth					
	Bottom 50%			Top 50%			Bottom 50%			Top 50%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔT	−18.738**	−21.404***	−19.401**	−11.051	−12.881*	−11.639*	20.078	28.089	28.494	−0.976	5.905	6.939
	(7.570)	(7.503)	(7.460)	(6.954)	(6.927)	(6.906)	(22.625)	(24.463)	(24.335)	(17.363)	(18.267)	(18.095)
ΔT^2	0.387***	0.437***	0.402***	0.260*	0.295**	0.273**	−0.357	−0.494	−0.522	0.073	−0.053	−0.078
	(0.148)	(0.146)	(0.145)	(0.136)	(0.135)	(0.134)	(0.434)	(0.470)	(0.468)	(0.333)	(0.351)	(0.348)
ΔP		−0.481	0.323		1.206	1.840		−0.924	3.897		−3.921	−0.402
		(1.933)	(1.950)		(1.785)	(1.805)		(8.538)	(9.054)		(5.541)	(5.673)
ΔP^2		−0.094	−0.126		−0.172	−0.202		0.304	−0.108		0.500	0.214
		(0.138)	(0.139)		(0.127)	(0.129)		(0.868)	(0.908)		(0.550)	(0.556)
ΔW			40.777**			29.598*			−77.807			−80.916**
			(17.011)			(15.749)			(53.944)			(36.588)
ΔW^2			−2.275**			−1.618*			4.911			4.764**
			(0.920)			(0.852)			(3.061)			(2.074)
$\Delta T \times$ Cold	19.150**	21.565***	19.692***	12.326*	13.911**	12.782*	−19.416	−27.866	−28.584	1.874	−5.304	−6.330
	(7.597)	(7.523)	(7.477)	(6.979)	(6.945)	(6.922)	(22.689)	(24.493)	(24.375)	(17.416)	(18.305)	(18.138)
$\Delta T^2 \times$ Cold	−0.390***	−0.439***	−0.404***	−0.261*	−0.295**	−0.273**	0.342	0.508	0.534	−0.051	0.097	0.128
	(0.150)	(0.148)	(0.147)	(0.138)	(0.137)	(0.136)	(0.447)	(0.483)	(0.481)	(0.342)	(0.361)	(0.357)
$\Delta P \times$ Cold		−3.448	−3.692		−4.688	−4.663		−8.704	−13.172		−1.946	−5.633
		(3.140)	(3.148)		(2.905)	(2.922)		(9.876)	(10.308)		(6.603)	(6.708)
$\Delta P^2 \times$ Cold		0.265	0.279		0.284	0.293		0.314	0.692		−0.099	0.182
		(0.229)	(0.229)		(0.212)	(0.212)		(0.918)	(0.955)		(0.594)	(0.599)
$\Delta W \times$ Cold			−12.744			2.728			79.478			75.770
			(25.699)			(23.789)			(68.731)			(47.128)
$\Delta W^2 \times$ Cold			0.730			−0.156			−5.394			−4.772*
			(1.350)			(1.250)			(3.726)			(2.553)
Constant	0.414	0.618	0.527	−1.316*	−1.124	−1.156	−0.758	−1.344	−0.500	−1.569	−1.968	−1.785
	(0.823)	(0.829)	(0.824)	(0.757)	(0.766)	(0.763)	(1.719)	(1.746)	(1.770)	(1.232)	(1.260)	(1.264)
Observations	210	210	210	210	210	210	146	146	146	162	162	162
R²	0.038	0.089	0.131	0.048	0.089	0.126	0.008	0.045	0.094	0.011	0.039	0.087
Adjusted R²	0.019	0.053	0.078	0.029	0.053	0.073	−0.020	−0.010	0.012	−0.014	−0.011	0.014
Residual Std. Error	4.633	4.554	4.493	4.257	4.204	4.160	7.524	7.489	7.406	5.863	5.854	5.782
F Statistic	2.035*	2.456**	2.470***	2.559**	2.458**	2.363***	0.302	0.815	1.147	0.444	0.778	1.186

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Bottom/Top 50% refers to the wealth distribution. Cold is an indicator equal to 1 for countries with average temperature below the sample median. Periods compared: 1996–2000 vs. 2018–2022. Standard errors in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D.6 Long-Difference Estimates from Data Cleaning

Table 8. Long-Difference Estimates: Relative Income Growth and Wealth Share

| | *Dependent variable:* | | | | | |
| | Δ Rel. Income Growth | | | Δ Wealth Share | | |
	(1)	(2)	(3)	(4)	(5)	(6)
ΔT	0.014	0.014	0.023	0.004	0.005	0.005
	(0.028)	(0.029)	(0.030)	(0.005)	(0.005)	(0.005)
ΔT^2	-0.001^*	-0.001	-0.001^*	-0.0001	-0.0001	-0.0001
	(0.001)	(0.001)	(0.001)	(0.0001)	(0.0001)	(0.0001)
ΔP		0.015	0.016		0.0001	0.0001
		(0.030)	(0.030)		(0.005)	(0.005)
ΔP^2		-0.001	-0.001		0.0001	0.0001
		(0.002)	(0.002)		(0.0004)	(0.0004)
ΔW			0.196			-0.005
			(0.257)			(0.045)
ΔW^2			-0.012			0.0001
			(0.013)			(0.002)
Europe	0.003	0.002	0.001	0.007	0.007	0.007
	(0.042)	(0.042)	(0.042)	(0.007)	(0.007)	(0.007)
Latin America	0.032	0.034	0.027	0.026***	0.026***	0.026***
	(0.041)	(0.041)	(0.042)	(0.007)	(0.007)	(0.007)
MENA	-0.039	-0.040	-0.036	0.020**	0.020**	0.020**
	(0.045)	(0.045)	(0.045)	(0.008)	(0.008)	(0.008)
N. America & Oceania	-0.008	-0.008	-0.008	0.012	0.012	0.012
	(0.044)	(0.045)	(0.045)	(0.008)	(0.008)	(0.008)
Russia & Central Asia	0.031	0.032	0.029	0.011	0.010	0.010
	(0.049)	(0.049)	(0.049)	(0.008)	(0.008)	(0.009)
S. & SE Asia	0.033	0.033	0.034	0.021***	0.021***	0.021***
	(0.044)	(0.044)	(0.044)	(0.008)	(0.008)	(0.008)
Sub-Saharan Africa	0.028	0.028	0.030	0.024***	0.024***	0.024***
	(0.041)	(0.041)	(0.041)	(0.007)	(0.007)	(0.007)
Constant	-0.012	-0.013	-0.016	-0.018^{**}	-0.018^{**}	-0.018^{**}
	(0.041)	(0.041)	(0.041)	(0.007)	(0.007)	(0.007)
Observations	212	212	212	212	212	212
R^2	0.086	0.087	0.097	0.160	0.160	0.161
Adjusted R^2	0.046	0.037	0.038	0.122	0.114	0.105
Residual Std. Error	0.092	0.093	0.093	0.016	0.016	0.016
F Statistic	2.119**	1.741*	1.635*	4.261***	3.468***	2.914***

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Region dummies are included with Asia (excl. S.&SE Asia) as the reference category. Standard errors in parentheses.