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# Climate Shocks and Income Inequality: Some first results

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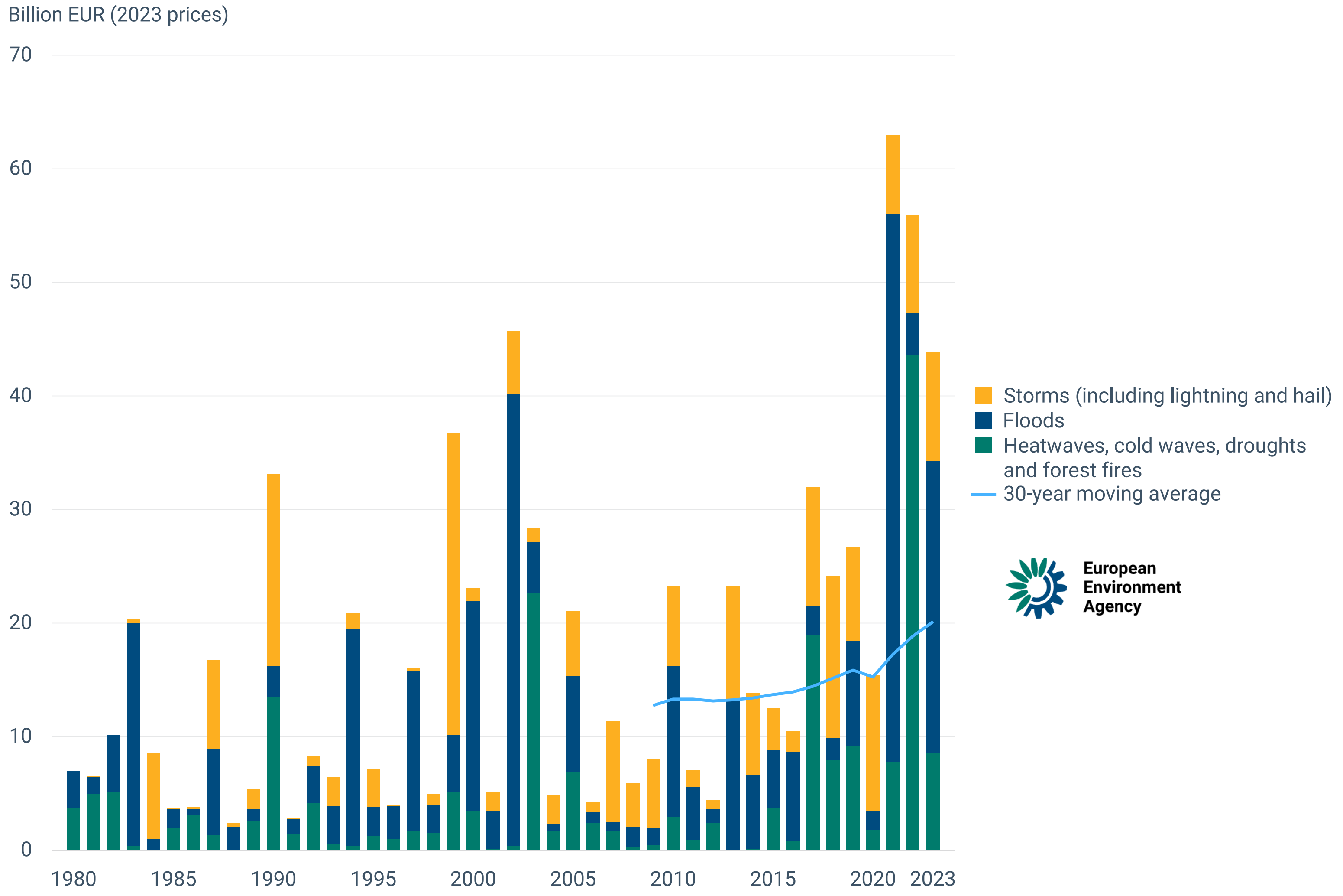
# Annual economic losses caused by weather-and climate-related extreme events (all EU)

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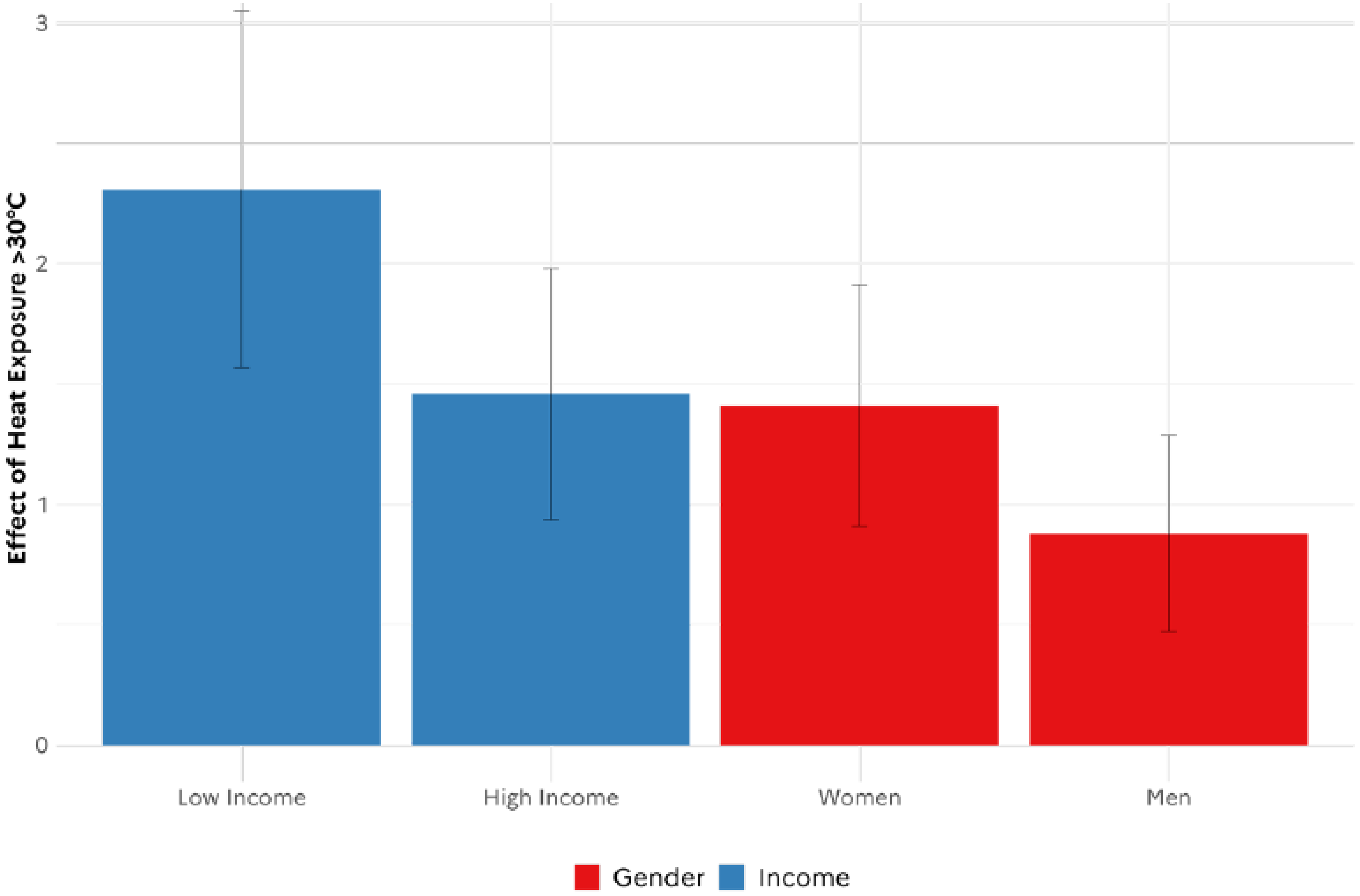
# The climate-income-gender inequality nexus: unequal effects of heat exposure on mental health in the US

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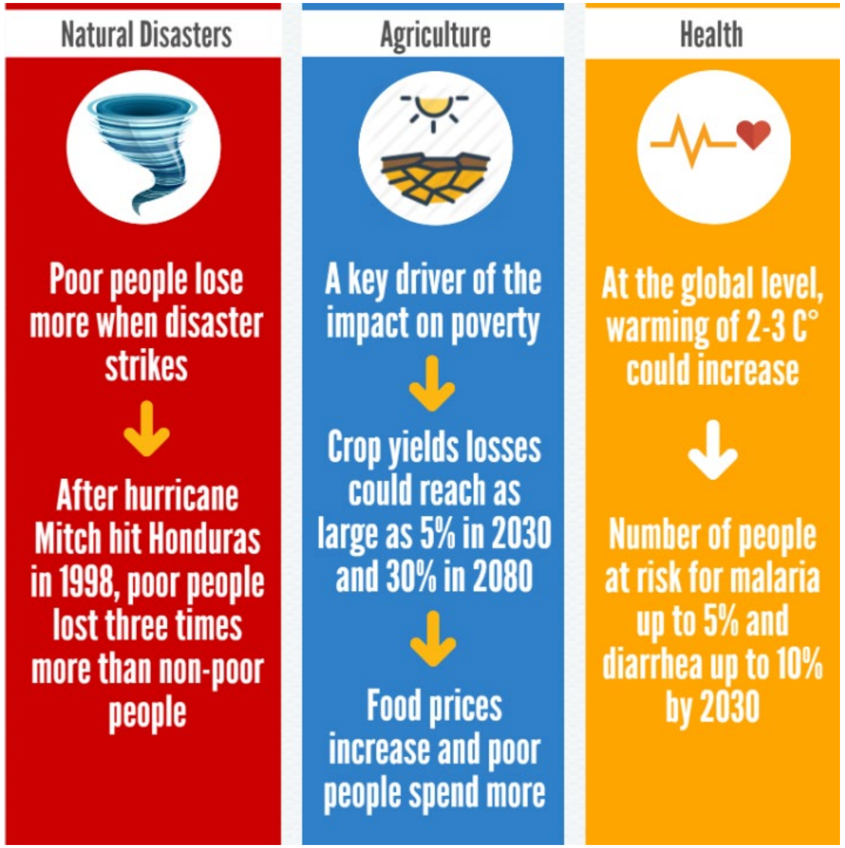
# Motivation

- This research links extreme weather to worsening income inequality
  - Findings from Vasilakos et al. *(2025)* use data from 145 countries and show that lower-income populations are consistently hit harder by extreme events.
- When disasters strike, informal workers, low-wage earners, and those in rural or precarious housing suffer the most, amplifying pre-existing inequalities.
- Our results show that extreme weather is associated with a disproportionately negative effect on the bottom 30% of the income distribution.
  - Lower-income groups often work in climate-sensitive sectors (e.g. agriculture, construction), lack insurance or savings, and live in areas more exposed to physical risk.
  - A feedback loop: As inequality rises, adaptive capacity falls, further entrenching vulnerability. This dynamic fuels social unrest, migration pressures, and long-run productivity losses.



How does climate change make people poorer? | World Economic Forum

# Methodology

- Our paper investigates how different types of extreme weather events affect income inequality across the entire income distribution, using decile regressions and inequality indicators such as 90/10 indicators and Gini coefficients, using panel data globally.

- By combining reanalysis climate data (ERA5), harmonised inequality metrics (PIP), and economic performance indicators, we estimate the extent to which climate risks drive regressivity in income outcomes, and how this varies by sector, region, and policy environment.
  - Climate variables included (so far): heatwaves, cold waves, icing days, hot days, droughts and extreme precipitation
  - Poverty and Inequality Platform (PIP), World Bank:
    - Comprehensive global poverty and inequality data.
    - Covers ~2,400 surveys across 160+ countries up to 2024.

# Methodology – Climate variables

**Measurement Approach & Definitions:**

- Extreme events - we follow the IPCC definition: "an extreme weather event is an event that is rare at a particular place and time of year', and an extreme climate event as 'a pattern of extreme weather that persists for some time, such as a season'" (Seneviratne et al., 2021, p. 1522).
    - Categorised into 'Hot and Cold' or 'Wet and Dry' events (Ranasinghe et al., 2021).
- For each climate event, we calculate both intensity and frequency and normalise the variables to account for differences in their measurement scales.
- We apply principal component analysis to combine intensity and frequency into a single representative variable for each climate event, denotes as $HW\_IF$, $CW\_IF$, $Icing\_IF$, $Hot\_IF$, and $R95dmax\_IF$ , and $Drought\_IF$.

| Index | Condition |
|---|---|
| Hot-days | Daily maximum temperature > 35°C |
| Heatwave | Excess Heat Factor is positive |
| Coldwave | Excess Cold Factor is negative |
| Icing days | Daily maximum temperature < 0°C |
| R95dIFmax_ IF | 95th percentile rain exceedance days over agricultural land |
| Drought | Number of days with affected land area |

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# Methodology – Economic variables

**Measurement Approach & Definitions:**

- Economic performance indicators :
  - Sectoral value-added (GDP): real GDP constant in 2017 (in logs) denoted as ln_real_Agri_GDP, ln_real_Ind_GDP, ln_real_Serv_GDP.
  - Household consumption expenditure: calculated as log of (Final Consumption Expenditure – Government Consumption) per capita, constant in 2017, denotes as $ln\_real\_per\_HFCE$.
  - Principal Component of Sectoral GDP: log of sectoral GDP (Agriculture, Manufacturing, Services) combined using Principal Component Analysis (PCA), denoted as $PC\_ln\_GDP$.
- Unemployment Rate
- Domestic Credit to Private Sector (as % of GDP) - captures financial development
- Working-Age Population (15–64 years)
- Female Labour Force Participation Rate (15+ years)
- Polarisation index (as in Esteban and Ray, 1994) – captures “group separation”
- Trade Openness, as net exports of goods and services (% of GDP).
- Governance Indicators
  - Six dimensions: Control of corruption, government effectiveness, political stability, rule of law, regulatory quality, voice and accountability. Dimensionality reduced using Principal Component Analysis (PCA). First principal component (explains 87.42% variance), denoted as: $IQ\_PC$.

# Methodology – Recentered Influence Functions (OLS)

- **Specification 1**

$$RIF\left(ln\_r\_avg\_wel_{p,i,t}; v^{90/10}\right) = \alpha_\tau + \boldsymbol{\gamma}_\tau^T \boldsymbol{C}_{i,t} + \boldsymbol{\beta}_\tau^T \boldsymbol{X}_{i,t} + \tau_i + \theta_t + \varepsilon_{p,i,t}$$

where

- $ln\_r\_avg\_wel_{p,i,t}$ denotes log of average real income for percentile $p$ in country $i$, year $t$..
- $\boldsymbol{CR}_{i,t}$ is a vector of frequency–intensity indicators for heatwaves, coldwaves, droughts, icing days and extreme rainfall.
- The vector $\boldsymbol{X}_{i,t}$ includes whether principal component of sectoral GDPs or each log of sectoral GDP, sectoral GDP shares, institutional quality, financial development, labour market characteristics, etc..
- Country fixed effects ($\tau_i$ + (year fixed effects ($\theta_t$ (absorb time-invariant country traits and global shocks.
- A
- Here the focus is on the **inter-percentile ratio (90/10)**, the ratio of incomes at the 90th to the 10th percentile, to summarise the gap between the top and bottom of the distribution.

# Methodology – Recentered Influence Functions (Gini)

## Specification 2

We complement decile regressions by estimating the effect of climate shocks on the Gini coefficient.

$$RIF\left(ln\_r\_avg\_wel_{p,i,t}; G_{i,t}\right) = \alpha_\tau + \boldsymbol{\gamma_\tau^T C_{i,t}} + \boldsymbol{\beta_\tau^T X_{i,t}} + \tau_i + \theta_t + \varepsilon_{p,i,t}$$

- For each country $i$and year $t$, let $\ln r\_avg\_wel_{i,p,t}$ be log average real income in percentile $p$, denote as $y$ here for demonstration. The Gini of the country–year income distribution is:

$$G_{i,t} = \frac{1}{2\mu_{i,t} n_{i,t}^2} \sum_{p=1}^{n_{i,t}} \sum_{q=1}^{n_{i,t}} |y_i - y_j|$$

where $p$ indexes one percentile (or observation) in country $i$, year $t$; $q$ indexes the other percentile (or observation) in the same country–year.

# Methodology – Models

- **Specification 3**

$$\ln\_\text{ave\_inc}^{q}_{\text{i,t}} = \alpha + \boldsymbol{\beta_1 CR_{i,t}} + \beta_2 \ln\_real\_sectorGDP^{s}_{i,t} + \boldsymbol{\beta_3 X_{i,t}} + \gamma_i + \theta_{\text{t}} + \epsilon_{it}$$

where

- $ln\_ave\_inc^{q}_{i,t}$ denotes our measure of income inequality in country $i$ and year $t$, represented as the logarithm of the average income of decile $q$.
- $\boldsymbol{CR_{i,t}}$ is a vector of extreme climate events, including $HW\_IF$, $CW\_IF$, $Icing\_IF$, and $Hot\_IF$.
- $ln\_real\_sectorGDP^{s}_{i,t}$ captures either three sector-specific specifications of real GDP, where $s$ refers to $\text{ln\_real\_Agri\_GDP}_{\text{i,t}}$, $\text{ln\_real\_Ind\_GDP}_{\text{i,t}}$, or $\text{ln\_real\_Serv\_GDP}_{\text{i,t}}$.
- The vector $\boldsymbol{X_{i,t}}$ refers to the control variables.
- $\gamma_i$ and $\theta_{\text{t}}$ represent country and time fixed effects, respectively; $\epsilon_{it}$ is the error term; and $\alpha$ is the intercept.

# Results

| VARIABLES | (1) 90-10th ratio ln_r_avg_wel | (2) 90-10th ratio ln_r_avg_wel | (3) 90-10th ratio ln_r_avg_wel | (4) 90-10th ratio ln_r_avg_wel | (5) Gini ln_r_avg_wel | (6) Gini ln_r_avg_wel | (7) Gini ln_r_avg_wel | (8) Gini ln_r_avg_wel |
|---|---|---|---|---|---|---|---|---|
| HW_IF | 0.021*** | 0.021*** | 0.021*** | 0.023*** | 0.003*** | 0.003*** | 0.002*** | 0.003*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.000) | (0.000) | (0.000) | (0.000) |
| CW_IF | 0.034*** | 0.032*** | 0.034*** | 0.038*** | 0.002*** | 0.002*** | 0.003*** | 0.003*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.000) | (0.000) | (0.000) | (0.000) |
| Icing_IF | 0.006*** | 0.007*** | 0.007*** | 0.006*** | 0.000** | 0.000*** | 0.000*** | 0.000* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| Hotdays_IF | 0.009*** | 0.007** | 0.007** | 0.007** | 0.002*** | 0.001*** | 0.001*** | 0.001*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.000) | (0.000) | (0.000) | (0.000) |
| R95dIFmax | 0.008*** | 0.005 | 0.003 | 0.007** | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.000) | (0.000) | (0.000) | (0.000) |
| ln_r_Agri_GDP | -0.937*** | | | | -0.243*** | | | |
| | (0.010) | | | | (0.002) | | | |
| ln_r_Ind_GDP | | -0.896*** | | | | -0.235*** | | |
| | | (0.010) | | | | (0.002) | | |
| ln_r_Serv_GDP | | | -0.922*** | | | | -0.239*** | |
| | | | (0.010) | | | | (0.002) | |
| PC_GDPsip | | | | -1.343*** | | | | -0.348*** |
| | | | | (0.014) | | | | (0.003) |
| Constant | -39.535*** | -40.246*** | -37.536*** | -57.154*** | -1.777*** | -1.847*** | -1.083*** | -6.834*** |
| | (1.838) | (1.840) | (1.828) | (1.805) | (0.178) | (0.179) | (0.181) | (0.156) |
| Observations | 153,492 | 153,592 | 153,692 | 153,492 | 153,492 | 153,592 | 153,692 | 153,492 |
| Time Effect | YES | YES | YES | YES | YES | YES | YES | YES |
| Country Effect | YES | YES | YES | YES | YES | YES | YES | YES |

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# Results

| VARIABLES | (1)<br>90-10<br>ln_r_avg_wel | (2)<br>90-10<br>ln_r_avg_wel | (3)<br>90-10<br>ln_r_avg_wel | (4)<br>90-10<br>ln_r_avg_wel | (5)<br>Gini<br>ln_r_avg_wel | (6)<br>Gini<br>ln_r_avg_wel | (7)<br>Gini<br>ln_r_avg_wel | (8)<br>Gini<br>ln_r_avg_wel |
|---|---|---|---|---|---|---|---|---|
| Drought_IF | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| ln_r_Agri_GDP | -0.740*** | | | | -0.259*** | | | |
| | (0.010) | | | | (0.003) | | | |
| ln_r_Ind_GDP | | -0.714*** | | | | -0.249*** | | |
| | | (0.010) | | | | (0.003) | | |
| ln_r_Serv_GDP | | | -0.714*** | | | | -0.252*** | |
| | | | (0.010) | | | | (0.003) | |
| PC_GDPsip | | | | -1.069*** | | | | -0.371*** |
| | | | | (0.015) | | | | (0.004) |
| Constant | -46.256*** | -42.169*** | -43.756*** | -58.999*** | -1.623*** | -1.011*** | -0.469** | -6.616*** |
| | (2.239) | (2.219) | (2.232) | (2.223) | (0.208) | (0.208) | (0.219) | (0.189) |
| Observations | 111,193 | 111,393 | 111,393 | 111,193 | 111,193 | 111,393 | 111,393 | 111,193 |
| Country Effect | YES | YES | YES | YES | YES | YES | YES | YES |

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# Results -- Full distribution (Agricultural sector)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Agri | Agri | Agri | Agri | Agri | Agri | Agri | Agri | Agri | Agri |
| VARIABLES | ln_ave_inc1 | ln_ave_inc2 | ln_ave_inc3 | ln_ave_inc4 | ln_ave_inc5 | ln_ave_inc6 | ln_ave_inc7 | ln_ave_inc8 | ln_ave_inc9 | ln_ave_inc10 |
| HW_IF | -0.016*** | -0.013*** | -0.013*** | -0.013*** | -0.013*** | -0.013*** | -0.013*** | -0.013*** | -0.013*** | -0.011*** |
| | (0.005) | (0.004) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) |
| CW_IF | -0.012** | -0.010** | -0.009** | -0.008** | -0.009** | -0.009** | -0.009** | -0.009** | -0.009** | -0.009** |
| | (0.006) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Icing_IF | -0.022** | -0.016** | -0.011 | -0.006 | -0.005 | -0.006 | -0.006 | -0.007 | -0.007 | -0.010 |
| | (0.010) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Hotdays_IF | -0.022*** | -0.015*** | -0.012** | -0.011** | -0.011** | -0.011** | -0.012** | -0.010* | -0.011** | -0.011* |
| | (0.008) | (0.006) | | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) |
| ln_real_Agri_GDP | 0.027*** | 0.024*** | 0.021*** | 0.019*** | 0.018*** | 0.019*** | 0.019*** | 0.019*** | 0.019*** | 0.009 |
| | (0.009) | (0.007) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) |
| ln_Pop_1564 | -0.489*** | -0.644*** | -0.681*** | -0.690*** | -0.680*** | -0.677*** | -0.666*** | -0.662*** | -0.662*** | -0.716*** |
| | (0.068) | (0.049) | (0.047) | (0.046) | (0.047) | (0.047) | (0.047) | (0.047) | (0.046) | (0.050) |
| Unemp_rate | -1.840*** | -1.408*** | -1.325*** | -1.267*** | -1.269*** | -1.297*** | -1.301*** | -1.282*** | -1.249*** | -1.394*** |
| | (0.189) | (0.138) | (0.131) | (0.130) | (0.131) | (0.131) | (0.131) | (0.131) | (0.130) | (0.139) |
| Female_rate | -0.234 | -0.189 | -0.173 | -0.180 | -0.180 | -0.154 | -0.128 | -0.124 | -0.143 | -0.247** |
| | (0.161) | (0.117) | (0.112) | (0.111) | (0.111) | (0.112) | (0.112) | (0.112) | (0.111) | (0.119) |
| Trade_Openess | 0.197** | 0.201*** | 0.194*** | 0.198*** | 0.210*** | 0.202*** | 0.204*** | 0.205*** | 0.208*** | 0.199*** |
| | (0.089) | (0.065) | (0.062) | (0.061) | (0.061) | (0.062) | (0.062) | (0.062) | (0.061) | (0.066) |
| DCPS | 0.057** | 0.078*** | 0.082*** | 0.081*** | 0.079*** | 0.076*** | 0.078*** | 0.081*** | 0.085*** | 0.105*** |
| | (0.026) | (0.019) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.018) | (0.019) |
| IQ_PC | 0.077*** | 0.077*** | 0.085*** | 0.089*** | 0.091*** | 0.090*** | 0.090*** | 0.090*** | 0.089*** | 0.071*** |
| | (0.013) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.010) |
| polarisation | -5.414*** | -3.628*** | -2.789*** | -2.273*** | -1.834*** | -1.393*** | -0.959*** | -0.501*** | 0.040 | 1.353*** |
| | (0.165) | (0.120) | (0.114) | (0.113) | (0.114) | (0.114) | (0.114) | (0.114) | (0.113) | (0.121) |
| Constant | 13.908*** | 16.320*** | 16.909*** | 17.090*** | 16.966*** | 16.913*** | 16.744*** | 16.709*** | 16.803*** | 18.188*** |
| | (1.089) | (0.790) | (0.753) | (0.749) | (0.750) | (0.754) | (0.754) | (0.753) | (0.749) | (0.801) |
| Observations | 1,300 | 1,300 | 1,300 | 1,300 | 1,300 | 1,300 | 1,300 | 1,300 | 1,300 | 1,300 |
| R-squared | 0.682 | 0.721 | 0.698 | 0.672 | 0.646 | 0.621 | 0.596 | 0.570 | 0.543 | 0.498 |
| Number of country_id | 145 | 145 | 145 | 145 | 145 | 145 | 145 | 145 | 145 | 145 |
| Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

# Robustness Check – whether a country agriculture dependent

| Climate Events | Non-dependent | Dependent | Difference |
|---|---|---|---|
| **Coldwave** | ↑ inequality | ~0 | Weaker |
| **Icing Days** | ↑ (small) | ~0 | Weaker |
| **Hot Days** | ~0 | ↑↑ inequality | Stronger |
| **Extreme Rain (R95dIFmax)** | ↑ inequality | ↑↑↑ inequality | Much Stronger |
| **Drought** | ↑ inequality | ~0 | Neutralised |

Note: ↑ = inequality-increasing; ↓ = inequality-reducing; ~0 = no significant effect; ↑↑ = stronger inequality-increasing; "Reversal" = sign flips between groups.

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# Robustness Check – K-G climate zone

| Climate Events | Arid (baseline) | Cold | Temperate | Trop-Temp | Tropical | Varied |
|---|---|---|---|---|---|---|
| Heatwave | ↑ (widen) | ~0 | ~0 | ↓ | ↓ | ~0 |
| Coldwave | ↑ | ↑↑ | ↑↑↑ | ↓ | ~0 | ~0 |
| Icing Days | ↑ (small) | ~0 | ~0 | unstable (↓) | unstable (↑) | ↓ |
| Hot Days | ↑ (small) | ↓ | ~0 | (weak) ↓ | ↑↑ | ~0 |

Note: ↑ = inequality-increasing; ↓ = inequality-reducing; ~0 = no significant effect; ↑↑ / ↑↑↑ = stronger inequality-widening; "unstable" = very large, noisy coefficients likely due to data sparsity.

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# Conclusions

- Extreme weather systematically widens income gaps
  - The 90/10 ratio, the Ginis and the decile regressions all show that climate extremes are, on average, associated with higher income dispersion within countries.

- Sectoral GDP matters: differences in impacts between sectors
- The magnitude of inequality effects varies across climate zones.

- Temperature and rainfall shocks are regressive in the short run
  - Heatwaves, coldwaves, icing days and extreme precipitation all raise inequality: lower-tail incomes fall more, while top-tail incomes are relatively protected, especially in climate-sensitive and informal sectors.

- These results highlight the complexity of climate impacts (and the importance of integrating climate justice into climate policy – at the European and global level).

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