



# The distributional effects of climate change. An empirical analysis<sup>☆</sup>

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## ABSTRACT

The role of climate change on output has been studied extensively in the empirical literature. However, its distributional implications have received little attention. This paper attempts to fill this gap by investigating if climate shocks affect income inequality. Using a Vector Autoregression for a large cross-country panel, we identify the climate shock in the frequency domain as the shock that explains the bulk of the variance of climate variables in the long-run. An adverse climate shock is associated with an increase in measures of income inequality, affecting mostly low income households. The impact of the shock is larger in magnitude for low income, hot countries with a significant agricultural sector and low degree of adaptation to climate change.

## 1. Introduction

Climate affects aspects of economic and social activity deeply. The economic effects of climate change have been long studied and a range of results, at times controversial, have been produced.

As shown by Nordhaus and Moffat (2017), the estimated effects of rising temperature on global output, vary from being large and negative (e.g.  $-2.14\%$  due to a  $3.1\text{ }^{\circ}\text{C}$  increase in temperature Roson and der Mensbrugge, 2012) to high and positive (e.g.  $2.3\%$  due to a  $1\text{ }^{\circ}\text{C}$  increase in temperature Tol, 2002). There is some consensus in the literature that Sub-Saharan countries may experience a loss of GDP as large as  $25\%$  (Rehdanz and Maddison, 2005) while East European and Former Soviet Union countries may experience a very small loss or even a gain (see Mendelsohn et al. (2000)) indicating a possible impact on inequality across countries.

However, to our knowledge, there has been limited focus on distributional implications of climate shocks *within* countries. This paper attempts to fill this gap in the literature. Using annual data for 153 countries ranging from 1900 to 2020, we employ a panel structural VAR model which includes climate, inequality indicators and macroeconomic variables. We identify climate shocks as those that explain the bulk of the change of climate variables at low frequencies (see Angeletos et al. (2020)). Our findings show that climate shocks that increase temperature by  $1\text{ }^{\circ}\text{C}$  are associated with a rise of the income Gini coefficient by  $0.63$  percent 6 years after the shock. This effect is stronger for less developed economies, with a large agricultural sector and for the ones classified as hot countries. Countries that have a low degree of adaptability to climate change are also found to be more affected by the shock.

This paper makes two contributions to the literature. To our knowledge, this paper is the first to carry out a systematic analysis of the possible effects of climate change on income inequality. Previous papers have focused largely on cross-country inequality. As discussed below, studies that discuss the effects of climate change on within-country inequality do not use the distribution of

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income within country but utilise proxies for inequality based on the cumulative distribution function (CDF) of aggregate GDP (see [Diffenbaugh and Burke \(2019\)](#)). Our paper also considers the heterogeneity of the effect of climate change on inequality across countries and investigates factors that may drive the differences. From an econometric point of view, we propose a novel identification strategy for climate shocks that is based on the work of [Angeletos et al. \(2020\)](#). Using the spectral density of the climate variables, we isolate shocks that affect their low-frequency dynamics. This procedure is consistent with the idea of climate change as a slow process.

The paper is organised as follows: Section 2 discusses the literature related to this paper. The data and the empirical model are described in Section 3 while Section 4 presents the main findings. Section 5 concludes.

## 2. Related literature

Our paper relates to the literature examining the impact of climate change on economic activity but focuses on its heterogeneous effects. The strand of literature which investigates the impact of climate change on economic activity is vast. A large proportion of papers utilise Integrated Assessment Models (IAMs) that combine knowledge from more than one discipline. These models are used to examine how CO<sub>2</sub> emissions can affect global warming and temperature under diverse policy responses. While the choice of model, structure and assumptions can have a large impact on the results and implications, the general consensus is that climate change leads to serious market and non-market damages, especially in the case of policy inaction.<sup>1</sup> For example, the 2016 DICE model ([Nordhaus, 2019](#)) finds that a 3 °C global warming will suppress global output by 2%.

Our work is closer to cross-country panel data studies.<sup>2</sup> For example, [Dell et al. \(2012\)](#) examine how annual variation in temperature and precipitation affect annual growth for 125 countries in 1950–2002 period. Their findings show a significant negative impact (−1.4% GDP per-capita to +1 °C warming) but only for low-income countries and only for a rise in temperature (and not a fall in precipitation). [Hsiang \(2010\)](#) finds an output loss of 2.5% for Caribbean countries to +1 °C warming in 1970–2006 period. [Kahn et al. \(2021\)](#), in a panel of 174 countries, find a negative impact of temperature rise on real output and estimate that a persistent increase of 0.04% °C on average per year will decrease world output by 7% until 2100, if mitigation policies are not implemented.

Some recent papers discuss distributional effects of climate change, but largely focus on inequality across countries or regions: [Burke and Tanutama \(2019\)](#) use longitudinal data on economic output from over 11,000 districts across 37 countries and find a nonlinear response of growth to the temperature distribution. Their results also indicate that additional warming will exacerbate inequality across countries. [Cevik and Jalles \(2022\)](#) examine the relationship between measures of climate change vulnerability and inequality and find that higher vulnerability is associated with higher income inequality. [Cashin et al. \(2017\)](#) use a Global Vector Autoregression to examine the effects of El Niño and find that these are heterogeneous across countries. Economic activity declines in countries such as Australia, Chile, Indonesia, India, Japan, New Zealand and South Africa, developed economies such as United States benefit from the shock. [Acevedo et al. \(2020\)](#) focus on the effect of shocks to temperature and precipitation and find that low income and hot countries are most negatively affected. [Diffenbaugh and Burke \(2019\)](#) estimate that global warming has increased between-country inequality by 25% in the last 50 years. By using counterfactual historical climate trajectories from a battery of global climate models, the authors estimate that GDP per-capita has been reduced by 17%–31% at the poorest four deciles of the population and the top to bottom ratio in percentiles is 25% larger than in a world without global warming. Interestingly, the authors note that although the difference between poor and rich countries has decreased in the last few decades, global warming has slowed down this process. [Islam and Winkel \(2017\)](#) discuss the impact of climate change on social inequality within countries. Social inequality is defined as a much broader concept, referring to demographic and economic characteristics and access to public resources. The paper discusses channels of transmission from a socioeconomic and policy point of view and presents some tentative correlations.

Two features distinguish our work from this recent literature. First, in contrast to [Cevik and Jalles \(2022\)](#) who focus on vulnerability, the aim of our work is to examine the effects of adverse climate shocks which are identified by using the long run properties of climate data and our estimates do not rely on constructed indices of vulnerability that may suffer from endogeneity. Second, our interest centres on the impact of climate shocks on within-country inequality. Unlike [Diffenbaugh and Burke \(2019\)](#), we utilise data on the distribution of income for each country in our sample derived from tax records and surveys. In contrast, the simulations in [Diffenbaugh and Burke \(2019\)](#) pertaining to economic inequality use measures that are calculated using the CDF of aggregate GDP per-capita across countries.<sup>3</sup> Our analysis is related to a recent paper by [Palagi et al. \(2022\)](#) who investigate the relationship between precipitation and income inequality in agricultural and non-agricultural countries. They find evidence that the relationship between precipitation and low income shares follows an inverted-U-shape, with extreme levels of precipitation associated with an increase in inequality. In contrast to [Palagi et al. \(2022\)](#), we show that the impact of climate shocks on the income distribution can depend on a range of factors beyond agricultural intensity.

<sup>1</sup> For a thorough review see [Nordhaus \(2019\)](#).

<sup>2</sup> A detailed survey on panel data papers with global samples research can be found in [Dell et al. \(2014\)](#).

<sup>3</sup> [Diffenbaugh and Burke \(2019\)](#) state on page 9813: 'Because of the lack of availability of long timeseries of subnational economic data, we calculate these ratios using the respective percentiles of the population-weighted empirical CDF of country-level per capita GDP values'.

### 3. Empirical model and data

The benchmark empirical model is the following Bayesian panel VAR:

$$Y_{it} = \alpha_i + r_j + \tau_t + \sum_{p=1}^P B_p Y_{it-p} + v_{it} \tag{1}$$

where  $var(v_{it}) = \Omega$ ,  $i = 1, 2, \dots, M$  indexes the countries in our panel,  $t = 1, 2, \dots, T$  denotes the time-periods. The model includes country, region and time-fixed effects ( $\alpha_i$ ,  $r_j$  and  $\tau_j$ ).

The matrix of endogenous variables includes two climate variables: temperature and precipitation. We control for national economic conditions by including real GDP per capita. Our main variable of interest is the Gini coefficient of pre-tax income. We also consider alternative measures of inequality such as income at different percentiles of the distribution.

Based on the Bayesian information criterion, we set the lag length to 5. Using lags longer than 1 also ameliorates the possible adverse effect of lag truncation on capturing the impact of shock at medium or long run horizons (see [Jordá et al. \(2020\)](#)).

We use a natural conjugate prior for the VAR coefficients  $\beta = vec([\alpha_i, r_j, \tau_t, B_p])$  and error covariance matrix  $\Omega$  with the prior tightness set to imply a loose prior belief. We draw from the posterior distribution using the MCMC algorithm described in [Banbura et al. \(2010\)](#). We employ 25,000 iterations with a burn-in of 20,000.<sup>4</sup>

#### 3.1. Identification of the climate shock

As climate change is a gradual process, our aim is to capture shocks that drive the low frequency movements in climate variables. Following [Angeletos et al. \(2020\)](#). We identify climate shocks as those that explain the bulk of the variance of climate variables at long-run frequencies.

Broadly speaking, the implementation of this scheme involves two steps: (a) isolating the low frequency component of temperature and precipitation by filtering out shorter term cycles in these variables (b) searching for a shock that explains the largest portion of the variance of the filtered series. A convenient way to implement these steps is to use the spectral density of the climate variables which can be calculated using the coefficients and the error covariance of the VAR model in Eq. (1). The spectral density is used to calculate the variance of the climate variables over the desired frequency while carrying out the search in step b.<sup>5</sup>

More formally, define the relationship between the reduced form  $v_{it}$  and structural shocks  $\epsilon_{it}$ :

$$v_{it} = A_0 \epsilon_{it}$$

where  $A_0$  is a  $N \times N$  contemporaneous impact matrix.  $A_0$  can be written as  $A_0 = \tilde{A}_0 Q$  where  $Q$  is an orthonormal matrix that rotates  $\tilde{A}_0$ , the Cholesky decomposition of  $\Omega$ . Without loss of generality, our interest centres on the first column of  $Q$ , denoted by  $q_1$ , which corresponds to the first structural shock. We choose  $q_1$  so that the contribution of the first shock to the long-run variance of temperature and precipitation (obtained from the VAR-implied spectral density) is maximised. As discussed in [Angeletos et al. \(2020\)](#), the contribution of the shock to the spectral density over a frequency band  $(\underline{\omega}, \overline{\omega})$  is given as  $q_1' S(\underline{\omega}, \overline{\omega}) q_1$  where:

$$S(\underline{\omega}, \overline{\omega}) = \int_{\underline{\omega}}^{\overline{\omega}} (\tilde{g}g) d\omega$$

where  $g = M_y(I - be^{-i\omega})^{-1} \tilde{a}_0$  and  $\tilde{g}$  is its complex conjugate. Note that  $b$  and  $\tilde{a}_0$  denote the VAR coefficients  $B_p$  and the matrix  $\tilde{A}_0$  in companion form. Finally,  $M_y$  denotes a selection vector. The vector  $q_1$  can be recovered as an eigenvector associated with the largest eigenvalue of  $S(\underline{\omega}, \overline{\omega})$ . We set the frequency band as  $(\underline{\omega}, \overline{\omega}) = (\infty, \frac{2\pi}{20})$  so that the long-run corresponds to cycles greater than 20 years. Rather than taking a stand on the precise definition of long-run movements in climate data, our aim is to filter out disturbances associated with shorter-term and regular changes in temperature and precipitation (e.g caused by El Niño or La Niña). Previous studies such as [Ghil and Vautard \(1991\)](#) and [Mann et al. \(2020\)](#) present evidence of the presence of cycles of about 10 to 20 years associated with such phenomenon.<sup>6</sup>

<sup>4</sup> The estimation algorithm and convergence diagnostics are presented in the technical appendix.

<sup>5</sup> This approach is related to ‘long-difference’ panel data models surveyed in [Kolstad and Moore \(2020\)](#). However, unlike these regressions our approach uses a multivariate dynamic model and focuses on shocks or unpredictable components of climate variables.

<sup>6</sup> Our main results are robust to using the lower bound of the frequency range associated with a period of 10 years or a longer period of 50 years. In addition, using an alternative identification scheme that identifies the climate shock as the only disturbance that can affect temperature in the long-run ([Blanchard and Quah, 1989](#)). This scheme has the drawback that the infinite horizon impulse response has to be estimated and this can be challenging using some of the shorter time-series in our unbalanced sample (see [Erceg et al. \(2005\)](#)). The method of [Angeletos et al. \(2020\)](#) is less susceptible to this computational issue as it works with medium to long-horizons.

### 3.2. Data

Our panel dataset covers 153 countries. The time series are unbalanced. The longest span of data covers the period 1901–2020. We restrict the shortest time-series to cover at least 20 years. We obtain annual data on temperature and precipitation from the Climatic Research Unit gridded Time Series (CRU TS) dataset produced by the UK's National Centre for Atmospheric Science at the University of East Anglia (see Harris et al. (2020)). Country-level observations on the climate variables are calculated as area-weighted averages. These series are available for each country from 1901 to 2020. Real GDP per capita for 17 advanced countries is taken from the Jordà-Schularick-Taylor data set where these data series are available from the beginning of the 20th century. These data are supplemented with real GDP per capita taken from the World Bank's world development indicators. We use these sources to obtain additional macroeconomic variables when required.

Our main variables of interest are measures of income inequality obtained from the World Inequality Database (WID). The benchmark measure is the Gini coefficient based on pre-tax national income (WID code PTINC). We also use average pre-tax income within 10 decile groups of income:  $P_1, P_2, \dots, P_{10}$ . For example,  $P_1$  denotes income averaged for individuals that fall below the 10th percentile of income.

While the climate variables are available over the full sample, GDP per capita and the Gini coefficient have missing observations. For most countries, the Gini coefficient is available from 1980 onwards providing 40 years of inequality data. The availability of GDP is more mixed with data for 38 countries in Eastern Europe, Central Asia and Africa only available after 1980. Table 1 in the Appendix shows data availability for each country. However, we show in the robustness section that extended versions of the benchmark model that allow the use of the longest possible series for climatic data lead to results that support our main conclusions.

## 4. Empirical results

### 4.1. Impact on income inequality

Fig. 1 plots the response to a climate shock normalised to an increase in temperature by 1 °C relative to trend.<sup>7</sup> The adverse shock reduces precipitation for about a year, while it takes more than 8 years for the temperature to go back to trend. The median response of GDP per capita is negative and persists for more than 10 years. The adverse climate shock is associated with a rise in inequality: The Gini coefficient rises gradually, with a maximum increase of 0.62 percent at the 6 year horizon.

In order to explore the source of the increase in income inequality, we estimate an extended version of the VAR model where we include average income in the ten decile groups  $P_1, P_2, \dots, P_{10}$  along with the climate variables and GDP. The top panel of Fig. 2 reports the median impulse response of income in each group to shock normalised to an increase in temperature by 1 °C. The bottom panels display the response at the 1 and 5 year horizon together with the error bands.<sup>8</sup> The results indicate that the climate shock has the largest effect at the left tail of the income distribution. At the 5 year horizon, the pre-tax income of the 10th percentile suffers the highest drop, falling by about 4 percent, while the income of the top group falls by less than 1 percent at the same horizon. In short, the adverse climate shock appears to make households at and below the median of the income distribution worse off relative to the rich ones.

The top panel of Fig. 3 displays the contribution of the climate shock to the forecast error variance of income in each decile.<sup>9</sup> In absolute terms, the contribution of the shock is small but statistically different from zero. The contribution is largest at the left tail of the income distribution. The identified shock explains about 1.4 percent of the income fluctuations of group  $P_1$ , while this contribution is only about 0.1 percent for the top income decile. The bottom panels display the decomposition of variance in the frequency domain—the contribution of the identified shock is largest at long-run frequencies associated with cycles greater than 20 years.

Figure 5 in the appendix plots the estimated climate shock averaged across countries in each region and compares this series with regional temperature and precipitation. Large positive (negative) values of the shock are associated with periods of drought (floods) in some regions. These include the droughts of 2008–2010 in the Middle-East and North Africa, the sub-Saharan drought of the early 1990s, the droughts of late 1980s and 2011 and the 2010 floods in Europe. This correlation is perhaps unsurprising as droughts and floods are a manifestation of global warming and climate change (see Rodell and Li (2023), for example). In order to assess the importance of the climate shock for each region, we carry out a counterfactual experiment. For each region in our panel, we simulate data for the average Gini coefficient using the posterior mean estimates from our benchmark VAR, under the assumption that the identified climate shock equals 0 over the sample period.<sup>10</sup> We then calculate the mean percentage difference over time between the actual Gini coefficient and the counterfactual estimate obtained from the simulation. A higher value of this statistic indicates that income inequality would have been *lower* in the absence of climate shocks. Moreover, as the magnitude of the historical shocks differs across regions, this contribution can differ geographically.<sup>11</sup> Fig. 4 shows a heat map that summarises the

<sup>7</sup> The time-effects in the panel VAR capture the global trend in the climate data.

<sup>8</sup> Figure 7 in the appendix shows the response for all decile groups at different horizons as an alternative to the 3-D plot.

<sup>9</sup> Figure 8 in the appendix shows the contribution for all decile groups at different horizons as an alternative to the 3-D plot.

<sup>10</sup> As the number of observations can be small for individual countries, we carry out this simulation at the regional level. We consider the following 8 regions: (1) East Asia, (2) Europe, (3) Latin America, (4) Middle East and North Africa, (5) North America and Oceania, (6) Russia and Central Asia, (7) South Asia and (8) Sub-Saharan Africa.

<sup>11</sup> The empirical model has homogeneous autoregressive coefficients across countries. Therefore, cross-region heterogeneity in the impact on the Gini coefficient is driven by the different realisation of the climate shock across regions and differing initial conditions.

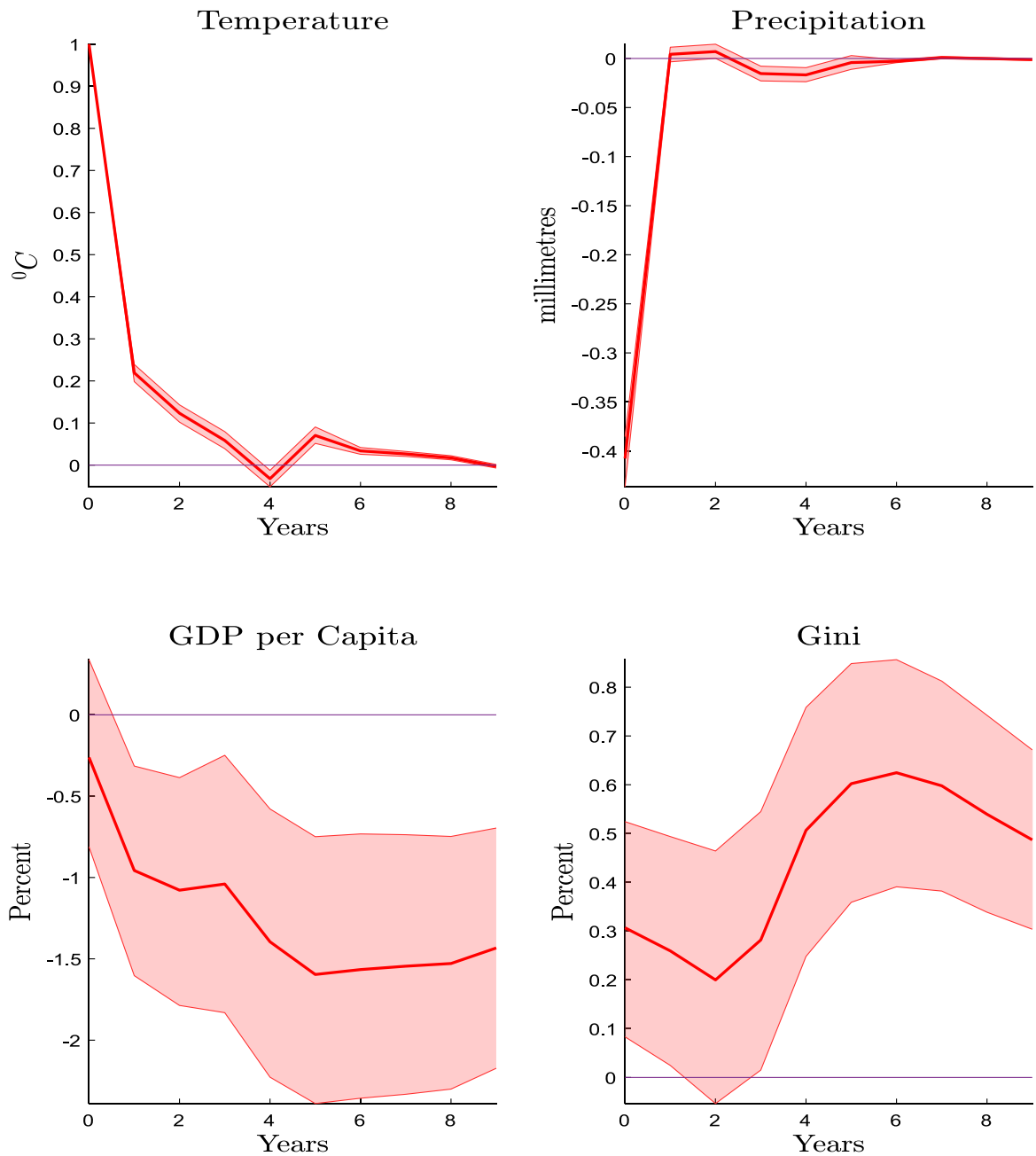


Fig. 1. Impulse response functions to a 1 °C increase in temperature. The vertical axis plots the response in percent. The horizontal axis indicates time in years. The dark line is the median estimate and the shaded areas are the 68% error bands.

results from this experiment. The contribution of the climate shock to the Gini coefficient is largest in countries located in South-East Asia, the Middle-East, Australia and Sub-Saharan Africa, with the largest impact at about 0.1 percent. In contrast, the contribution is negative for former Soviet republics and European countries. It is interesting to note that the estimated contribution of the shock in some high-income countries such as the United States and Canada estimated to be small but positive. Next, we turn to a more detailed examination of the factors that may explain the heterogeneity of the impact of the climate shock on income inequality across countries.

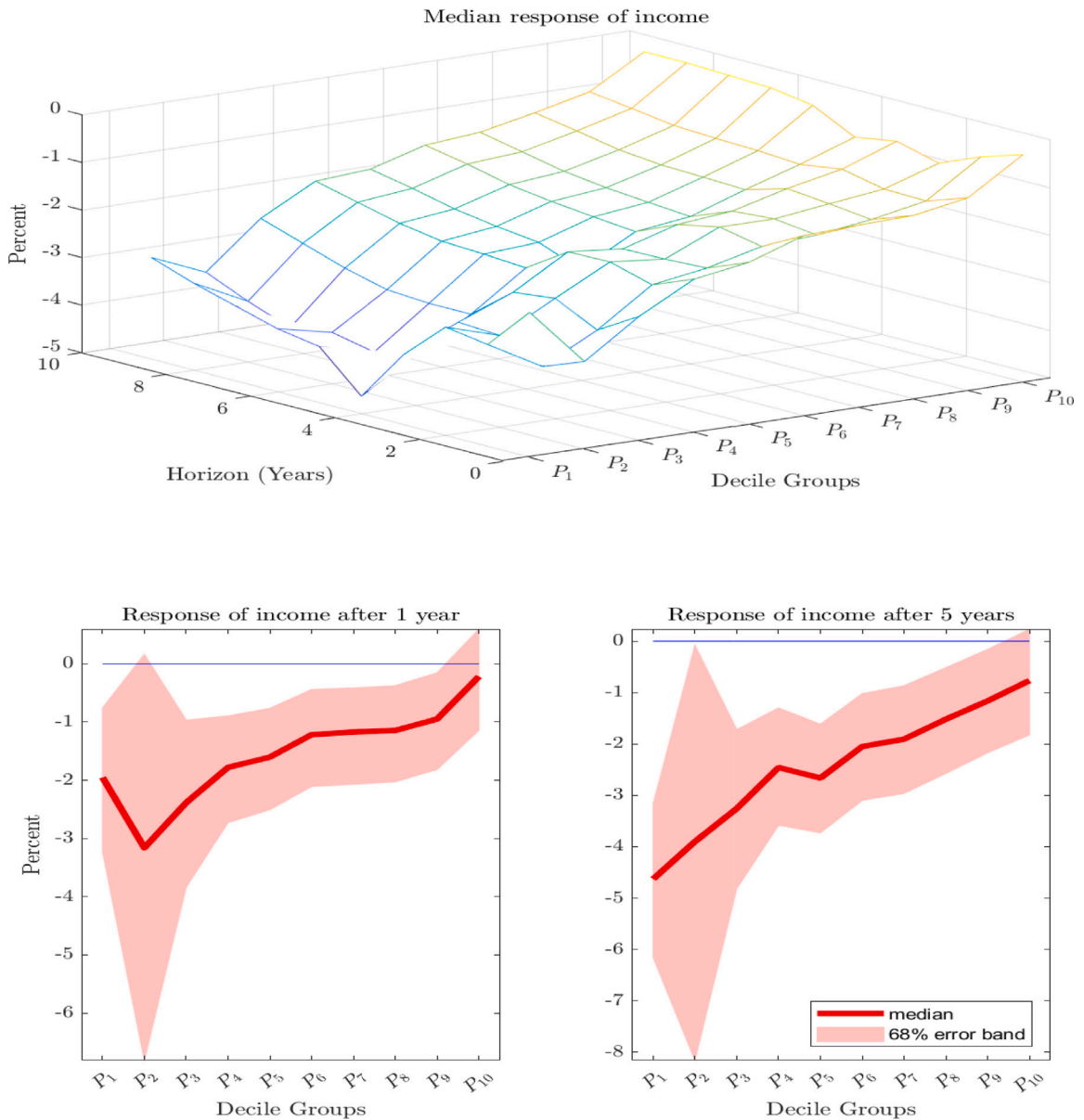


Fig. 2. Impulse response functions of income percentiles to 1 °C increase in temperature. The top panel plots the median response. In this panel, the vertical axis plots the response in percent. The Y-axis indicates the response horizon in years and X-axis indicates the decile groups. The bottom panels plot the response at selected horizons. The dark red lines are the median estimate and the shaded areas are the 68% error bands.

#### 4.2. Heterogeneity and channels of transmission

To investigate the drivers of the transmission of the climate shock to inequality we consider if the effect varies with country characteristics.

*Income.* As demonstrated in papers such as Dell et al. (2012), the effect of adverse climate shocks is asymmetric between poor and rich countries, with the former bearing the brunt of the negative effects on output. In order to investigate if the level of income is also a propagation mechanism for the impact on inequality, we extend our baseline VAR as follows:

$$Y_{it} = \alpha_i + r_j + \tau_i + \sum_{p=1}^P B_p Y_{it-p} + \sum_{p=1}^P b_p (z_{it-p} \times D_{it}) + v_{it} \tag{2}$$

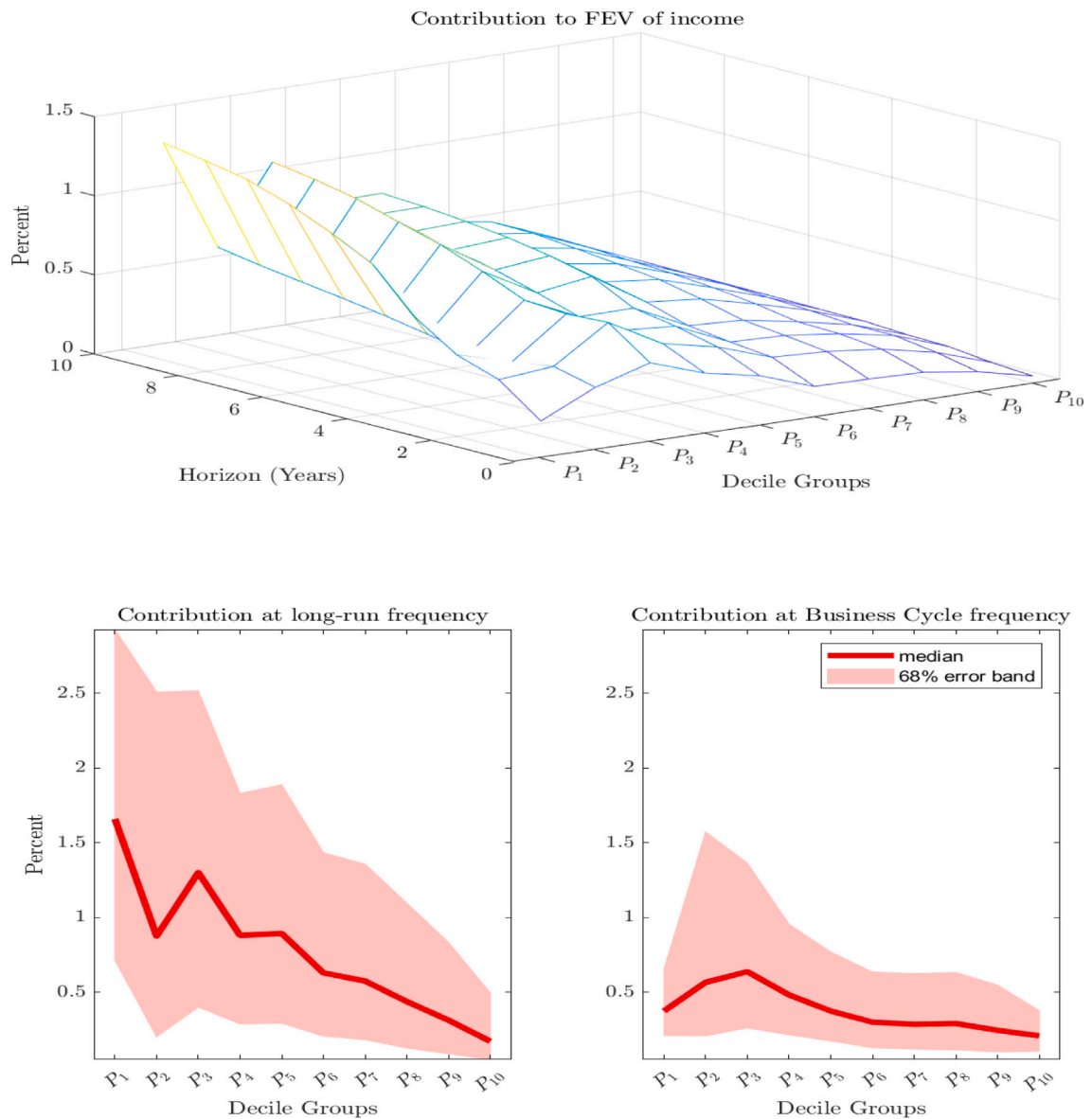


Fig. 3. The top panel plots the median contribution to the forecast error variance. In this panel, the vertical axis plots the contribution in percent. The Y-axis indicates the horizon in years and X-axis indicates the decile groups. The bottom panels plot the contribution to the variance in the frequency domain. Long-run frequencies correspond to cycles greater than 20 years, while business cycle frequencies correspond to cycles of 2 to 8 years. The dark red lines are the median contribution and the shaded areas are the 68% error bands.

where  $z_{it}$  denotes the Gini coefficient and  $D_{it}$  is a dummy variable that equals 1 for countries classified as low and lower-middle income by the World Bank.<sup>12</sup>

The top-left panel of Fig. 5 shows the cumulated response of the Gini coefficient at the 10 year horizon. The solid circle shows the median response, while the horizontal lines represent the 68 percent error band. It is clear that the rise in inequality after the climate shock is substantially larger in low-income countries with a cumulated effect on the Gini coefficient estimated to be more than twice as large.

*Agriculture and manufacturing.* Agriculture is the only economic sector inextricably intertwined with climatic conditions as it is directly affected by temperature and precipitation. Its size and contribution to national income but also the ability of a country to technologically adapt to climate changes are all important elements of this transmission channel. To test the importance of this

<sup>12</sup> These countries are those where Gross National Income per capita was less than 4095 US dollars in 2020.

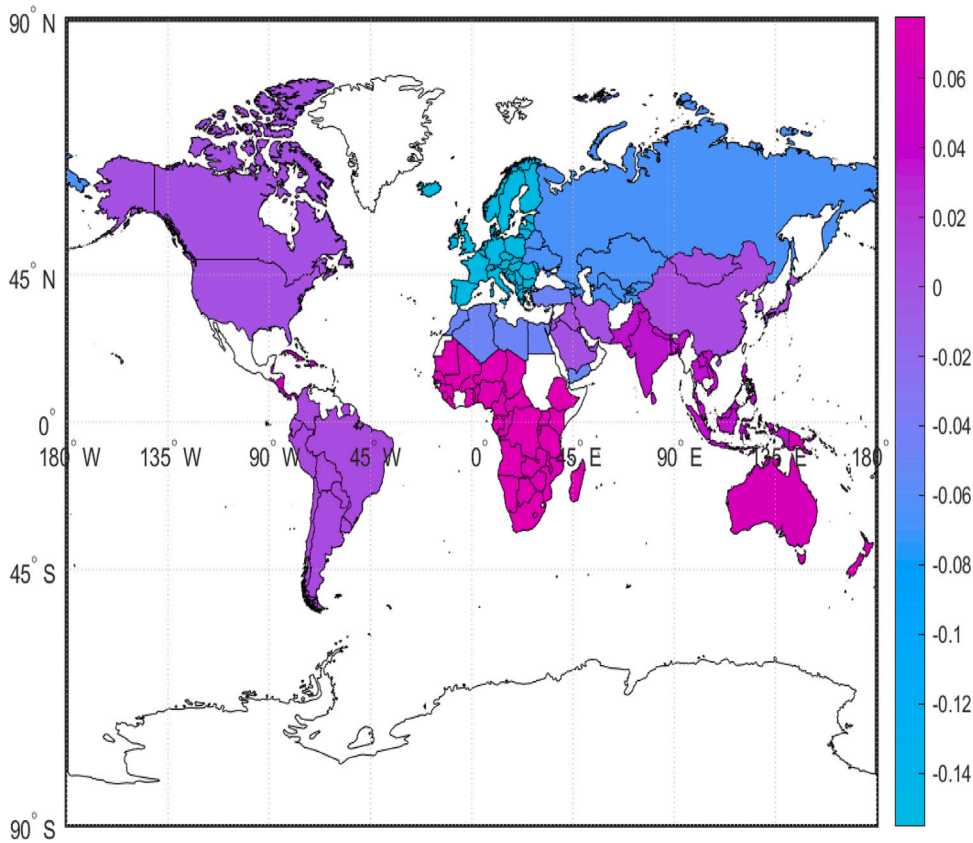


Fig. 4. Contribution of the climate shock to the Gini coefficient in percent calculated as the average Gini coefficient in each country minus the estimate under the assumption of no climate shock. Higher values (darker shades) indicate that the Gini coefficient would have been lower in the absence of climate shocks. Countries not included in the dataset are shaded white.

channel we estimate the following extended version of our model:

$$Y_{it} = \alpha_i + r_j + \tau_i + \sum_{p=1}^P B_p Y_{it-p} + \sum_{p=1}^P b_p (z_{it-p} \times y_{it-p}) + v_{it} \tag{3}$$

where  $y_{it}$  denotes the ratio of value added from agriculture to GDP. Note that  $y_{it}$  is also included as an additional endogenous variable. The interaction term implies that the impulse responses depend on initial conditions. We estimate the response using the simulation methods described in Koop et al. (1996), using deciles of  $y_{it}$  to set the initial conditions.<sup>13</sup>

The second panel of Fig. 5 depicts the cumulated response of the Gini coefficient conditioned at difference percentiles of the share of agriculture. There is some evidence that higher agricultural intensity is associated with a larger effect of the shock, especially in the top quartile of the distribution. In contrast, using the share of manufacturing to GDP as  $y_{it}$  in Eq. (3) suggests that this feature is unimportant in driving the main results.

**Vulnerability and adaptation.** The resilience of an economy to climate change may also determine the severity of the impact on aggregate economic variables and inequality. To measure resilience we use the indices constructed by the University of Notre Dame. The vulnerability index measures the exposure, sensitivity and adaptive capacity of six sectors in each country: food, water, health, ecosystem services, human habitat and infrastructure. A higher value of the index indicates that a country is more vulnerable to climate change. The ND-Gain index measures the readiness of each country net of the degree of vulnerability. The measure of readiness approximates the ability of the investment in climate, governance and social conditions to facilitate adaptation. Higher values of the ND-Gain index indicate a larger degree of readiness. The fourth and fifth panels of Fig. 5 set the vulnerability and ND-gain index, respectively, as the interacting variable. Countries who fall on the right tail of the vulnerability distribution are most negatively affected by an increase in temperature while countries who fall on the left tail of the ND-Gain distribution will have the

<sup>13</sup> The generalised impulse response of Koop et al. (1996) at horizon  $h$  is defined as a difference between the expectation of  $Y_{t+h}$  conditioned on a shock and initial conditions and the expectation assuming no shock. These conditional expectations are calculated using Monte Carlo integration using 100 replications for each MCMC iteration.

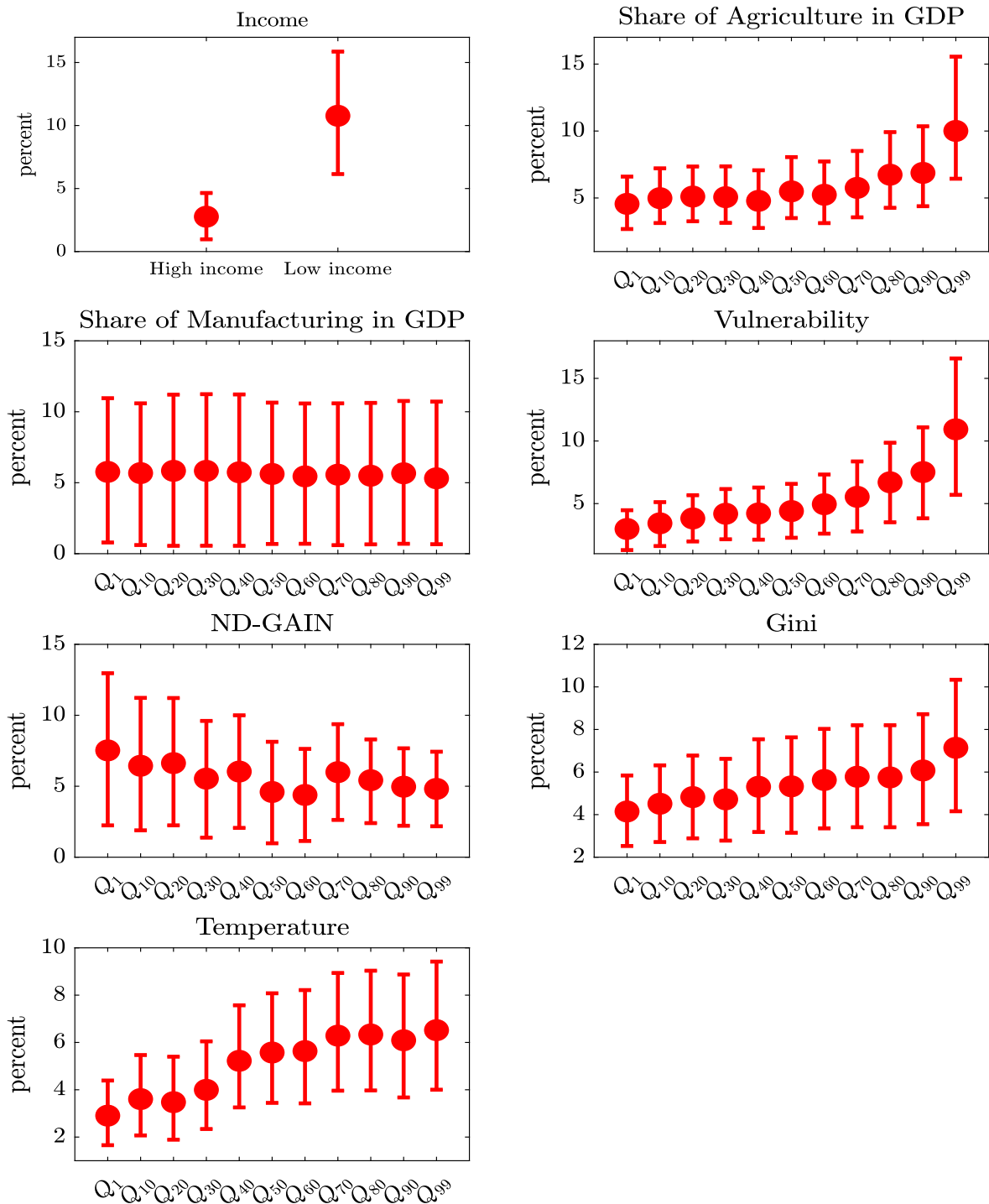


Fig. 5. Cumulated response of the Gini coefficient at the 10 year horizon to 1 °C increase in temperature. The vertical axis plots the response in percent. The horizontal axis in the remaining subplots indicates percentiles of the variable in the title. The solid dot is the median response while the vertical lines show the 68% error bands.  $Q_1, \dots, Q_{99}$  denote the percentiles of the distribution of the respective variable.

lowest gain from the shock. Thus, the fourth panel shows that the effect of the climate shock is substantially larger at the right tail of the distribution of the vulnerability index. In contrast, a higher degree of readiness appears to ameliorate the impact of the shock on inequality, and countries at the right tail of the ND-Gain distribution experience the smallest impact on inequality, as can be seen in the fifth panel.

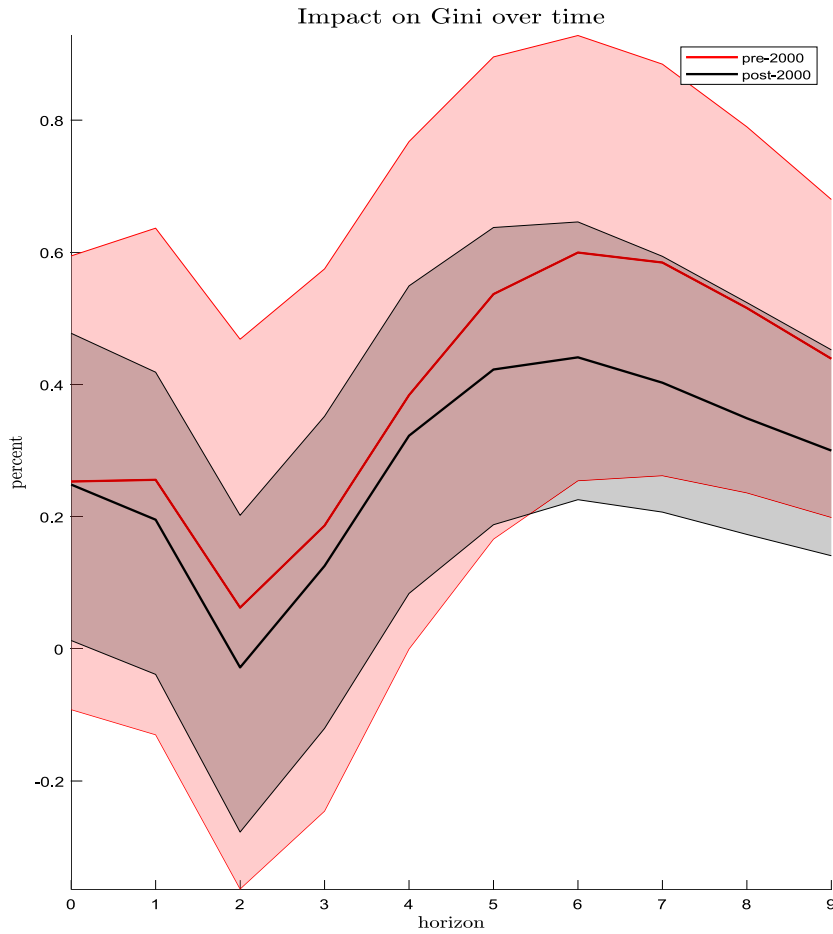


Fig. 6. Impulse response functions of the Gini coefficient to a 1 °C increase in temperature before and after 2000. The vertical axis plots the response in percent. The horizontal axis indicates time in years. The dark line is the median estimate and the shaded areas are the 68% error bands.

*Nonlinear effects.* The final two panels of Fig. 5 use the interacted VAR with temperature and the Gini Coefficient as the variable  $y_{it}$  in Eq. (3), respectively. The last two panels of the figure show that the effect of the shock on inequality is larger for countries that are hot and have higher levels of income inequality. The former result is consistent with the argument that a hot climate is associated with poorer health outcomes (see Deschenes and Greenstone (2011)) and this may, in turn, affect productivity and income. Similarly, higher levels of the Gini may be associated with limited access to social security and health services further exacerbating the effect of the shock.

*Changes over time.* The effect of the climate shock on income inequality may have become smaller over time because of changes in government policies related to climate or an increase in climate adaptation. We consider the possibility of time-variation by estimating the following model:

$$Y_{it} = \alpha_i + r_j + \tau_t + \sum_{p=1}^P B_p Y_{it-p} + \sum_{p=1}^P b_p (z_{it-p} \times D_{it}) + v_{it} \tag{4}$$

where  $z_{it}$  denotes the Gini coefficient and  $D_{it}$  is a dummy variable that equals 1 after 2000.<sup>14</sup> Fig. 6 presents the impulse response of the Gini coefficient in the two sub-samples. While there is some indication that the posterior median response is smaller in the post-2000 period, the large error bands suggest that this difference is not statistically different from zero.<sup>15</sup>

<sup>14</sup> Note that we choose 2000 as a cut-off date to ensure that there are sufficient observations in the two sub-samples for most countries in our panel.

<sup>15</sup> The posterior distribution of the difference in impulse responses is shown in the appendix.

### 4.3. Robustness

We carry out an extensive sensitivity analysis and challenge our results from different perspectives. We try different identification strategies for the temperature shock, alternative time series for the climate data, different model specifications, and estimation techniques. Our benchmark results remain robust and detailed descriptions of these experiments are presented in the appendix.

*Identification.* The benchmark model uses a partial identification scheme of [Angeletos et al. \(2020\)](#) where we identify one shock. We extend this model to jointly identify an ‘economic shock’ and a climate shock. The former disturbance is defined as one that explains the bulk of the variance of GDP in long-run frequencies and is orthogonal to the climate shock. Second, we use long-run restrictions as in [Blanchard and Quah \(1989\)](#) to identify the climate shock. Under this alternative scheme, the shock is identified as the only innovation that can have a non-zero impact on the level of temperature in the long run. Third, we vary the definition of the long-run in the benchmark scheme changing the lower bound of the period to 10 and 50. In all cases, the impact of the climate shock on the Gini coefficient is similar to the benchmark.

*Data.* As discussed above, the mixed availability of GDP data reduces the length of the time-series for some countries. In order to check if the identification of the shock is affected by this we consider three approaches to maximise the length of sample of climatic data used for identification. First, we use a two-step approach: we estimate a panel VAR using just temperature and precipitation, using over 100 years of data for each country. We identify the climate shock using the benchmark scheme and obtain an estimate of the structural shock  $\hat{\epsilon}_{it}$ . In the second step, we estimate a panel VAR that includes  $\hat{\epsilon}_{it}$ , the climate variables, GDP per capita and the Gini coefficient. The impulse response is calculated to the exogenous shock  $\hat{\epsilon}_{it}$ . In our second approach, we treat missing observations in the macro-economic variables as unobserved states and estimate them along with the parameters of the VAR using a state-space approach. In the third approach we obtain data for GDP per capita from the Penn world tables for countries where limited data is available from the World Bank. We then retain countries that have at least 40 years of data available for all series and estimate the VAR using this sample. As shown in the technical appendix, the impulse response of the Gini coefficient is very similar to benchmark in all three cases.

The benchmark results are also preserved when we use climate data aggregated to country level using population weights.

*Specification.* Similarly, the results are robust to using different lag lengths and adding time trends. Our estimates do not depend on the choice of the Panel VAR. We show in the appendix that we obtain results similar to benchmark when we use linear or non-linear panel local projection models.

## 5. Conclusions

We show that a climate shock that increases temperature by 1 °C is associated with an increase in the Gini coefficient by 0.62 percent after about 6 years and poor households incur a higher loss in their income. The effect on inequality is larger in poor countries and those characterised by a hot temperature, a larger agricultural sector or lower level of climate adaptation.

This paper contributes to the literature on the economic impact of climate change but adds an important but still largely unexplored dimension: The rise of within-country inequality. Climate change does not only harm countries economically but makes them also more unequal. In terms of policy implications, our results re-iterate the importance of readiness in ameliorating the effects of climate change. By using policies to channel resources towards increasing climate adaptability, policy-makers can help to protect the most vulnerable households in their countries.

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.eurocorev.2024.104828>.

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