The distributional effects of climate change. An empirical analysis

Haroon Mumtaz and Angeliki Theophilopoulou

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School of Economics and Finance

Queen Mary University of London

The distributional effects of climate change. An empirical analysis*

Haroon Mumtaz[1] and Angeliki Theophilopoulou[2]

[1]Queen Mary University of London
[2]Brunel University London

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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.

JEL Classification: C32, E32, Q54

Keywords: Climate shock; income inequality; economic growth; frequency domain identification; panel VAR.

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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^oC increase in temperature (Roson and der Mensbrugghe (2012)) to high and positive (e.g. 2.3% due to a 1^oC 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^oC 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 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_2 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[1]. For example, the 2016 DICE model (Nordhaus (2019)) finds that a 3^oC global warming will suppress global output by 2%. Our work is closer to cross-country panel data studies [2]. 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 $+1^0C$ 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 $+1^oC$ 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 $0.04\%^oC$ 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. Diffenbaugh and Burke (2019) estimate that global warming has increased between-country inequality

[1]For a thorough review see (Nordhaus (2019)).

[2]A detailed survey on panel data papers with global samples research can be found in Dell *et al.* (2014).

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 centers 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[3]. 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.

[3]Diffenbaugh and Burke (2019) state on page 9813: 'Because of the lack of availability of long time-series 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 $var\left(v_{it}\right) = \Omega$, $i = 1, 2, ..M$ indexes the countries in our panel, $t = 1, 2, .., T$ denotes the time-periods. The model includes country, region and time-fixed effects (α_i, r_j and τ_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 $\beta = vec\left([\alpha_i, r_{j,}, \tau_t, B_p]\right)$ and error covariance matrix Ω 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.[4]

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.

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

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

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 Ω. Without loss of generality, our interest centers on the first column of Q, denoted by q_1,

[4]The estimation algorithm and convergence diagnostics are presented in the technical appendix.

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 $(\underline{\varpi}, \overline{\varpi})$ is given as $q_1' S(\underline{\varpi}, \overline{\varpi}) q_1$ where:

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

where $g = M_y(I - be^{-i\varpi})^{-1}\tilde{a}_0$ 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 $S(\underline{\varpi}, \overline{\varpi})$ We set the frequency band as $(\underline{\varpi}, \overline{\varpi}) = (\infty, \frac{2\pi}{20})$ so that the long-run corresponds to cycles greater than 20 years. [5]

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 20^{th} 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 are 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: $P_1, P_2, \ldots, P_{10}$. For example, P_1 denotes income averaged for individuals that fall below the 10^{th} percentile of income.

[5] Our main results are robust to using an alternative identification scheme that identifies the climate shock as the only disturbance that can affect temperature at long horizons (Blanchard and Quah (1989)).

4 Empirical results

4.1 Impact on income inequality

Figure 1 plots the response to a climate shock normalised to an increase in temperature by 1^0C relative to trend.[6] 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 $P_1, P_2, \ldots, P_{10}$ along with the climate variables and GDP. The top panel of Figure 2 reports the median impulse response of income in each group to shock normalised to an increase in temperature by 1^0C. The bottom panels display the response at the 1 and 5 year horizon together with the error bands. 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 10^{th} 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 Figure 3 displays the contribution of the climate shock to the forecast error variance of income in each decile. 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_{10}, 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. 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.[7]. We then calculate the mean percentage difference over time between the actual Gini coefficient and the counterfactual estimate obtained from the

[6]The time-effects in the panel VAR capture the global trend in the climate data.

[7]As the number of observations can be small for individual countries, we carry out this simulation at the regional level

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. Figure 4 shows a heat map that summarises the 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.

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:

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

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.[8].

The top-left panel of figure 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 precip-

[8]These countries are those where Gross National Income per capita was less than 4,095 US dollars in 2020

itation. 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 channel we estimate the following extended version of our model:

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

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.[9]

The second panel of Figure 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 equation 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 Figure 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 lowest gain from the shock. Thus, the fourth

[9]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.

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.

Nonlinear effects The final two panels of Figure 5 use the interacted VAR with temperature and the Gini Coefficient as the variable y_{it} in equation 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.

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. In both cases, the impact of the climate shock on the Gini coefficient is similar to the benchmark.

Data The benchmark results are 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^{o}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.

References

Angeletos, George-Marios, Fabrice Collard and Harris Dellas, 2020, Business-Cycle Anatomy, *American Economic Review* **110**(10), 3030–70.

Banbura, Marta, Domenico Giannone and Lucrezia Reichlin, 2010, Large Bayesian vector auto regressions, *Journal of Applied Econometrics* **25**(1), 71–92.

Blanchard, Olivier Jean and Danny Quah, 1989, The Dynamic Effects of Aggregate Demand and Supply Disturbances, *American Economic Review* **79**(4), 655–673.

Burke, Marshall and Vincent Tanutama, 2019, Climatic Constraints on Aggregate Economic Output, *NBER Working Papers 25779*, National Bureau of Economic Research, Inc.

Cevik, Serhan and João Tovar Jalles, 2022, For Whom the Bell Tolls: Climate Change and Inequality, *IMF Working Papers 2022/103*, International Monetary Fund.

Dell, Melissa, Benjamin F. Jones and Benjamin A. Olken, 2012, Temperature Shocks and Economic Growth: Evidence from the Last Half Century, *American Economic Journal: Macroeconomics* **4**(3), 66–95.

Dell, Melissa, Benjamin F. Jones and Benjamin A. Olken, 2014, What Do We Learn from the Weather? The New Climate-Economy Literature, *Journal of Economic Literature* **52**(3), 740–98.

Deschenes, Olivier and Michael Greenstone, 2011, Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US, *American Economic Journal: Applied Economics* **3**(4), 152–85.

Diffenbaugh, Noah S. and Marshall Burke, 2019, Global warming has increased global economic inequality, *Proceedings of the National Academy of Sciences of the United States of America* **116**(20), 9808–9813.

Harris, Ian, Timothy J Osborn, Phil Jones and David Lister, 2020, Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset, *Scientific data* **7**(1), 1–18.

Hsiang, Solomon M, 2010, Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America, *Proceedings of the National Academy of Sciences of the United States of America* **107**(35), 15367–72.

Islam, S. Nazrul and John Winkel, 2017, Climate Change and Social Inequality, *Working Papers 152*, United Nations, Department of Economics and Social Affairs.

Jordá, Óscar, Sanjay R. Singh and Alan M. Taylor, 2020, The Long-Run Effects of Monetary Policy, *Working Paper Series 2020-01*, Federal Reserve Bank of San Francisco.

Kahn, Matthew E., Kamiar Mohaddes, Ryan N.C. Ng, M. Hashem Pesaran, Mehdi Raissi and Jui-Chung Yang, 2021, Long-term macroeconomic effects of climate change: A cross-country analysis, *Energy Economics* **104**(C).

Koop, Gary, M. Hashem Pesaran and Simon M. Potter, 1996, Impulse response analysis in nonlinear multivariate models, *Journal of Econometrics* **74**(1), 119–147.

Mendelsohn, Robert, Wendy Morrison, Michael Schlesinger and Natalia Andronova, 2000, Country-Specific Market Impacts of Climate Change, *Climatic Change* **45**, 553–569.

Nordhaus, William, 2019, Climate Change: The Ultimate Challenge for Economics, *American Economic Review* **109**(6), 1991–2014.

Nordhaus, William D. and Andrew Moffat, 2017, A Survey of Global Impacts of Climate Change: Replication, Survey Methods, and a Statistical Analysis, *NBER Working Papers 23646*, National Bureau of Economic Research, Inc.

Palagi, Elisa, Matteo Coronese, Francesco Lamperti and Andrea Roventini, 2022, Climate change and the nonlinear impact of precipitation anomalies on income inequality, *Proceedings of the National Academy of Sciences of the United States of America* **119**, e2203595119.

Rehdanz, Katrin and David Maddison, 2005, Climate and happiness, *Ecological Economics* **52**(1), 111–125.

Roson, Roberto and Dominique Van der Mensbrugghe, 2012, Climate change and economic growth: impacts and interactions, *International Journal of Sustainable Economy* **4**(3), 270–285.

Tol, Richard S.J., 2002, Estimates of the Damage Costs of Climate Change. Part 1: Benchmark Estimates, *Environmental and Resource Economics* **21**(1), 47–73.

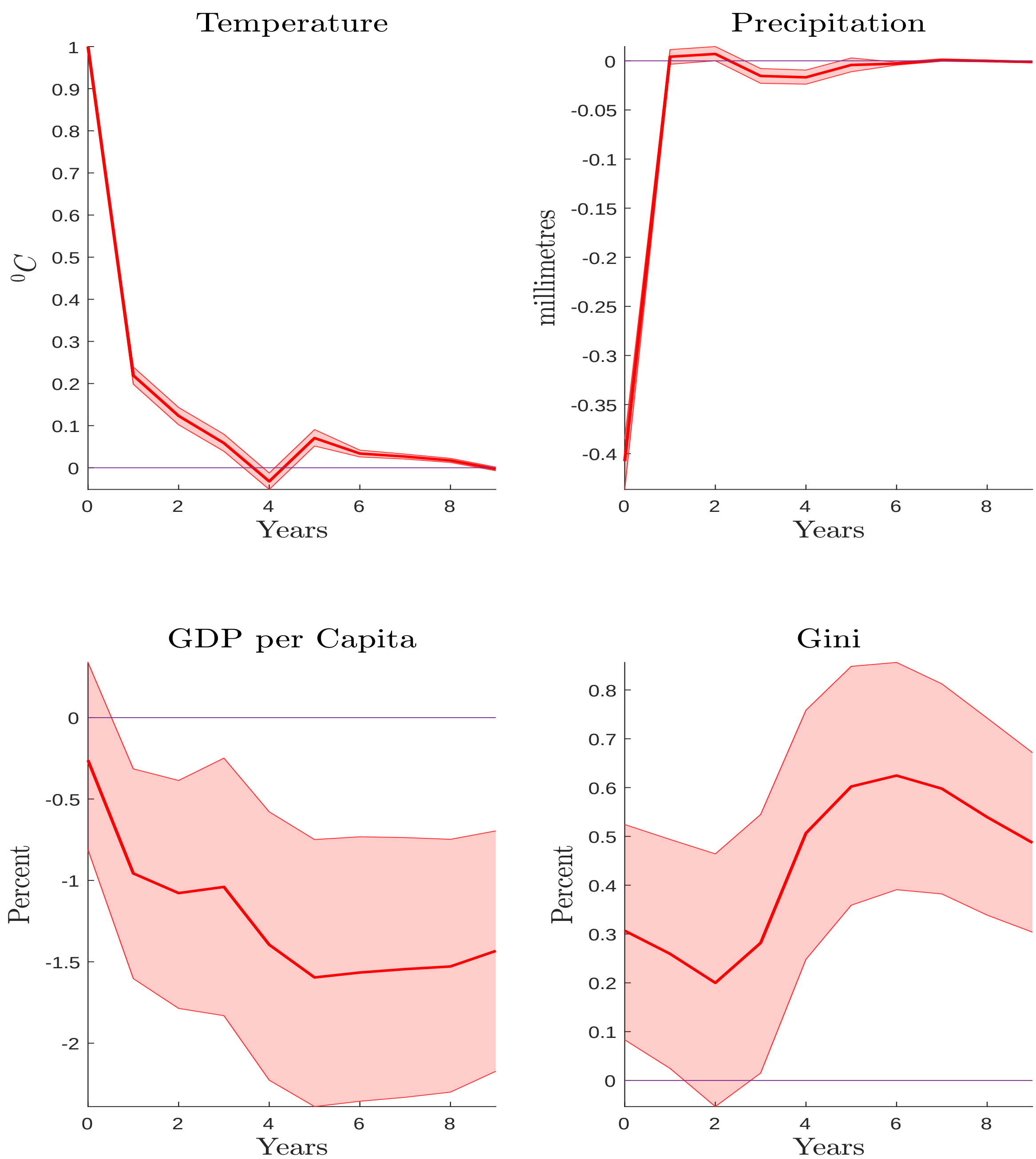

Figure 1: Impulse response functions to a 1^0C increase in temperature. The vertical axis plots the response in percent. The horizontal axis indicates time in years. The dark line is the median estimate and the shaded areas are the 68% error bands.

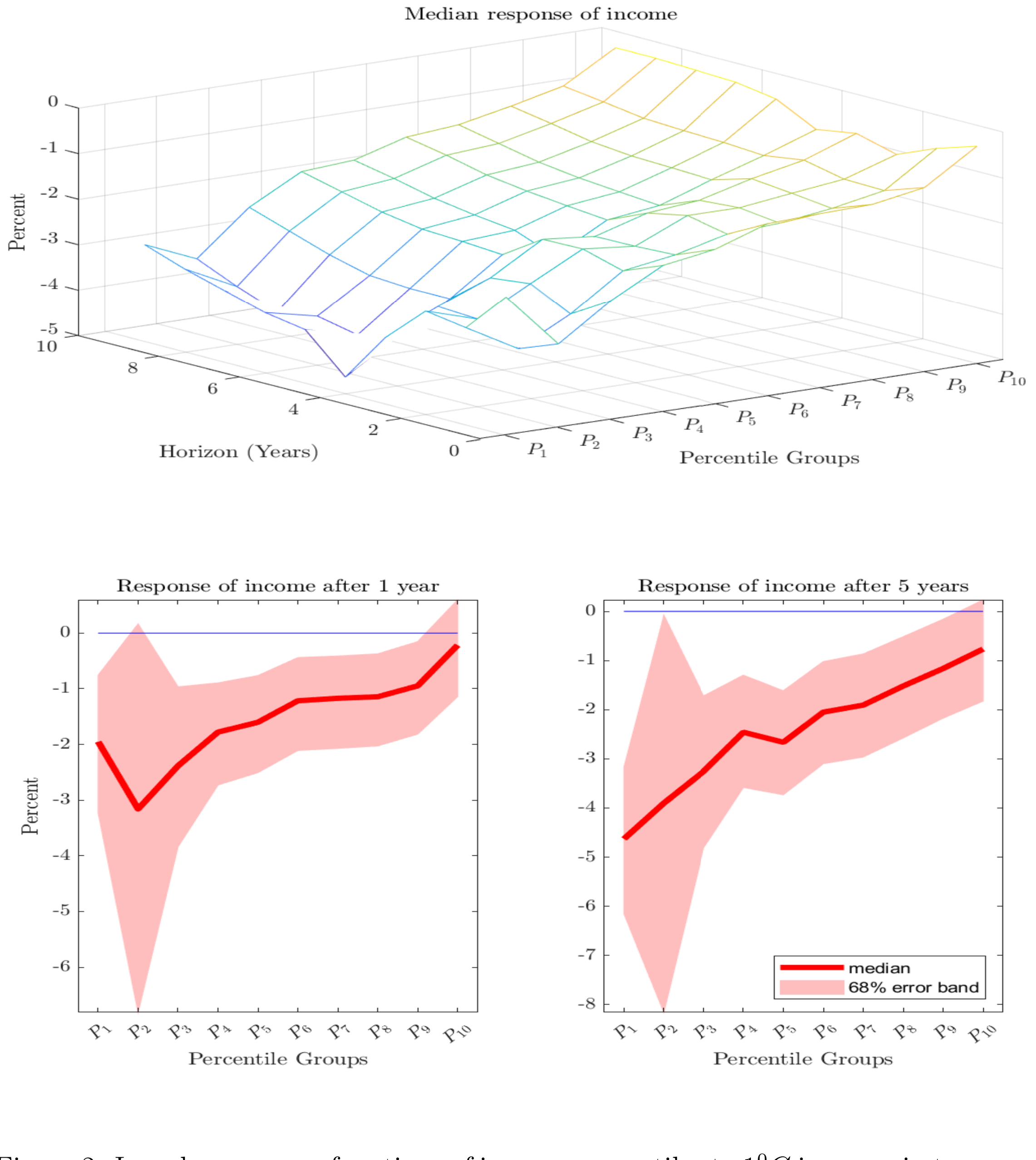

Figure 2: Impulse response functions of income percentiles to 1^0C increase in temperature. The vertical axis plots the response in percent. The horizontal axis indicates time in years. The dark red line is the median estimate and the shaded areas are the 68% error bands.

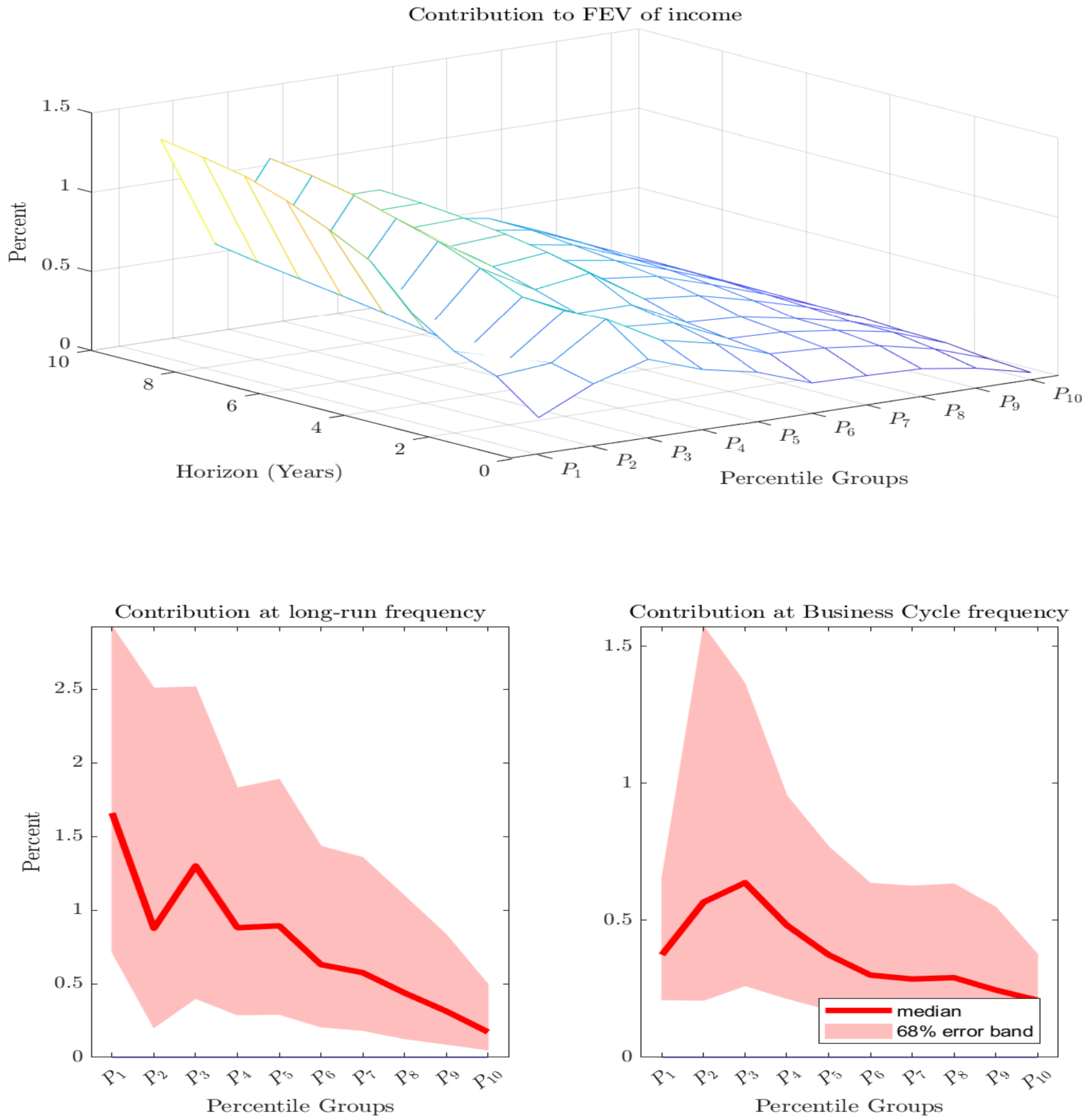

Figure 3: Contribution to the FEV of income. The vertical axis plots the contribution in percent. The horizontal axis indicates time in years. The dark red line is the median estimate and the shaded areas are the 68% error bands.

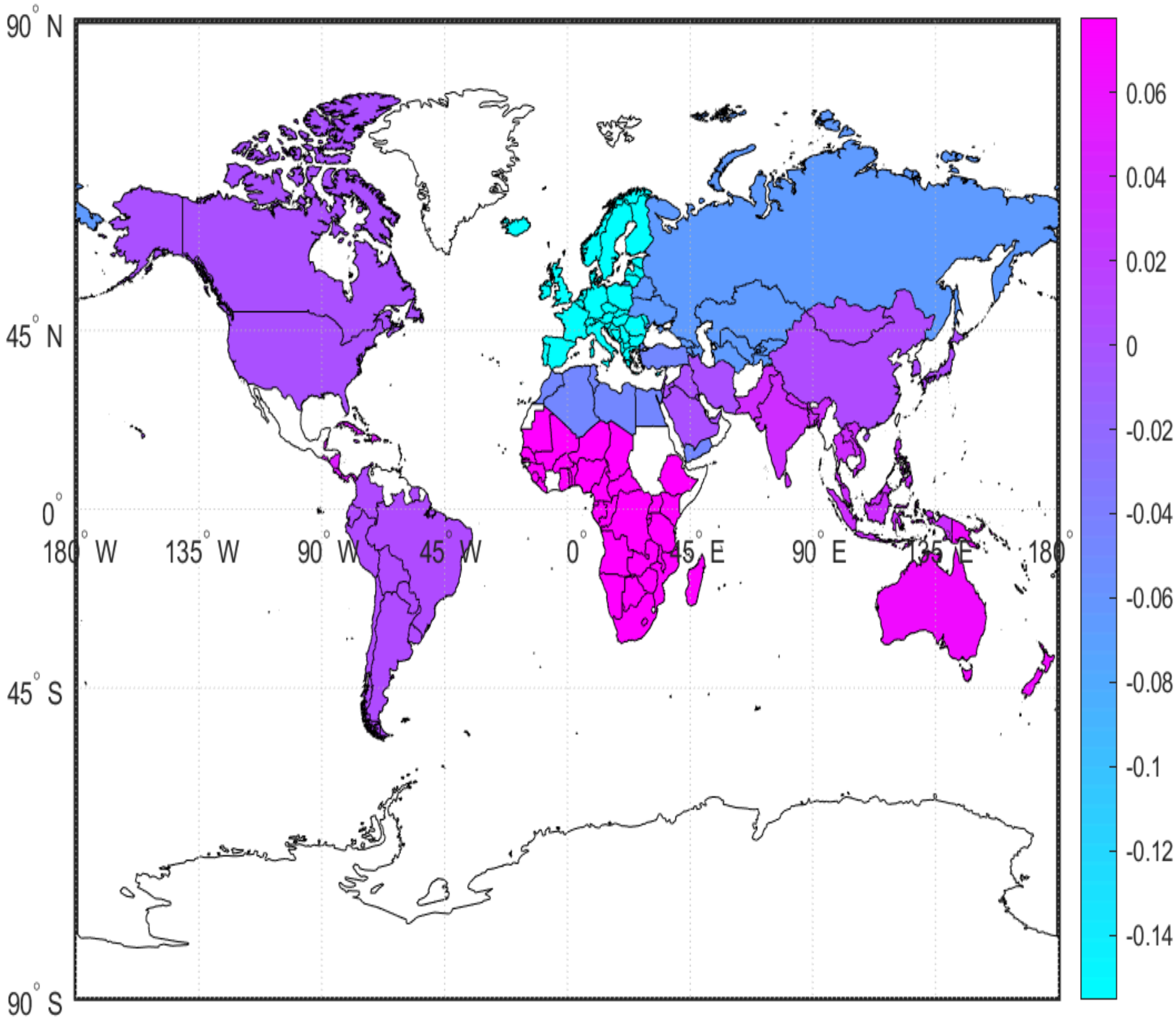

Figure 4: Contribution of the climate shock to the Gini coefficient in percent calculated as the average Gini coefficient in each country minus the estimate under the assumption of no climate shock. Higher values (darker shades) indicate that the Gini coefficient would have been lower in the absence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

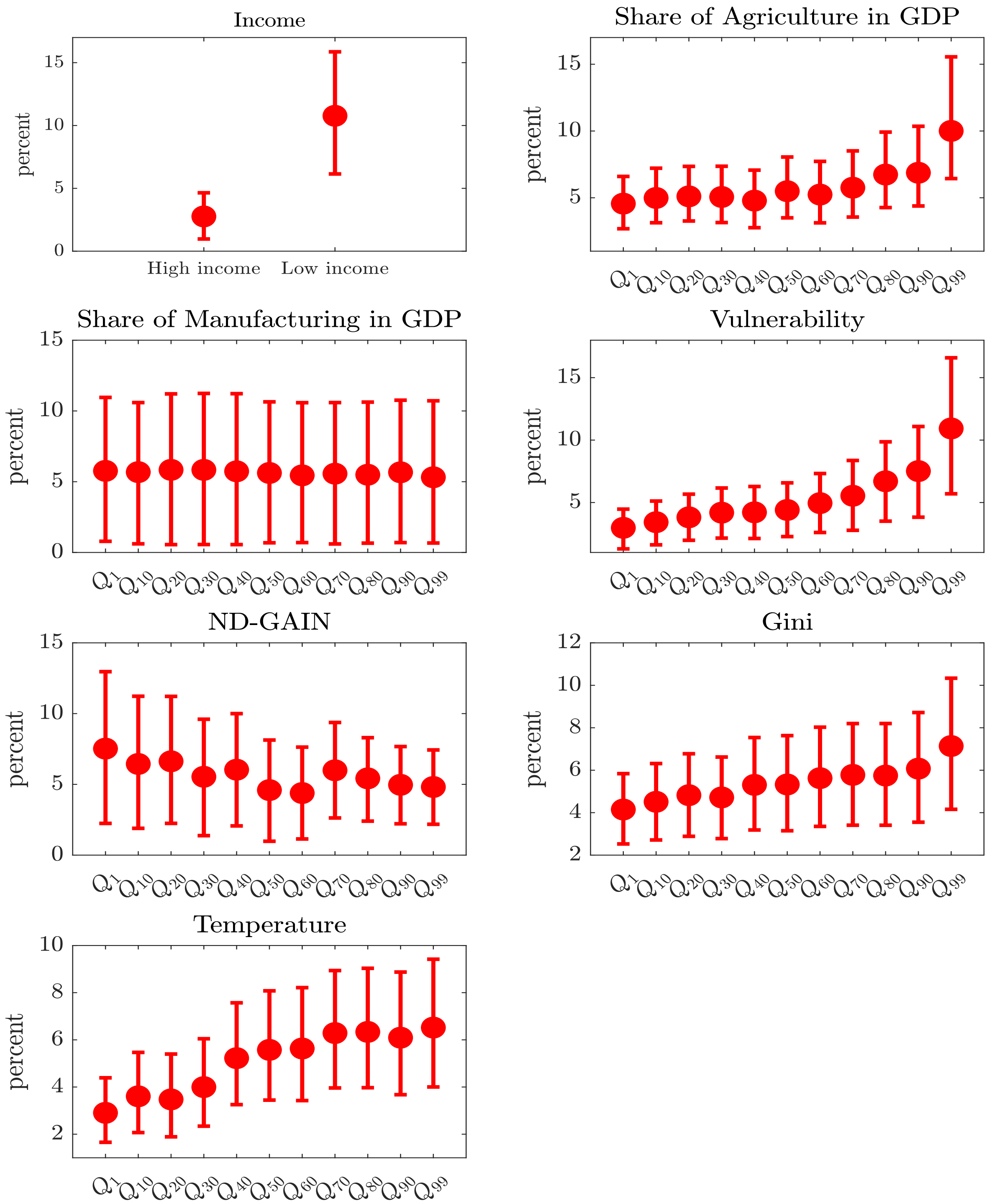

Figure 5: Cumulated response of the Gini coefficient at the 10 year horizon to 1^0C increase in temperature. The vertical axis plots the response in percent. The horizontal axis in the remaining subplots indicates percentiles of the variable in the title. The solid dot is the median response while the vertical lines show the 68% error bands. $Q_1, \ldots Q_{10}$ denotes the deciles of the distribution of the respective variable.

The distributional effects of climate change. An empirical analysis. Appendix

Haroon Mumtaz[1] and Angeliki Theophilopoulou[2]

[1]Queen Mary University of London
[2]Brunel University

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1 Model estimation

The panel VAR model is defined as:

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

where $var\left(v_{it}\right) = \Omega$, $i = 1, 2, ..M$ indexes the countries in our panel, $t = 1, 2, .., T$ denotes the time-periods. The model includes country and region fixed effects (α_i and r_j). Let $b = vec\begin{pmatrix} B_1 \\ . \\ . \\ B_P \\ c \end{pmatrix}$ where the vector $\underbrace{c}_{EX\times 1} = vec\begin{pmatrix} \alpha_i \\ r_j \\ \tau_t \end{pmatrix}$ collects the exogenous regressors.

1.1 Priors

We follow Banbura *et al.* (2007) and use a Natural Conjugate prior implemented via dummy observations. The priors are implemented by the dummy observations y_D and x_D that are defined as:

$$y_D = \begin{bmatrix} \frac{diag(\gamma_1 s_1 ... \gamma_n s_n)}{\kappa} \\ 0_{N\times(P-1)\times N} \\ diag\,(s_1 ... s_n) \\ .... \\ 0_{EX\times N} \end{bmatrix}, \qquad x_D = \begin{bmatrix} \frac{J_P \otimes diag(s_1 ... s_n)}{\kappa} & 0_{NP\times EX} \\ \multicolumn{2}{c}{..............} \\ \multicolumn{2}{c}{0_{N\times(NP)+EX}} \\ \multicolumn{2}{c}{..............} \\ 0_{EX\times NP} & I_{EX}\times 1/c \end{bmatrix} \tag{1}$$

where $J_P = diag(1, 2, ..., P)$, γ_1 to γ_n denote the prior mean for the parameters on the first lag obtained by estimating individual AR(1) regressions, s_1 to s_n is an estimate of the variance of the endogenous variables obtained individual AR(1) regressions, κ measures the tightness of the prior on the autoregressive VAR coefficients, and c is the tightness of the prior on the remaining regressors. We set $\kappa = 1$ and $c = 1000$. We also implement priors on the sum of coefficients (see Banbura *et al.* (2007)). The dummy observations for this prior are defined as:

$$\tilde{y}_D = \frac{diag\,(\gamma_1\mu_1 ... \gamma_n\mu_n)}{\tau}, \tilde{x}_D = \begin{pmatrix} (1_{1\times P}) \otimes \frac{diag(\gamma_1\mu_1 ... \gamma_n\mu_n)}{\tau} & 0_{N\times EX} \end{pmatrix} \tag{2}$$

where μ_i is the sample average of the ith variable. As in Banbura *et al.* (2007) we set $\tau = 10\kappa$.

1.2 Posterior and MCMC algorithm

Banbura *et al.* (2007) show that posterior distribution can be written as:

$$g\,(\Omega|Y)\,\tilde{}\,iW\left(\bar{\Omega}, NT + 2 + NT - K\right) \tag{3}$$

$$g\,(b|\Omega, Y)\,\tilde{}\,N\left(\bar{b}, \Omega \otimes (X_*' X_*)^{-1}\right) \tag{4}$$

where iW denotes the inverse Wishart distribution, NT is the total number of observations, K denotes the number of regressors in each equation of the VAR model. Note that $Y_* = \begin{pmatrix} Y \\ y_D \\ \tilde{y}_D \end{pmatrix}$ and $X_* = \begin{pmatrix} X \\ x_D \\ \tilde{x}_D \end{pmatrix}$ and

$$\begin{aligned} \tilde{b} &= (X_*' X_*)^{-1} (X_*' Y_*) \\ \bar{b} &= vec\left(\tilde{b}\right) \\ \bar{\Omega} &= \left(Y_* - X_*\tilde{b}\right)' \left(Y_* - X_*\tilde{b}\right) \end{aligned}$$

Posterior draws can be easily generated by drawing Ω from the marginal distribution in 3 and then b from the conditional distribution in equation 4. We set the number of draws to 10,000 with a burn-in of 8,000. For each retained draw, we calculate the impulse vector using the method of Angeletos *et al.* (2020) outlined in the main text and estimate the impulse response.

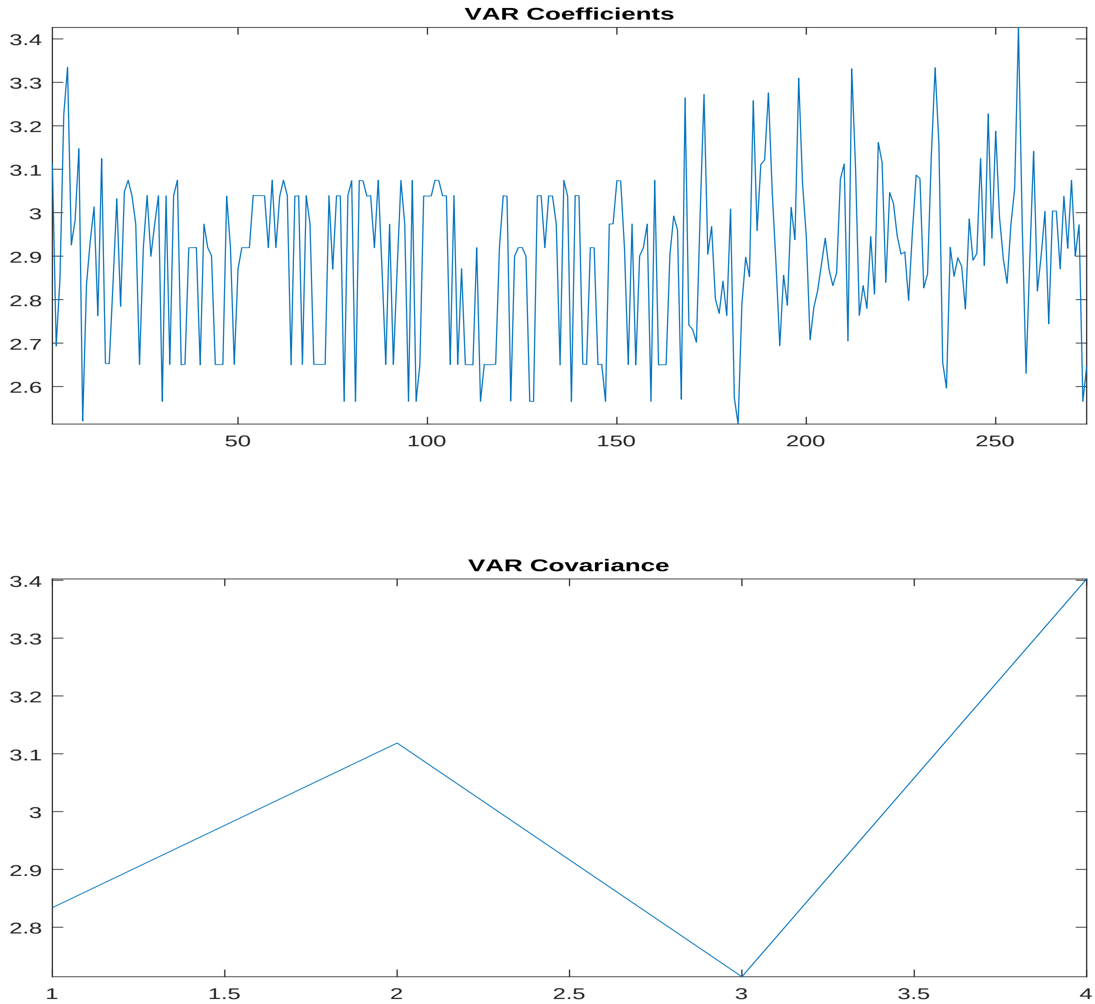

Figure 1: Inefficiency Factors

Figure 1 shows that inefficiency factors are below 20. This suggests that there is strong evidence that the MCMC algorithm has converged.

2 Robustness

We carry out a number of robustness checks. These can be divided in the following categories:

2.1 Identification

The 'economic shock' is ordered first and is estimated by solving the maximisation problem $\max_{q_1} q_1' S(\underline{\varpi}, \overline{\varpi}) q_1$. The second shock is defined as the climate shock. As before, this shock is chosen so that the contribution of this disturbance to the long-run variance of temperature and precipitation is maximised. However, we also require this shock to be orthogonal to the 'economic shock'. As shown in the top left panel of figure 2, the response of the Gini coefficient to the climate shock remains largely unchanged in this extended model.

Second, we use long-run restrictions of 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.[1] The second panel in the top row of figure 2 plots the response of the Gini coefficient to a climate shock that increases the change in temperature by one percent.[2] As in the benchmark case, the shock is associated with an increase in the Gini coefficient.

The third panel in the top row of the figure shows the response from a version of the benchmark model where we define the long-run in the frequency domain as corresponding to cycles greater than 10 years. This change has minimal effects on the benchmark results.

2.2 Data and specification

Our benchmark data set consists of temperature and precipitation that are aggregated to the country-level using area weights. In this section, we check if our results are sensitive to the aggregation method. We employ the climate data set compiled by Dell *et al.* (2012). Dell *et al.* (2012) aggregate temperature and precipitation using population weights. The fourth panel in the top row of figure 2 shows that the response of the Gini coefficient is qualitatively similar to the benchmark case.

The benchmark results are also preserved when we include country-specific time-trends in the benchmark model (see first panel in the second row of figure 2).

[1] Note that for the purposes of this model, all variables enter the VAR in first differenced form.

[2] Temperature enters this model in first differences as the long-run impact matrix represents the infinite-horizon cumulated response. Restrictions on this long-run impact matrix thus represent restrictions on the impulse response of the level of temperature in the long-run.

2.3 Local projections

Recent papers (see Jordá *et al.* (2020)) have shown that lag truncation in VAR models can result in biased estimates of medium and long-run impulse responses. In contrast, local projections (LP) are less susceptible to this bias. As noted above, we include a relatively large number of lags in our benchmark VAR model to reduce the possibility of lag truncation bias. In this section, we estimate the impulse responses to the climate shock using a panel local projection as a cross-check on our benchmark model. The LP for horizon h is defined as:

$$Y_{it+h} = \alpha_{i,h} + r_{j,h} + \tau_{t,h} + \sum_{p=1}^{P} B_{p,h} Y_{it-p} + v_{it} \tag{5}$$

As described in Jorda (2005), the impulse response can be calculated as $B_{1,h}A_0^{(1)}$ where $A_0^{(1)}$ denotes the contemporaneous affect of the climate shock obtained using the benchmark VAR model.[3]The second panel in the second row of figure 2 shows that the LP-based response of the Gini coefficient is very similar to the benchmark results. Note that this also provides some reassurance that the number of lags included in the benchmark model is sufficient to approximate the medium and long-run response.

In order to check if non-linearities play an important role, we extend the LP to include quadratic terms:

$$Y_{it+h} = \alpha_{i,h} + r_{j,h} + \tau_{t,h} + \sum_{p=1}^{P} B_{p,h} Y_{it-p} + \sum_{p=1}^{P} D_{p,h} Y_{it-p}^2 + v_{it} \tag{6}$$

Jorda (2005) shows that, in this extended model, the impulse response is given by $B_{1,h}A_0^{(1)} + D_{1,h}\left(2Y_{it-1}A_0^{(1)} + \left(A_0^{(1)}\right)^2\right)$. We evaluate this non-linear response at the mean of the data: $Y_{it-1} = \bar{Y}$. The resulting response of the Gini coefficient is quite similar to the benchmark case (see third panel in the second row of figure 2).

[3]Note that at horizon 0, the VAR and local projection coincide.

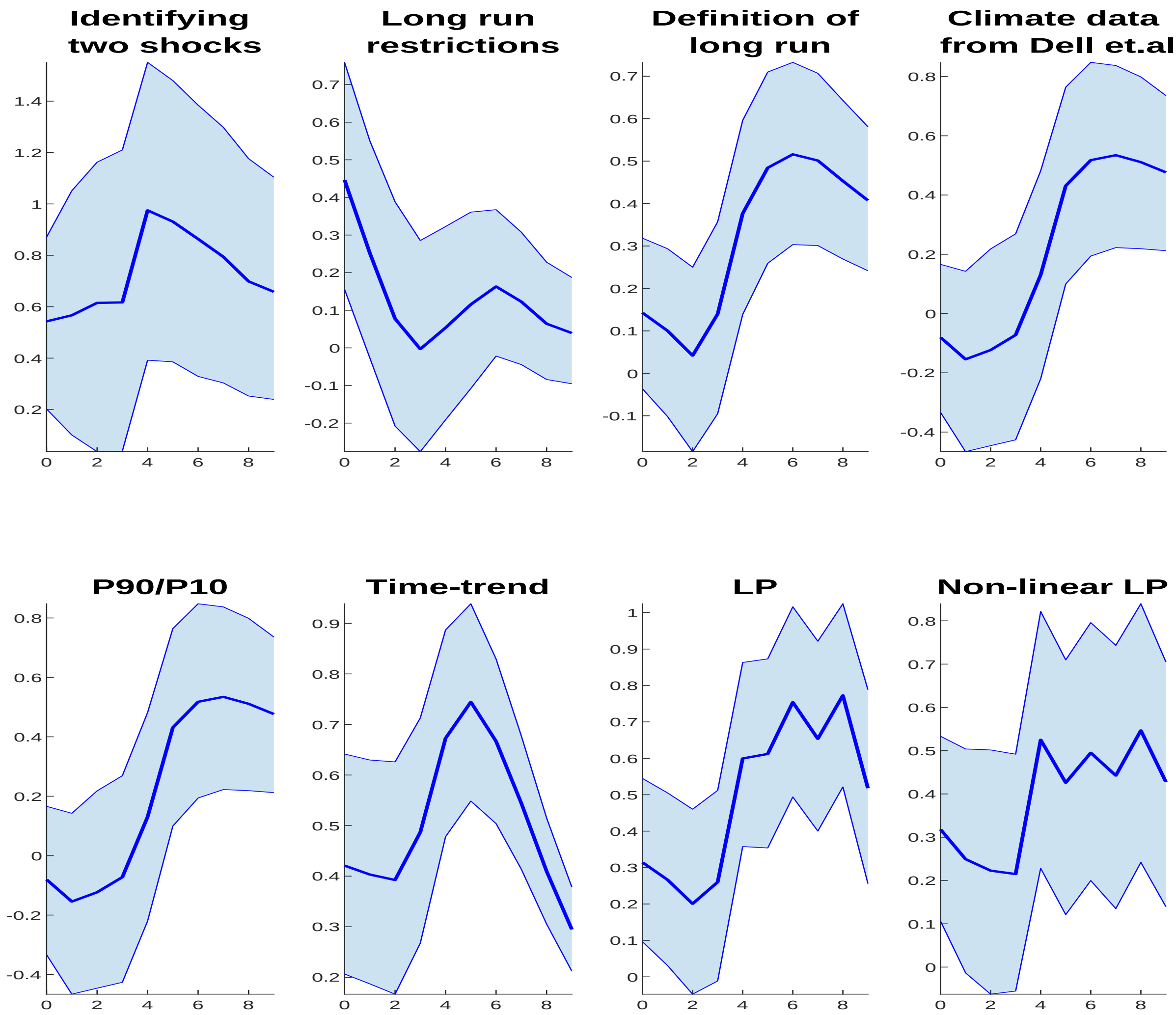

Figure 2: Robustness Analysis

References

Angeletos, George-Marios, Fabrice Collard and Harris Dellas, 2020, Business-Cycle Anatomy, *American Economic Review* **110**(10), 3030–70.

Banbura, Martha, Domenico Giannone and Lucrezia Reichlin, 2007, Bayesian VARs with large panels, *CEPR Discussion Papers* **6326**.

Blanchard, Olivier Jean and Danny Quah, 1989, The Dynamic Effects of Aggregate Demand and Supply Disturbances, *American Economic Review* **79**(4), 655–673.

Dell, Melissa, Benjamin F. Jones and Benjamin A. Olken, 2012, Temperature Shocks and

Economic Growth: Evidence from the Last Half Century, *American Economic Journal: Macroeconomics* **4**(3), 66–95.

Jorda, Óscar, 2005, Estimation and Inference of Impulse Responses by Local Projections, *American Economic Review* **95**(1), 161–182.

Jordá, Óscar, Sanjay R. Singh and Alan M. Taylor, 2020, The Long-Run Effects of Monetary Policy, *Working Paper Series 2020-01*, Federal Reserve Bank of San Francisco.

School of Economics and Finance

Queen Mary
University of London

School of Economics and Finance
Queen Mary University of London
Mile End Road
London E1 4NS
Tel: +44 (0)20 7882 7356
Fax: +44 (0)20 8983 3580
Web: www.econ.qmul.ac.uk/research/workingpapers/