Climate change and income inequality. An empirical analysis

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Working Paper No. 966 September 2023 ISSN 1473-0278

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September 2023

Abstract

Preliminary draft

The role of climate change on economic performance and output has been studied extensively in the empirical literature, however, its distributional effects have received little attention. This paper attempts to fill this gap by investigating whether climate shocks affect income inequality in a large number of countries. We use data on climate indicators, income and inequality measures for 153 countries spanning a long time period. The climate shock is identified as the disturbance that explains the bulk of the climate fluctuations in the long run. Our findings suggest that an adverse climate shock is associated with an increase in measures of income inequality. We find a heterogeneous impact of the on the left and right tail within-country income distribution. The impact of the shock is larger in magnitude for low income and hot on average countries with a significant agricultural sector and low expenditure on health sector.

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

JEL Classification: C32, E32, Q54.

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1 Introduction

Climate deeply affects aspects of economic and social activity. The economic effects of climate change have been long studied and a range of results, at times controversial, have been produced. Studies on climate change show that excessive CO_2 emissions lead to global warming, extreme weather conditions and volatility, rise of sea levels, change in precipitation patterns etc. Economically, these changes impact a number of sectors such as agriculture, health, energy, but also labour productivity, institutional quality, political stability and ultimately national output and its growth rate. Cross sectional studies using global samples estimate this impact and present high variation in their findings. For example, Kahn *et al.* (2021a), in a panel of 174 countries, find that an average increase of $0.04\%^oC$ per year will reduce world output by 7% until 2100 if no mitigation policies are implemented. However, in a global sample of 125 countries, Dell *et al.* (2012a), find that a rise in temperature lowers the growth rate of income per capita by 1.3% but only in poor countries. The effect on rich countries and the role of precipitation have not found to be significant in this study.

Investigating the effects of a certain rise in temperature on global output, results coming from various studies vary from large negative ones (e.g. -2.14% by a 3.1^oC increase in temperature (Roson and der Mensbrugghe (2012))) to very small ones (e.g. Mendelsohn, Morrison, Schlesinger and Andronova (2000)) and to high positive ones (e.g. 2.3% by a 1^oC increase in temperature (Tol (2002)) [1]). It is also clear that not all regions will be affected the same way. There is some consensus in the literature that Sub Saharan countries may experience a significant 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 benefit on their output (for example Mendelsohn, Morrison, Schlesinger and Andronova (2000) estimate a 4% rise by a 2.5^oC warming).

Since climate change effects vary according to geographical location, economic development and structure, one could naturally ask how climate change affects the way income is distributed among households. The research findings mentioned above, by showing heterogeneous impact among countries, implicitly indicate inequality ef-

[1] The numbers we use here are coming from Nordhaus and Moffat (2017), who review estimates on global output from 27 studies. The authors use a systematic research synthesis of these studies and estimate an income loss of 2.04% to a 3^oC global warming and sharp convexities as temperature goes up.

fects. However, to our knowledge, there are very few studies which explicitly examine distributional implications within a country. For example, how a poor and a rich household will be affected by global warming in Mexico or in Norway? We know that due to their location and economic characteristics these countries will be affected differently. However, we do not know how the income of poor and rich households can be affected in each country and whether specific economic characteristics can exacerbate or mitigate movements on income distribution.

To our knowledge, this paper is one of the first attempts to shed light on the impact of climate change on inequality. More specifically, we investigate whether shocks in climatological factors, such as temperature and precipitation, impacts inequality measures. We gather annual data for 153 countries ranging from 1900 (for some countries) to 2020. We employ a panel structural VAR model which includes climate, inequality indicators and macroeconomic variables. In our benchmark model, we identify climate shocks as those that explain the bulk of the change of climate variables at low frequencies (see for example Angeletos *et al.* (2020)). We are interested in the long run effects of climate change. As Dell *et al.* (2014) point out, these type of effects are particular and differ from the short run ones as they can be stronger due to intensification or smaller due to adaptation. Our findings show that climate shocks of rising temperature are associated with rise in inequality measures. More specifically, a rise in temperature by 1^oC increases the Gini coefficient by 0.63 percent on average in six years. This effect is stronger for less developed economies, with a large agricultural sector and for the ones classified as hot countries laying on certain climate zones.

Related literature

Our paper relates to the literature examining the impact of climate change on economic activity but focus on its heterogeneous effects. It is motivated by studies on global samples which find heterogeneous impact on GDP across geographical regions. Our research moves forward to examine the distributional, within country income effects. The strand of literature which investigates the impact of climate change on economic activity is vast, highly served by Integrated Assessment Models (IAMs).

IAMs combine a large area of knowledge from more than one disciplines, such as climate science, ecology, economics, game theory, law, politics etc. These models have been used extensively to answer complicated questions, examining multiple scenaria on how CO_2 emissions can affect global warming and temperature in different aspects of life, under diverse policy responses. The choice of model, structure and assumptions determine largely their results and implications. Although these models have been highly criticised on the basis of assumptions and estimations used, they all agree on serious market and non-market damages, especially in the case of policy inaction[2]. They agree that CO_2 emissions will peak first and then decrease for specific global warming targets. For example, the 2016 DICE model (Nordhaus (2019)) finds that a 3^oC global warming will suppress global output by 2%, while a 6^oC one will amass to 8% output loss indicating loss hikes in a non-linear fashion.

We relate to panel data studies which use global samples[3]. For example, Dell *et al.* (2012a) 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 pc to $+1^0C$ warming) but only for poor 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.* (2021b), 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.

The following papers discuss distributional effects and some aspects on inequality but mostly across countries or regions: Burke and Tanutama (2019) by using longitudinal data on economic output from over $11,000$ districts across 37 countries, find a nonlinear response of growth to 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. They find that these measures are associated with higher income inequality. In contrast, the focus of our work is on the effects of adverse climate shocks which are identified by using the long run properties of climate data therefore our estimates do not rely on constructed indices of vulnerability that may suffer of endogeneity.

Diffenbaugh and Burke (2019) estimate that global warming has increased the between country inequality by 25% in the last 50 years. By using counterfactual

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

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

historical climate trajectories from a battery of global climate models, the authors estimate that GDP pc 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 than the income one, 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.

The heterogeneous impact across countries and regions can be explained by a number of factors which act as channels of transmission. Naturally, geographic location and actual climate of a country play a crucial role. Dell *et al.* (2009) find that 61% of income variation in municipal level across 12 American countries is attributed to these factors. Gallup *et al.* (1999) show that countries close to the equator are poorer and grew at a slower rate between 1965 and 1995 due to malaria and losses in the agricultural sector among other factors. Barrios *et al.* (2010) find that deterioration of rainfalls explain $15-40\%$ in the income gap between sub-Saharan countries and the rest of the developing countries.

An economic sector which is closely interlinked to climate is agriculture. Its size and importance to aggregate national income but also the ability of a country to technologically adapt to climate changes are all important elements of this transmission channel. There is a consensus for significant output losses in developing economies; for example, Schlenker and Lobell (2010) estimate negative yields for the sub-Saharan countries, Guiteras (2009) for India, Feng *et al.* (2010) for Mexico, etc. Findings for developed economies, however, indicate a smaller or not significant effect (see for example the debate in Deschenes and Greenstone (2007) and Fisher *et al.* (2012) for the US).

Rise in temperature affects negatively health and mortality especially in countries which have already a hot climate. Deschenes and Greenstone (2011) report that a hotter than average day rises the annual mortality rate in the US by 0.11% while in the developing countries the effect is dramatically higher: Burgess *et al.* (2011) finds that an additional excess heat day increases the annual mortality rate in India by

0.75%. Poor health and limited access to health services contribute directly to lower productivity and income and eventually to higher inequality.

The relationship between energy consumption and climate change has been also investigated in the literature. Energy consumption is interlinked to weather volatility. During excessive hot days the demand for cooling energy is higher while during the excessive cold ones, demand for heating is higher. Countries which are naturally cold will consume less energy for heating to a rise in temperature, while countries which are naturally hot will consume more energy for cooling. The net effect is likely to be a higher demand for energy (Deschenes and Greenstone (2011)). Although this is only demand for residential energy, this factor can directly influence disposable income espcecially for low income households. Therefore it has distributional effects on income which can further vary between rich and poor countries where the level of heating and cooling technology is different. Given rising energy prices, we investigate further this channel to see whether a country being a net importer or exporter of energy could have important distributional effects on income.

The remainder of the paper is structured as follows: Section 2 describes the estimation of the panel VAR model and identification scheme for the climate shocks. Section 3 describes the variables used in the empirical analysis. Section 4 presents the main results for the inequality measures and discusses heterogeneous responses among countries of different income levels. It also carries out robustness checks. Section 5 concludes.

2 Empirical model

The empirical model is the following Bayesian panel VAR:

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

where $var\,(v_{it}) = \Omega$, $i = 1, 2, ..M$ 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).

In the benchmark case, 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. However, as discussed below, we also consider alternative measures of inequality such as ratio of income at different percentiles of the distribution.

Recent papers (e.g. Óscar Jordá *et al.* (2020)) highlight the adverse effects of lag truncation of VAR models especially if interest centers are capturing the impact of shock at medium or long run horizons. Therefore we consider the possibility of lags longer than 1. Based on the SIC we find that 5 lags provide the best fit.

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. As described in Banbura *et al.* (2010) the posterior distribution has a convenient normal-inverse Wishart form that can be factored in to the marginal posterior for Ω that is inverse Wishart and the conditional posterior for the VAR coefficients that is Gaussian. Thus, it is straightforward to draw from posterior using the MCMC algorithm described in Banbura *et al.* (2010). We employ 25,000 iterations with a burn-in of 20,000. Figure 1 in the Appendix presents inefficiency factors that suggests that the algorithm has converged.

2.1 Identification of climate shocks

Climate change is a gradual process when compared to economic fluctuations. As reported widely (see for example Climate.Gov), global average surface temperature has increased by about 1 degree centigrade since the pre-industrial era. However, the impact of this change on weather volatility is substantial and is driving extremes in temperature and rainfall. Our aim is to capture shocks that drive the low frequency movements in climate variables. For this purpose, we adopt the identification scheme of Angeletos *et al.* (2020). We identify climate shocks as those that explain the bulk of the variance of climate variables in the long-run.

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

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

where A_0 is a $N \times N$ contemporaneous impact matrix. Note that 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. The structural moving average representation of the VAR model is:

$$Y_{it} = \beta(L) A_0 \varepsilon_{it}.$$

Without loss of generality, our interest centers 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 is maximised. We define the long-run in the frequency domain as corresponding to cycles greater than 20 years. As discussed in Angeletos *et al.* (2020), the contribution of the shock to the spectral density over a frequency band is given as $q_1' S(\underline{\varpi}, \overline{\varpi}) q_1$ where:

$$S(\underline{\varpi}, \overline{\varpi}) = \left(\frac{\int_{\underline{\varpi}}^{\overline{\varpi}} \tilde{g} g}{\int_{\underline{\varpi}}^{\overline{\varpi}} g \tilde{g}} \right)$$

where $g = M_y (I - b e^{-i\varpi})^{-1} \tilde{a}_0$ 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 eigenvector associated with the largest eigenvalue of $S(\underline{\varpi}, \overline{\varpi})$

3 Data

Our panel data-set 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 addi-

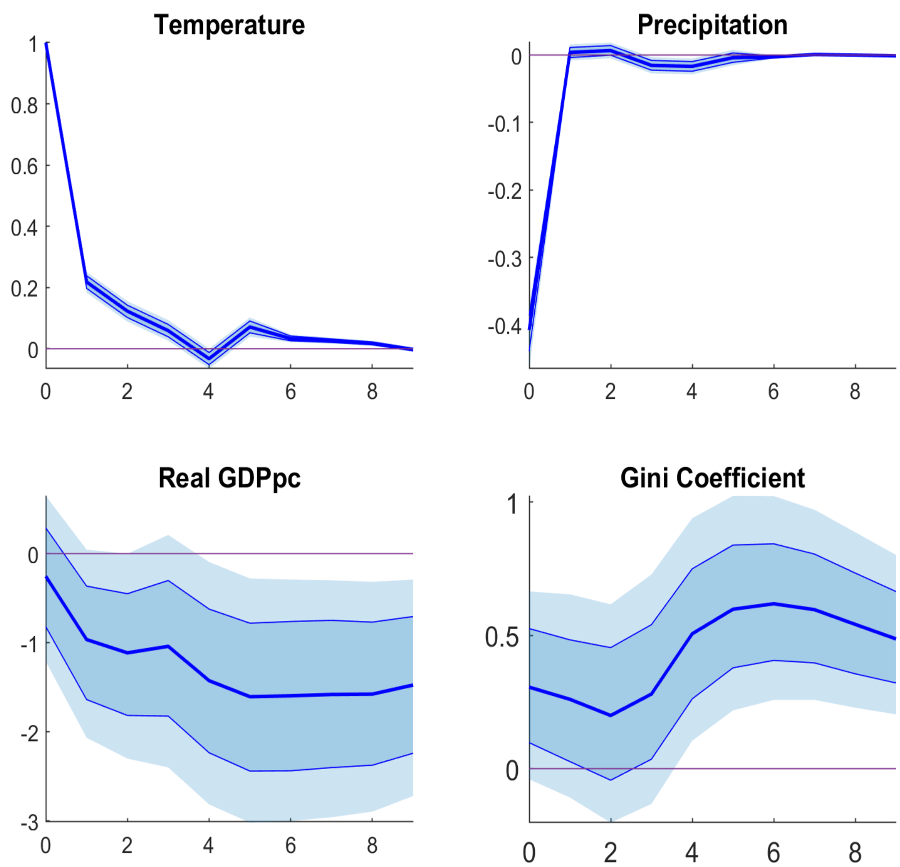

Figure 1: Impulse response functions to $1^0 C$ increase in temperature. The vertical axis of GDP and Gini coefficient plots measures the response in percent. The horizontal axis indicates time in years. The dark blue line is the median estimate and the shaded areas are the 68% and 95% error bands.

tional macroeconomic variables when required.

Our main variables of interest are measures of income inequality. The benchmark measure is the Gini coefficient based on pre-tax national income. We also use the ratio of log income at different percentiles of the income distribution. The inequality data are obtained from the World Inequality Database (WID).

4 Empirical results

4.1 Baseline model

Figure 1 plots the response to a climate shock normalised to an increase in temperature by 1^0C. As discussed above, the climate shock is defined as the shock that explains the bulk of the variance of temperature and precipitation in the long-run, thus in the benchmark specification, countries with less than 20 observations have been excluded. As it can be seen in Figure 1, the adverse shock reduces precipitation for about a year after the shock while it takes more than 8 years to temperature to go back to its equlibrium. The median response of GDP in levels is negative and persists for more than 10 years. The response of GDP is in line with Dell *et al.* (2012a) where GDP growth falls to a positive temperature shock even though the result is more pronounced to an interaction with poor countries. The response of the Gini coefficient rises slowly and picks after 5 years with a maximum rise of 0.62 percent. The Null can be rejected in the 95 percent error bands for both variables. To see what the model predicts by setting the targets of Paris Agreement for global warming, a 2^0C rise in temperature will increase the Gini coefficient by 1.24 percent in 5 years while the more strict but less feasible target of 1.5^0C rise augments the inequality measure by 0.93 percent.

4.2 Heterogeneity

Our baseline results indicate that a rise in temperature increases the Gini coefficient in the long run. However, given that a rise in Gini indicates a generic rise in inequality but does not reveal which percentiles are mostly affected by the shock, we need to decompose further this result. Thus, we proceed in collecting the 10^{th}, 50^{th} and 90^{th} percentiles of pretax income for the years available in each country and include all three variables in the benchmark VAR. The results shown in Figure 2 indicate that the pre-tax income of the 10^{th} percentile suffers the highest drop. It falls by 3.8 percent in four years while the median income falls by 2.6 percent in the same horizon. The 90^{th} percentile experiences a much smaller fall on its income, with a maximum drop of 1.1 percent in the second year. It also demonstrates the shortest lived significant effect.

Interestingly, if we define a rise in inequality as the growing difference among

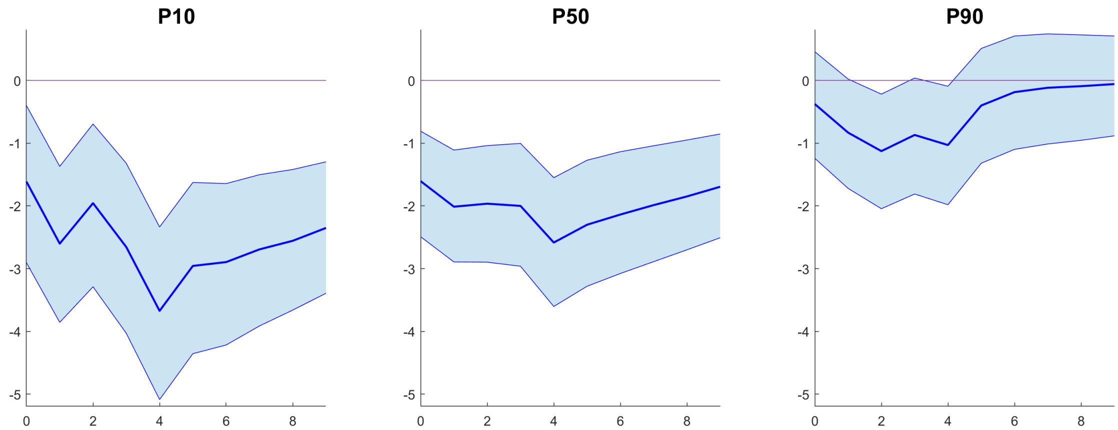

Figure 2: Distributional effects of the climate shock by percentiles. The figure reports the impulse response functions of 10^{th}, 50^{th}, and 90^{th} percentiles of households' pre-tax income distribution to 1^0C increase in temperature shock. The vertical axis measures the response in percent. The horizontal axis indicates time in years. The dark line is the median estimate and the shaded area is the 68% error band.

income percentiles, then the higher difference appears in the right tail of income distribution. This is possibly because the 90^{th} percentile encounters the smallest loss from the shock. The other two percentiles, both, experience comparable losses and their between difference is smaller. For a visual representation, we construct the $P50/P10$ ratio which is the log difference of the median ($P50$) to the 10^{th} percentile ($P10$) to examine the impact on the left tail of the income distribution, and the $P90/P50$ ratio, for the right tail. Figure 3 shows the responses of these tails to the climate shock. While both ratios rise to the shock, a higher rise is observed in the right tail of the income distribution. The $P90/P50$ ratio has a peak response of 2 percent in the sixth year while the $P50/P10$ ratio has a peak response of 1.4 percent after about four years.

5 Channels of transmission

To understand better the ways inequality measures respond to a climate shock in the baseline model, we investigate whether specific economic or climatological factors play a role. We group countries according to these characteristics and see if the responses to climate shock are heterogeneous. We start with climate and geographical factors and proceed with economic characteristics.

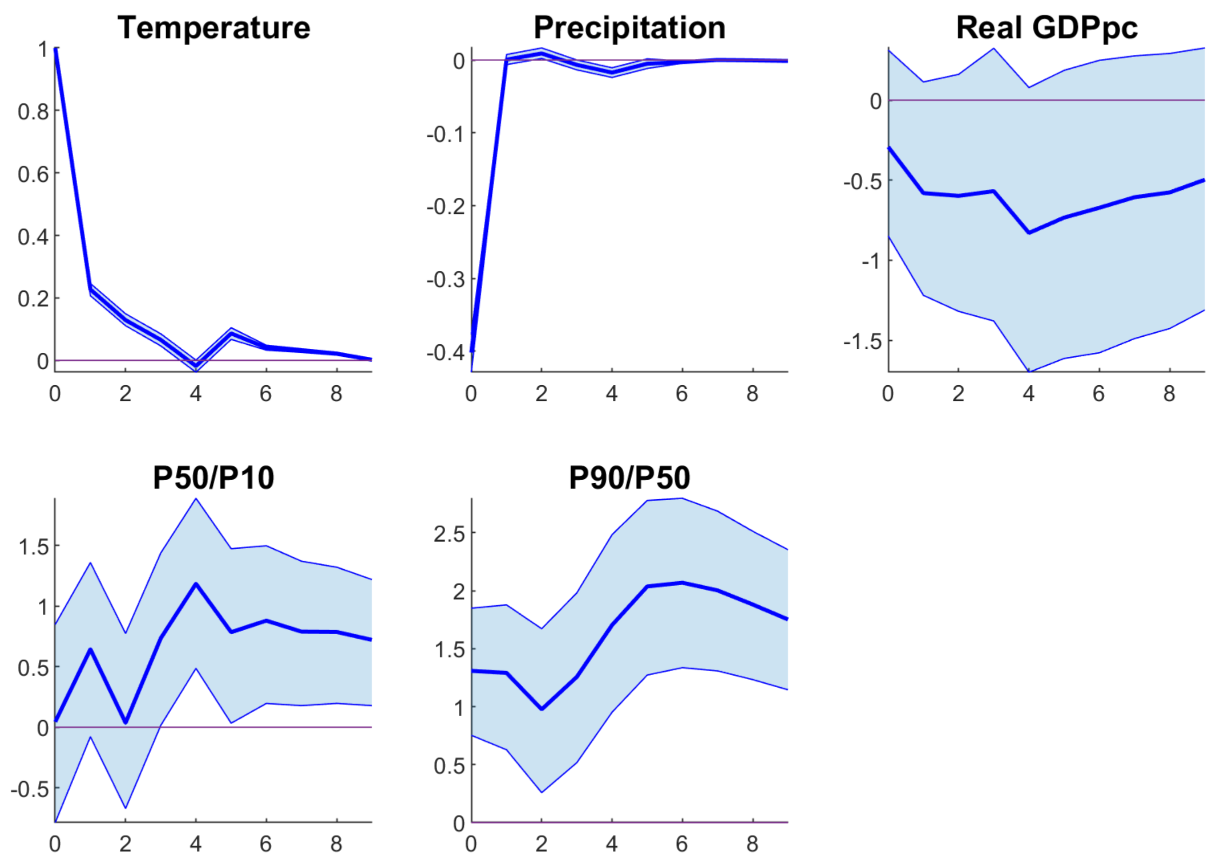

Figure 3: Distributional effects of the climate shock by income ratios. The figure reports the impulse response functions of P50/P10 and P90/P50 pre-tax income ratios to 1^0C increase in temperature shock. The vertical axis measures the response in percent while the horizontal axis indicates time in years. The shaded area is the 68% error band.

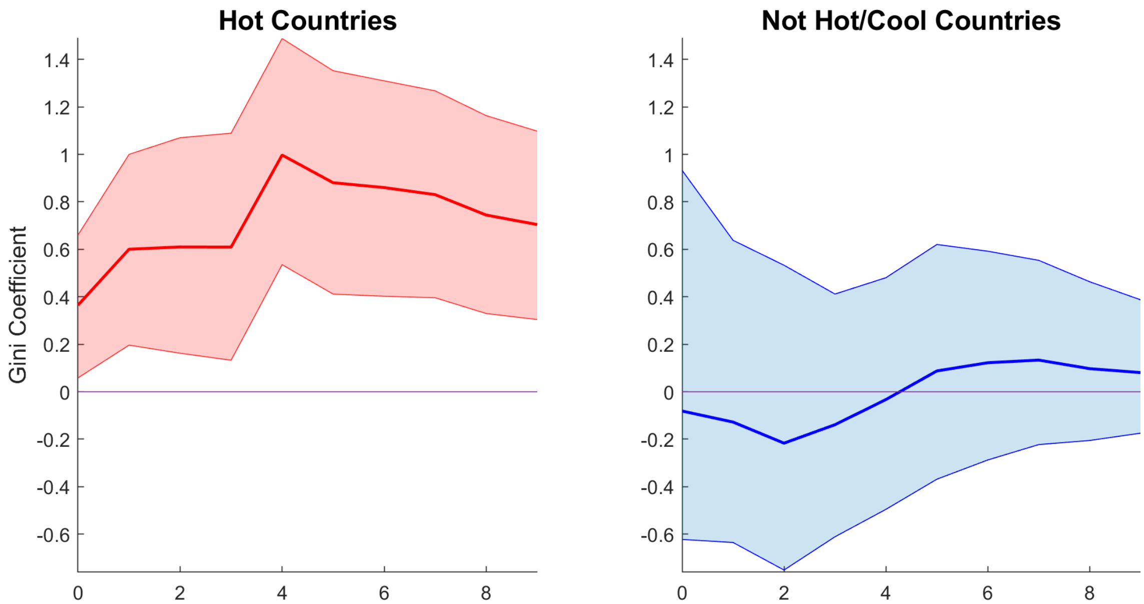

Figure 4: Impulse response functions of the Gini Coefficient to 1^0C increase in temperature in samples of hot and cool countries respectively. The vertical axis measures the response in percent while the horizontal axis indicates time in years. The shaded area is the 68% error band.

5.1 Average temperature and geographic location

As the negative cross sectional correlation between temperature and economic aggregates has been widely registered in the literature, the importance of geographical location (e.g. Mendelsohn, Schlesinger and Williams (2000), Dell *et al.* (2012a), Rehdanz and Maddison (2005), Tol (2002) etc.) indicates towards heterogeneity. To investigate whether the average temperature of a country influences inequality, we split our sample to hot and not hot or cool countries and carry out the benchmark experiment to these two sub samples. Following Dell *et al.* (2012a), we use the median temperature for all countries in the sample between 1950-1960, which is 21.3^OC as the cut off point. Countries above this temperature are considered "hot "while the rest are named "not hot" or "cool". Figure (4) shows that the Gini coefficient significantly rises by 1% in four years in hot countries while it does not have a significant response in the cooler ones.

Countries closer to equator are hotter and this has been found to have a negative impact on labour productivity, agriculture, health, among other factors (see for example Gallup *et al.* (1999)). Here, we attempt to evaluate whether geographical location is a significant transmission mechanism of the temperature shock to inequality, following a large literature stressing the importance of geography on economic development. However, it comes with its own caveats when studied on a national level: A country may be large and/or long and cover a range of environments and climate zones. It may not only have significant income heterogeneity but also a climate one. For example, Argentina reaches out to South pole or Pakistan, which includes parts of Himalayas on its northern part, are both classified as hot countries since their average annual temperature is above the median of the sample. Other notably large countries, which lay on a number of climate zones, are the USA and China.

Figure 5 shows that the Gini coefficient will increase in European, South Asian and most notably sub Saharan countries while no significant impact is found in some regions like MENA and North America. Large northern countries like Russia and the central Asian ones may experience a fall in inequality. Although this is an interesting result for the eleven former Soviet countries which compise this sample, we do find that the level of their GDP per capita falls to a temperature shock. One possible explanation is that the right tail of the income distribution is more adversely affected and/or there are other significant channels of transmission than the geographic location. A caveat of this exercise is that some of these geographic sub samples suffer from small number of cross sections.

5.2 Income level

The asymmetric effect of a rise in temperature to rich and poor countries as stated in the literature, leads to the investigation of the average income level as a propagation mechanism. We test the hypothesis that low income countries may experience a higher rise of inequality to a climate shock. For example, Dell *et al.* (2012a) found that a rise in temperature by 1^0C can decrease income by 1.4% only in poor countries (with no adaptation) but no significant impact has been found for the rich ones. Low income countries are usually warm, located near the equator, have a larger agricultural sector which is more susceptible to weather conditions and a lower ability to adapt to climatic changes (Mendelsohn *et al.* (2006))

We split our sample to poor and rich countries. Low income countries are classified by the World Bank as the ones with Gross National Income (GNI) per capita less than $\$1,045$ in 2020. High income countries have their GNI per capita equal or

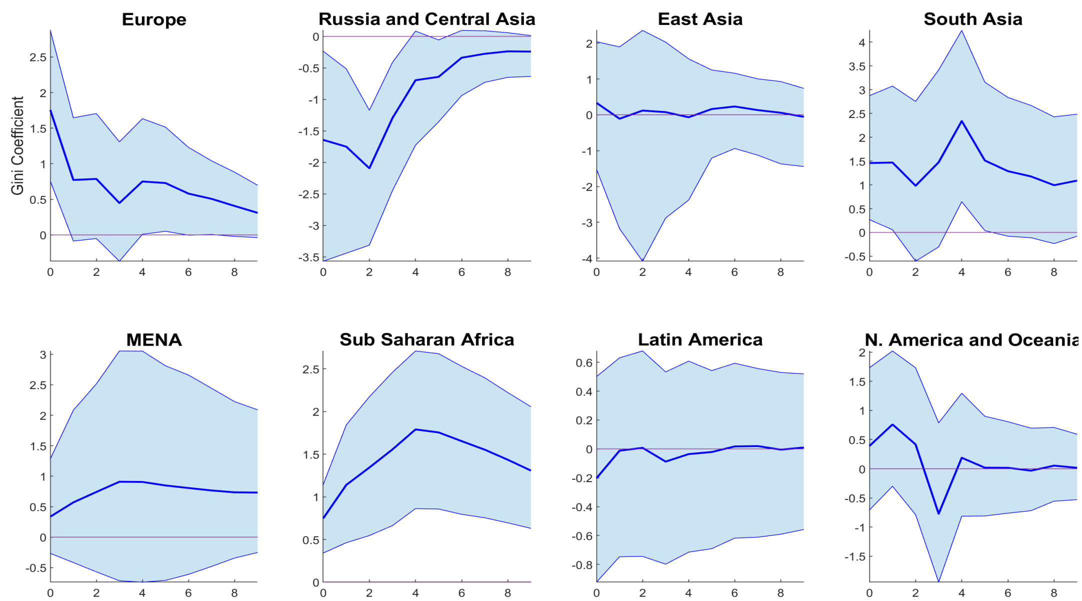

Figure 5: Impulse response functions of the Gini Coefficient to 1^0C increase in temperature in different geographic regions.

more than $\$12,696$ in the same year. Figure 6 shows the Gini responses of poor and rich countries to climate shock. The Gini coefficient rises substantially and peaks by 0.9 percentage points in the fourth year for the low income countries, while there is no significant evidence for rising inequality in high income countries. Thus, we find that not only low income countries will be more negatively affected by climate shocks in terms of GDP, but also inequality within these countries is expected to rise. This result is in line with findings that demonstrate an asymmetric economic effect among poorer and developed economies stressing the fact that the developing world is more vulnerable to climate change (e.g. Mendelsohn, Morrison, Schlesinger and Andronova (2000), Tol (2002)).

5.3 Agriculture

Agriculture is the only economic sector inextricably intertwined with climatic conditions as it is directly affected by temperature and precipitation. Its contribution to national income and technological ability to adjust and protect production from climate change can affect considerably different income brackets. To test whether the size of agricultural sector acts as a propagation mechanism to inequality, we di-

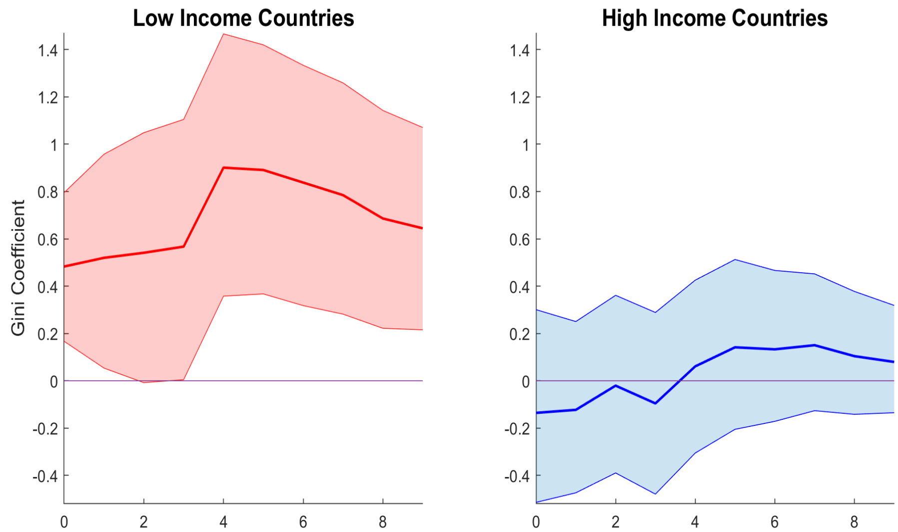

Figure 6: Impulse response functions of the Gini Coefficient to 1^0C increase in temperature in samples of low and high income countries respectively.

vide our sample to agricultural and non agricultural countries. We collect the value added of agricultural, forestry, and fishing production as a percentage of GDP for each country and for all years available. Following Dell *et al.* (2012a), agricultural countries are classified as the ones whose share of agriculture to GDP in 1995 is above the median of the sample (12.32%). For industrialised countries we take the 38 OECD countries in our sample.

Figure 7 shows that the Gini coefficient rises on the impact by around 0.8% and remains high in the countries with large agricultural sector. The impact is positive but noticeably smaller for the rest of the sample (non agricultural countries) where the Gini still rises but by half relative to agricultural countries. To see whether technologically advanced countries can adapt quicker to weather adverse conditions we create a third sample. Using the Global Finance 2023 ranking of the world's most technologically advanced countries, we select the ones with positive index as the most advanced technologically countries. The results show a negative but insignificant response of the Gini coefficient to temperature shock, supporting the idea that these countries adapt better and are more independent to weather conditions.

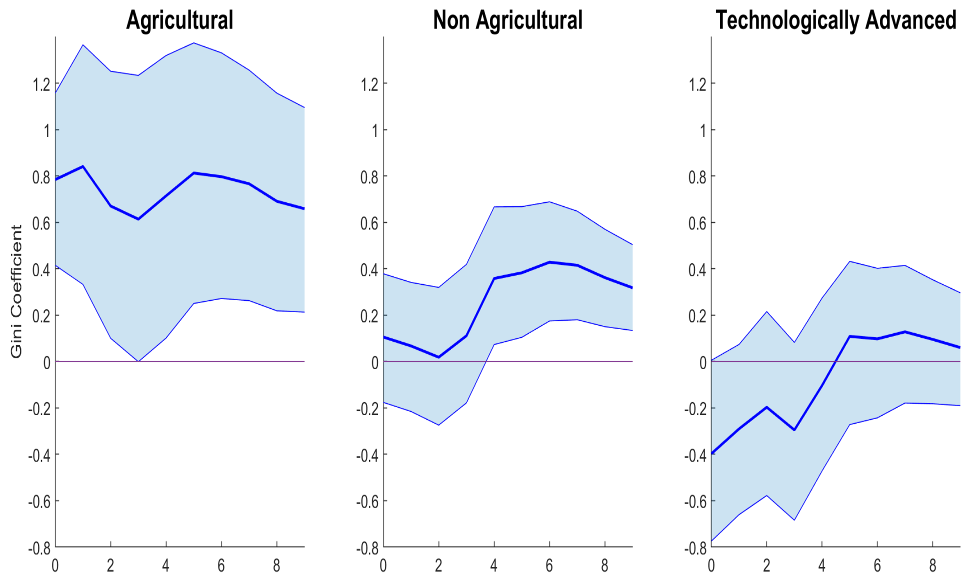

Figure 7: Impulse response functions of the Gini Coefficient to 1^0C increase in temperature in samples of agricultural, non agricultural and technologically advanced countries respectively.

5.4 Energy

The relationship between climate change and energy production and consumption is bilateral and interactive. High climate volatility induces higher demand for energy (for example cooling or heating) which in turn leads to higher production and consumption of energy with its well known environmental repercussions. In this section, we only try to capture the one directional effect of climate change to inequality through the channels of energy production and prices, setting aside the feedback effects of energy consumption to climate change.

One way to capture the effect of energy consumption to inequality is by looking at the response of CPI energy inflation and its feedback effects on the Gini coefficient. Energy expenditure comprises an important component of disposable income and can affect more the vulnerable households. To investigate this effect we augment our benchmark specification with CPI energy inflation series from World's Bank Global Database of Inflation for each country in the sample.

Our benchmark model does not indicate any significant effect of temperature shocks on CPI energy inflation and Gini coefficient (see Figure 8, first row). However, when we look at countries' classifications we find some significant responses of

CPI energy inflation for certain types. We repeat this exercise for subsamples with high and low income countries, average hot and cool climate, agricultural versus industrialised. In this section, we also try a new specification, which is net energy importers and exporters. Energy producing countries such as Iran, Qatar, Saudi Arabia, Turkey and Nigeria have reportedly the lowest electricity prices per Kwh in 2020 (Statista.com) so it is interesting to see whether these countries experience high energy prices which may contribute to higher inequality. By using data from World Bank Indicators, net energy importers are defined as countries which have positive energy imports as a percentage of their energy needs in 2000 and on average in the sample years. Respectively, net exporters are the ones who have a negative ratio. The majority of countries in our sample are net importers (85 countries). This is a highly heterogeneous group containing most of the OECD, industrialised and high income countries. In contrast, net energy exporters, (38 countries) are mostly hot countries of low income per capita, located near the equator.

In Figure 8 we report the types of countries where the response of energy inflation is significant to the shock. For the rest, not a significant response was found. The results indicate that CPI energy inflation has a positive response for low income and agricultural countries. In these countries, the Gini coefficient rises to the shock thus energy inflation can be a factor which exacerbates inequality. CPI energy inflation falls only for net energy exporters but the inequality indicator increases slightly and only in the long run. Thus for these countries there is no clear evidence that lower energy prices can improve equality.

5.5 Health Expenditure

Higher than average temperatures and heat events have a negative effect on many aspects of human healht and mortality rates. For example, they can negatively impact prenatal and infancy health, people with pre-existing respiratory and cardiovascular diseases (Deschenes and Greenstone (2011)). As higher temperature challenges certain health conditions and strain public health services, medical coverage and access to health care remain crucial. Government spending on public health services can be linked to income inequality as in a poor public health services environment, individuals may have to use their disposable income or savings to access private health services. Poor health combined with low income can have serious effects on

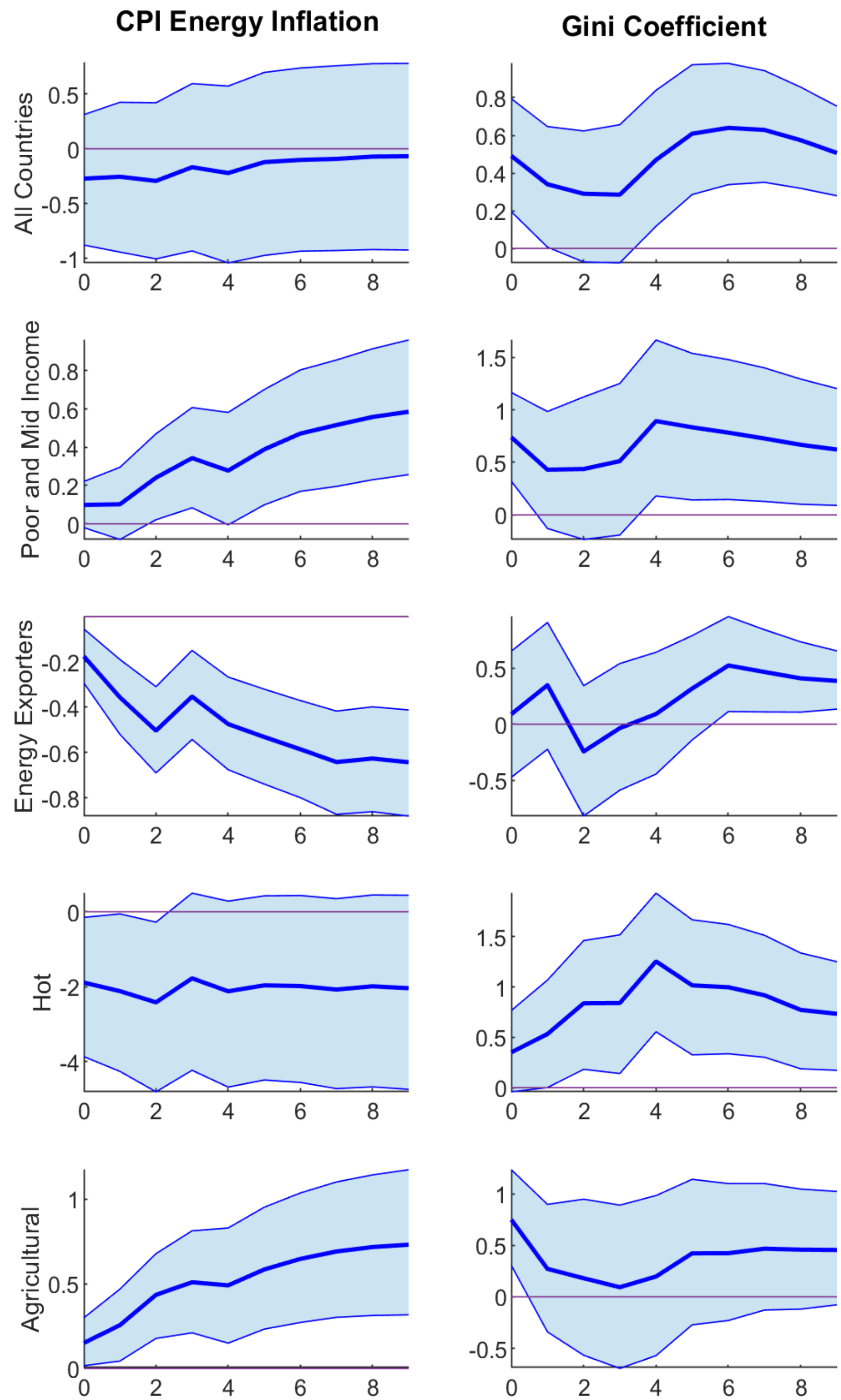

Figure 8: Impulse response functions of CPI Energy Inflation and Gini Coefficient to 1^0C increase in temperature for all countries and subsamples.

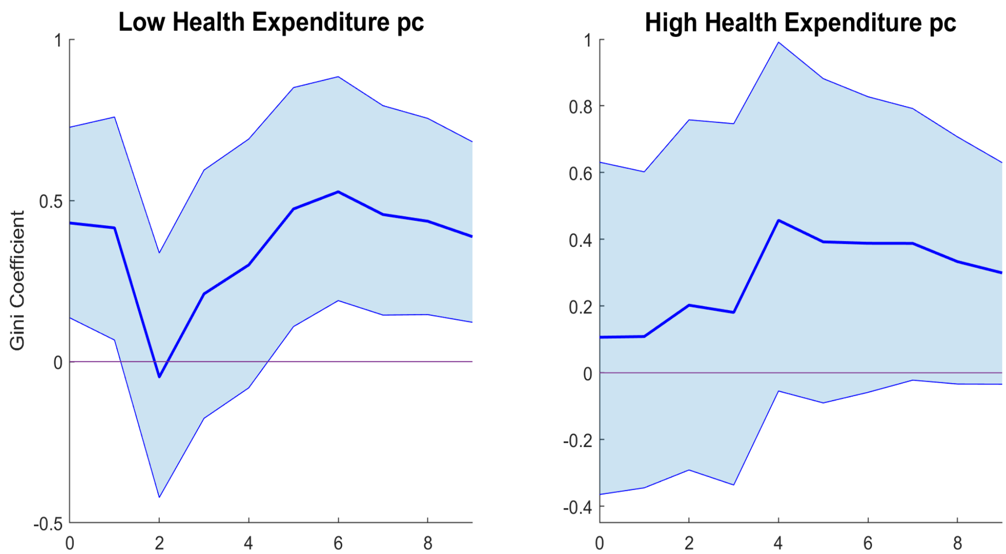

Figure 9: Impulse response functions of the Gini Coefficient to 1^0C increase in temperature in samples of countries with low and high expenditure per capita on health sector respectively.

hours worked, productivity, employment and earnings. To investigate the role of public expenditure on health as a contributor to inequality during heat shocks, we include this variable in our benchamark model. More specifically, we collect the current expenditure on health per capita normalised by GDP from 2000 onward and derive the mean for each country. Then we obtain the median expenditire accross countries and divide our sample into two groups: the low health expenditure group, which has a ratio of health expenditure to GDP lower than the median and the high health expenditure group, which has a ratio above the median. Next, we perform the benchmark experiment to both groups.

Figure 9 indicates that temperature shocks increase the Gini coefficient by 0.53% in six years in low health expenditure countries. Although the coefficent increases also in high health expenditure ones, we cannot reject the Null. This result indicates inequality will be higher in countries with lower expenditure than the average on health sector.

6 Robustness

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

6.1 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 at long-run frequencies. 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 10, 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.[4] The second panel in the top row of figure 10 plots the response of the Gini coefficient to a climate shock that increases the change in temperature by one percent.[5] 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.

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

[5] 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.

6.2 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.* (2012b). Dell *et al.* (2012b) aggregate temperature and precipitation using population weights. The fourth panel in the top row of figure 10 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 10).

6.3 Local projections

Recent papers (see Óscar 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:

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

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.[6]The second panel in the second row of figure 10 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

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

include quadratic terms:

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

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 10).

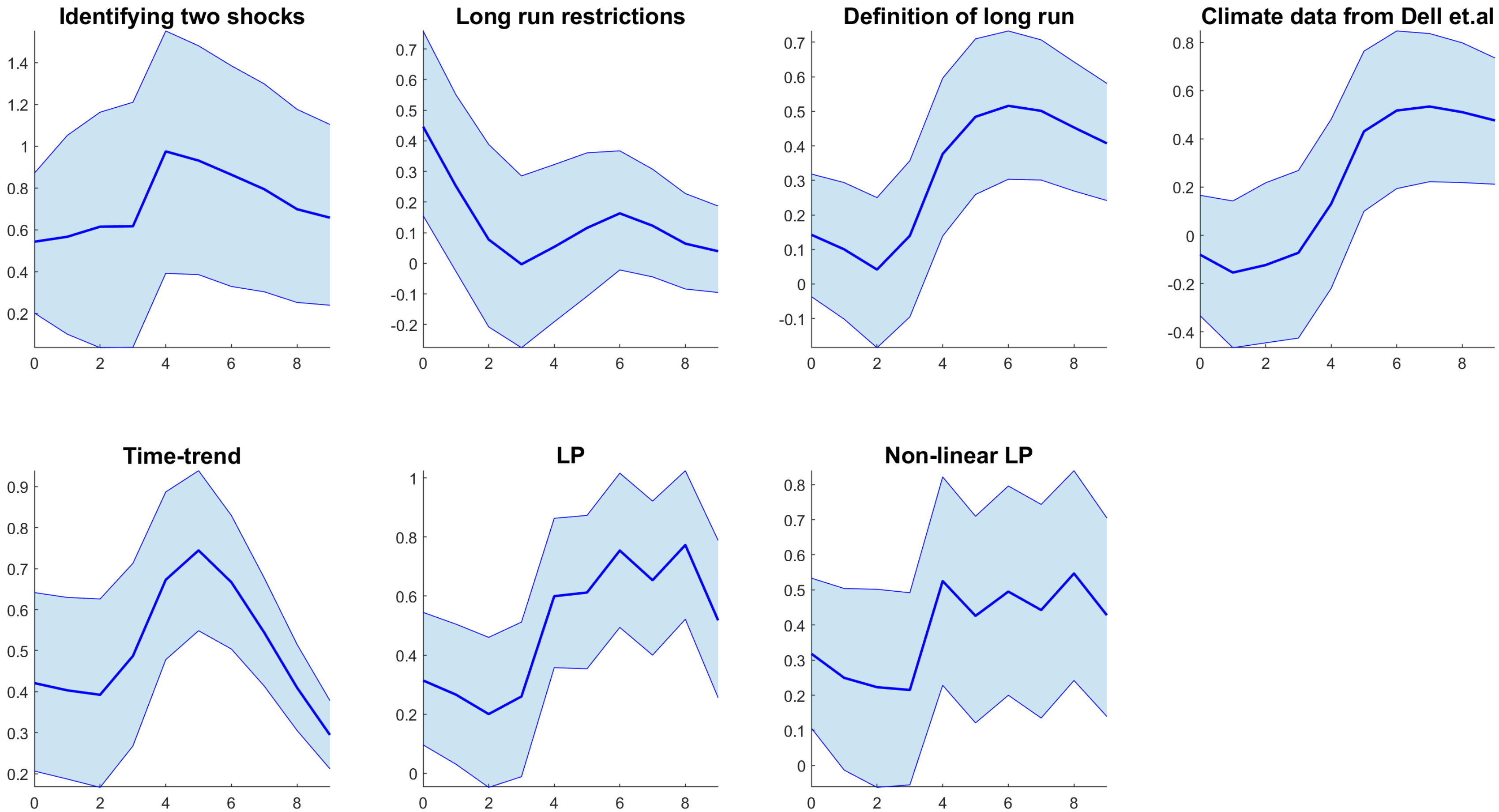

Figure 10: *Robustness*: Impulse response functions of the Gini Coefficient to 1^0C increase in temperature for a number of alterations of the benchmark model. The vertical axis of each plot shows the response in percent and the horizontal axis the number of years. The thick line is the median estimate and the shaded area is the 68% confidence bands.

7 Conclusions

In this paper we consider the impact of climate change on income inequality. Using a recently developed identification scheme, we estimate the shocks as those that explain most of the variance of temperature and precipitation at long run frequencies. 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 5 years and persists for more than 10 years. Our findings also suggest that the shock has a heterogeneous impact across the income distribution, and the poor households incur a higher loss in their income. The right tail of the income distribution is mostly affected as the distance between the rich and the median households increases the most to the shock. Investigating whether country specific characteristics can play a role to heterogeneity, we find a stronger effect on the Gini coefficient on lower income and hot on average countries and economies with an important agricultural sector and a lower spending on health sector. Energy inflation can play a role to certain subsamples but not overall. In contrast, the impact on inequality for high income, technologically advanced economies or countries with cooler on average temperature is close to zero.

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