"The far-reaching distributional effects of global warming: Evidence from half a century of climate and inequality data"

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Abstract:

Climate change is already impacting several development outcomes, including economic growth, human health and mortality, agricultural productivity and even conflict. Moreover, the impact of climate change is expected to be unevenly distributed across locations and population groups. In particular, the worst effects of climate change are expected to be felt in low-income countries. Similarly, within countries, the most vulnerable to these effects are typically low-income regions and households. While the literature to date has provided evidence of the between-countries inequality-increasing effect of global warming, evidence for inequality within countries remains limited. In this paper, we empirically explore the connection between climate change and long-run distributional dynamics within countries. To do so, we first build a global panel dataset combining gridded data on climate variables with gridded population data, and country-level data on a range of inequality measures and development outcomes. We use these data to test climate effects on several dimensions of inequality, including the (interpersonal) distribution of income, using traditional Gini coefficients, indices of concentration of both income and wealth, proxies of inequality in the spatial distribution of economic activity within countries, and measures of inequality in life expectancy. We complement our country-level analysis with an analysis at the subnational level for selected countries (US, Russia and Spain). Our evidence shows a clear positive and statistically significant relationship between higher temperatures and increases in different measures and dimensions of inequality, both at the country and subnational level. The role of higher temperatures is robust to a wide range of controls, different specifications and estimation techniques.

Keywords: inequality; climate change; development;

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1. Introduction

Climate has been shown to be a key driver of a range of development outcomes, including economic growth, human health and mortality, agricultural productivity and even conflict (Dell et al. 2014; Carleton and Hsiang 2016; Castells-Quintana et al. 2017). There is now increasing concern that climate change will heavily impact prospects for development. According to latest estimates from the IPCC, global average temperatures are expected to rise by between 1.5 and 5.7 degrees Celsius by the end of the century, depending on the evolution of greenhouse gas emissions (IPCC 2021). Along with gradual changes in global temperatures there will be an increase in the frequency and intensity of extreme weather events. For 2 degrees of warming, the frequency of droughts, for instance, will more than double, while the frequency of a one-in-50-year extreme heat event will increase almost 14-fold. Understanding the socio-economic consequences of these changes is of first-order importance not just for informing climate change mitigation and adaptation strategies, but also for the design of development policies.

The impacts of climate change are not felt homogeneously, but rather they are unevenly distributed across locations and population groups, with potential consequences for inequality. In particular, the worst effects of climate change are expected to be felt in low-income countries, and within countries the most vulnerable to these effects are typically low-income regions and households (Castells-Quintana et al. 2018). Recent evidence suggests that climate change is increasing inequality between countries (Diffenbaugh and Burke 2019). And there is also recent empirical evidence suggesting that climate change has an impact on the spatial concentration of economic activity (Cattaneo and Peri 2021; Castells-Quintana et al. 2021), with important consequences on how income and wealth is generated and captured across space. However, to date, there continues to be limited evidence at the international level of the within-country distributional impacts of climate change.

In this paper, we empirically explore the connection between climate change and distributional dynamics within countries. To do so, we first build a global panel dataset combining gridded data on climate variables with gridded population data, country-level data on a range of income inequality measures and data on several development outcomes. We use these data to test climate effects on several dimensions of inequality, including the (interpersonal) distribution of income, using traditional Gini coefficients, indices of concentration of both income and wealth, proxies of inequality in the spatial distribution of economic activity within countries, and measures of inequality in life expectancy. Our country-level data includes information for more than 140 countries worldwide, over the 1955-2015 period. We complement our country-level analysis, with an analysis at the subnational level for the US, Russia and Spain. Using panel-data econometric techniques, we test whether (and how) climatic variation is associated with changes in the distribution of income within countries. Specifically, we isolate the effect of climate on distributional outcomes by exploiting random variation in weather conditions over time. In a long-differences set up, we also exploit the fact that different countries have experienced different amounts of warming over the past half century. Finally, we look at distributional impacts of higher temperatures beyond income dynamics. These far-reaching distributional consequences of global warming are robust to a wide range of controls, different specifications and estimation techniques.

Our paper relates to several strands in the literature. First, we relate to the literature on the socio-economic impacts of climate change (for recent reviews see Castells-Quintana et al, 2017; Patel et al, 2021). Second, we relate to the literature on the determinants of income inequality (for a recent review see Furceri and Ostry 2019). Finally, we relate to recent papers exploring the distributional effects of climate change, either looking at individual countries (Mideksa 2020; Chisadza et al., 2023), between countries (Tol et al, 2004; Harrington 2018; Diffenbaugh and Burke 2019; Noah and Burke 2019) and within them (Palagi et al, 2022; Paglialunga et al, 2022). We contribute to this nascent literature in a number of ways: First, by providing empirical evidence on the role of global warming on the long-run evolution of income-inequality within countries, using a large and novel global panel dataset; second, by looking not only at aggregate income inequality measures, like the Gini coefficient, but also at other dimensions of inequality, including concentration of income and wealth, as well as of economic activity across space; third, by providing evidence on the warming-inequality relationship at different subnational levels for several countries; and finally, by providing empirical insights on the distributional impacts of higher temperature beyond income dynamics.

Our focus on measuring inequality over longer time periods is significant for at least two reasons. First, recent papers that test the effect of climate on within country income inequality have tended to rely on annual measures of inequality that involve imputing values, whereas our data are based on newly assembled and more consistent data on income inequality with observations at 5-year intervals. Second, and perhaps more importantly, the finding of a short-run relationship between climate and inequality (based on annual data) is perhaps unsurprising, given the well-established evidence on differential impacts of climate-related disruptions and extreme weather events across income groups. Our evidence suggests that these inequality-enhancing effects are persistent. Or in other words, that current and historical adaptation to climate changes (including, for example, relocation across space or between economic sectors) are insufficient to mitigate the disproportionate impact of climate on lower income groups.

The remainder of the paper is structured as follows. In Section 2, we briefly review the literature and provide some theoretical insights behind the potential impact of changes in climatic conditions on the distribution of income. In Section 3, we present our global data and derive stylised facts on global trends over the past half century. Section 4 reports results of our econometric analysis: First, estimating a long-run (i.e., 50-year change) relationship between climate and inequality; second, estimating the climate-inequality relationship using our full global panel data; third, looking at measures of concentration of income and wealth; and finally, exploring distributional impacts of rising temperatures beyond income dynamics. Section 5 concludes and derives policy implications from the results.

2. Inequality within countries: the potential role of changing climatic conditions

The determinants of inequality

There is growing concern about income inequality within countries, as data show that, in many countries, it has increased significantly during the last decades (see for instance Milanovic, 2011; Cairo-i-Cespedes and Castells-Quintana, 2016; Castells-Quintana 2018; Gradin 2022). There is indeed a long strand in the literature studying the determinants of economy-wide inequality. Papers in this literature usually consider inequality *at the country level* (i.e., Fields, 1979, for Least Developed Countries; Milanovic, 1994; Li et al., 1998; Gustafsson and Johansson, 1999; Barro, 2000; Vanhoudt, 2000; Frazer, 2006; and Roine, et al. 2009, for world samples; Odedokun and Round, 2004, for Africa; and Castells-Quintana and Larrú, 2015, for Latin America). Other papers study inequality *at the regional level* (i.e., Perugini and Martino, 2008; Tselios, 2008, 2014; Rodríguez-Pose and Tselios, 2009; Royuela et al., 2014; Castells-Quintana et al., 2015).[3]

As highlighted by most of these papers, one key and common determinant of inequality is the level of development (and urbanization), in the spirit of Kuznets (1955). The literature has also focused on other dynamics that potentially influence the evolution of inequality at the country level. One of these dynamics relates to socio-economic factors, including economic growth, investment, and human capital accumulation (i.e., education). Another relates to demographics, including total population and fertility rates. A third group considers institutional and socio-political factors, beginning with the level of democracy, the level (and portfolio) of government spending, levels of

[3] Another strand of literature studies income inequality *at the city level* (i.e., Duncan and Reiss, 1956; Richardson, 1973; Haworth et al., 1978; Nord, 1980; Long et al., 1977; Alperovich, 1995; Baum-Snow and Pavan, 2013; Behrens and Robert-Nicoud, 2014; Glaeser et al., 2015; Sarkar et al., 2016; Ma and Tang, 2016; Castells-Quintana et al., 2020).

corruption and the incidence of social tensions and conflict. A fourth strand focuses on economic structure, including sectoral shares, and in particular the role of mineral rents and the size of the agricultural sector.

A final group of dynamics found to play a role in the evolution of inequality relates to external factors. Recent papers have shown the relevance of the level and profile of exports (see for instance Nguyen and Su, 2022). Similarly, other papers point to a potential role of aid and microfinance flows (Castells-Quintana et al, 2019). Finally, external prices, in particular commodity price shocks, have also been found to significantly affect the evolution of income inequality (Mohtadi and Castells-Quintana 2021). However, to the best of our knowledge, there remains limited evidence on the role of changes in climatic conditions on long-run inequality dynamics.

The potential role of climate change

Climate change has important socioeconomic consequences. On the one hand, direct economic (and human) impacts, including the destruction of fields, infrastructure, repair costs, etc. On the other hand, and probably more important in the long run, indirect impacts. These include lower long-run economic growth and macro and financial instability (Dell et al. 2012; Burgess et al. 2017), higher probability of conflict and institutional change (Miguel et al. 2004; Ciccone 2013; Hsiang et al. 2013) and a spatial reallocation of population and economic activity, usually from rural to urban areas (Barrios et al. 2006; Henderson et al. 2017; Carleton & Hsiang 2017; Peri & Sasahara 2019; Castells-Quintana et al., 2018, 2020). Castells-Quintana et al. (2017) review these potential long-run impacts of climate change on development outcomes.

Climate change can also have distributional consequences. As recent evidence shows, climate change is aggravating inequalities between countries (Harrington 2018; Diffenbaugh and Burke 2019; Noah and Burke 2019). And there are various ways in which climate change may also be expected to exacerbate within-country inequality. To begin with, climate change usually has greater impacts in rural than urban areas, and rural areas are, on average, poorer than urban areas. Moreover, in both rural and urban areas, climate change usually hits disproportionally the more vulnerable: they tend to live in riskier locations, and are the first to be displaced by climatic shocks; they depend more on climate-dependent activities and have fewer coping mechanisms to deal with climatic shocks (i.e., savings, access to financial services, etc.); and public response (adaptation) is usually addressed to protect valuable assets owned by the rich. In this line, Islam and Winkel (2017) identify three main channels through which climate change can increase inequality by affecting disproportionally disadvantaged groups: i) due to higher exposure, ii) due to higher susceptibility to damage caused by climate change because of the lack of finances or asset diversification, and iii) due to lower ability to cope and recover from the damage of climate change. Climate change can also alter distributional dynamics through several socio-economic impacts. Higher temperatures, for instance, affect access to basic services, like clean water, sanitation facilities and affordable food, health outcomes, and finally labour productivity (Dasgupta et al., 2021). Changes in climatic conditions also impact agricultural productivity (Ortiz-Bobea et al., 2021) as well as productivity in non-agricultural sectors, in both developing and developed countries (e.g. Deryugina and Hsiang 2014; Zhang et al. 2018). Furthermore, climatic shocks can also reinforce poverty traps, conflict and instability, which usually affect the poor more than the rich (see the review in Castells-Quintana et al. 2018).

While some recent papers have provided theoretical insights on the connection between climate change and inequality (see Mideksa 2010; Islam and Winkel 2017), very few papers have empirically explored the within-countries distributional effects of climate change. Recently, Cappelli et al., (2021) study the connection between climate change-induced natural disasters and inequality in a sample of 149 countries. Palagi et al. (2022) show how rainfall anomalies are associated with annual changes in inequality, while Paglialunga et al. (2022) also look at annual temperature increases for the period 2003-2017. These papers focus on annual income inequality data as measured by Gini coefficients, and mostly focus on agriculture as the fundamental channel in the climate-inequality nexus. We aim to contribute by i) focusing on the *long-run* impact of global warming on the evolution of inequality within countries, using a large and novel global panel dataset for over half a century (1955-2015), ii) looking at several inequality measures, including Gini coefficients and measures of concentration of income, wealth and economic activity in space, iii) providing evidence on the warming-inequality nexus at different subnational levels for several countries, and iv) exploring distributional impacts of rising temperatures beyond income dynamics.

3. Climate change and inequality: a look at global data

To explore the connection between climate change and the evolution of inequality within countries, we build a global dataset combining gridded data on climate variables with gridded data on population, country-level data on several measures of income inequality, concentration of wealth and economic activity in space, and inequality in life expectancy, complemented with data on several development outcomes. Our global panel includes information for more than 140 countries worldwide, over a long period of time (1955-2015).[4]

For climatic variables, we draw on country-level datasets obtained from the World Bank's Climate Change Knowledge Portal (CCKP)[5], as well as gridded weather data from the CRU TS version 4.03 dataset from the University of East Anglia (Harris et al. 2014).[6] As our focus is in long-run dynamics, and in order to merge with the inequality data that we use, we aggregate for every country in five-year periods from 1955 to 2015.[7] We focus on average annual temperatures, capturing variations in the climate from one five-year period to the next, and long-run changes, capturing variation (in warming) over a 50-year period. We also control for total annual rainfall as another key climatic variable discussed in the related literature. As our focus is on socio-economic consequences, it is natural to look at the spatial distribution of population. Changes in climatic conditions will have a stronger socio-economic impact where more people live. We thus match our gridded weather data with gridded population data (both on a 0.5-degree grid) from the Global Population of the World v4 dataset.[8] This allows us to construct *population-weighted* versions of our climatic variables. Appendix A provides more information on the construction of our climatic variables.

For interpersonal income inequality, we rely on the World Income Inequality Databases (WIID) compiled by United Nations University World Institute for Development Economics Research (UNU-WIDER).[9] The WIID databases (version 31 May 2021) include information for up to 208 countries or territories between 1950 and 2019, including estimates for the percentile share of each country's total net income. This allows us to look at different income inequality measures, including Gini coefficients, but also the concentration of income in different population groups, like the Top 10%, Middle 50% and Bottom 40%. Furthermore, previous papers that look at annual data have used Solt (2020) database, which heavily relies on interpolations and requires multiple imputation analysis. By using WIID databases in 5-year periods, we significantly reduce this issue (see Gradin 2021 for more on the properties of the WIID databases).

In addition to income inequality at the national level, we also compile data on income inequality at the sub-national level, for select countries: the US (both at State and County level), Spain

[4] In practice, our baseline sample used throughout most of our empirical analysis includes 143 countries and covers the time period 1955-2015.
[5] These are simple area-weighted country means, derived from the University of East Anglia's Climate Research Unit (CRU) time-series (TS) dataset of high resolution gridded monthly climatic observations.
[6] The data are available from https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/ (last accessed June 2020).
[7] Our 5-year aggregates are constructed to be backward looking, such that an observation of temperature in 2015 is actually the mean temperature in the preceding 5-year period (i.e., 2010-2014). This is so that outcomes in our analysis are always related to weather over the preceding period.
[8] The data are available from https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-adjusted-to-2015-unwpp-country-totals-rev11/data-download (last accessed June 2020). We use the version of the population data adjusted to match UN country totals, and we take population estimates for the earliest available year in the data (2000).
[9] The WIID Companion database compiles information, mostly obtained from household surveys, from a variety of countries, either reported by various sources like PovcalNet, ECLAC, SEDLAC, National Statistics Authorities, etc., or estimated directly from microdata (in the case of LIS and Eurostat). The corresponding series were standardized to be comparable over time and across countries (see details in the corresponding WIID Companion technical notes).

and Russia, in each case based on official national statistics. Descriptive statistics for these sub-national inequality data, and corresponding temperature data, are included in Appendix A.

We complement our income inequality data with measures of concentration of wealth from the World Inequality Database (WID) and measures of spatial concentration of economic activity, built from satellite data on night-time lights (see Appendix A for more on the construction of these measures). We also consider inequality in life expectancy, as an alternative outcome, relying on data from the United Nations Development Program (UNDP).

Finally, additional data used in our analysis include a range of other development outcomes, including measures of socio-political stability and conflict as well as measures of human health. As part of a suite of robustness tests on our main findings, we further control for potential determinants of inequality, including GDP per capita, total population, fertility rates, export rates and urbanisation rates, among others. These additional variables are based on data from the World Bank Development Indicators, the Penn World Tables and the International Country Risk Guide (ICRG-PRS group). Table A.1 in the Appendix provides definitions and sources for the different variables included in our data, while Table A.2 provides descriptive statistics for our main variables of interest at the national level, while Table A.3 includes summary statistics for sub-national data. In the rest of this section, we highlight some stylised facts for our key variables.

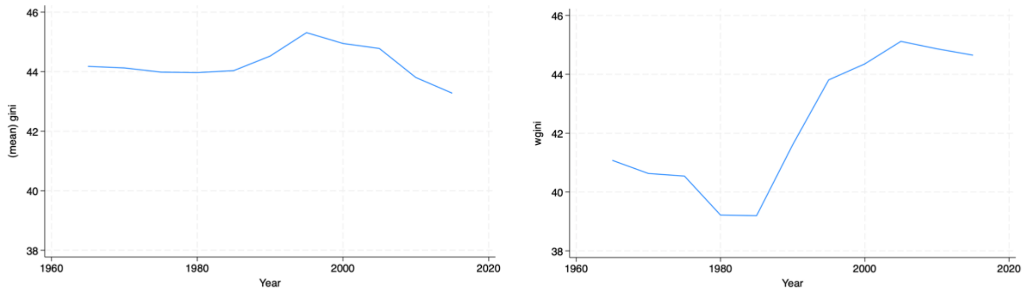
Rising inequality within countries

Figure 1 shows the evolution of income inequality for our global sample: in Panel A, simply averaging across countries in our sample, and in Panel B, weighting by population of each country. Panel A shows a relatively stable evolution, with a slight increase in the last decades of the 20th century, followed by a decrease after the year 2000 (mainly driven by progress in some developing countries, especially in Latin America). However, when weighting by population (Panel B), inequality within countries shows a significant increase, going from a Gini of less the 40 in 1980 to a Gini of around 45 in recent years. In other words, a majority of people in our sample has seen inequality increase in their country over most of our period of analysis (in line with Gradin 2022). A second clear fact relates to the important differences across countries. Figure 2 provides maps of inequality levels in 2015 (in Panel A) and the change in inequality over a 50-year period (1965-2015) in Panel B.[10] Figure A.1 in Appendix A provides similar maps for concentration of income at the top (i.e., Top10). Inequality is especially high in countries in Sub-Saharan Africa, Latin America and South Asia. While within-country inequality has increased globally in the last 50 years, that increase has not been uniform, with some countries experiencing declines in inequality over the period, while others have experienced sharp increases (as shown in Figure 2, panel B, and Figure A.1, panel B).

[10] For our long-run changes, we focus on the 50-year change between 1965 and 2015 to avoid potential issues with the data at the beginning and end of the full sample period. All our results using long-run changes are robust to using different 50-year periods or using a 70-year period (1950-2020).

Figure 1: Within-countries income inequality over time, global average, 1965-2015

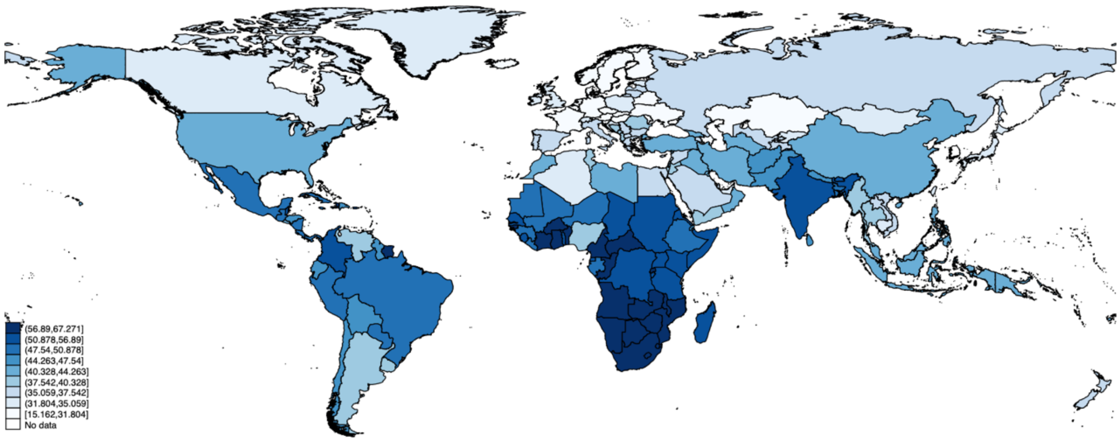
Panel A: simple average | Panel B: population-weighted average



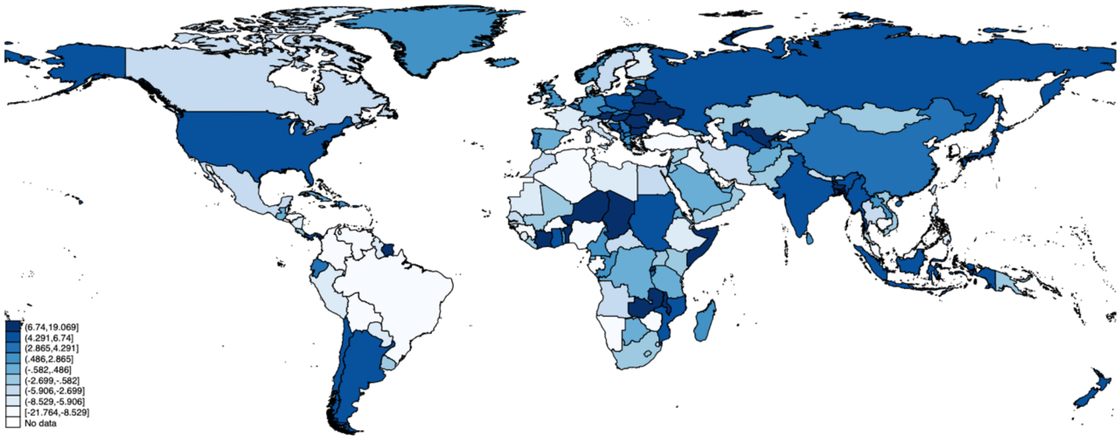
Note: Figure plots the evolution of the average in Gini coefficients for our global sample. In panel A, a simple average across countries, while in panel B weighting by the population of each country.

Figure 2: Within-countries income inequality maps

Panel A – Gini cross-section (2015)



Panel B – 50-year change in Gini (1965-2015)

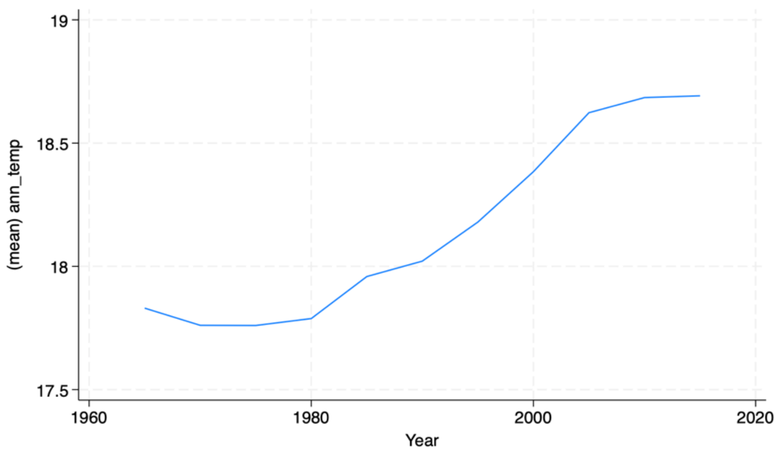


Note: Panel A shows estimated Gini by country in 2015, according to data from WIID. Panel B shows the change in the estimated Gini by country over a 50-year period (1965-2015).

Global warming

Turning to our climatic data, we can clearly see the recent process of global warming. Figure 3 shows the global trend in temperatures over the last decades for our sample of countries. The global average of temperatures increased by almost 0.9 degrees Celsius over our 50-year period, tracking closely with scientific observations of global warming. Figure 4 shows a global map of increases in temperatures by country. The increase in temperatures is not uniform across countries, with some countries experiencing faster warming than others.[11] Two countries in our data, Bolivia and Paraguay, actually experienced modest decreases in population-weighted temperature from 1965-2015. On the other hand, a number of countries in our sample experienced warming of more than 1.5 degrees Celsius over this period, with the largest increase of 1.73 degrees Celsius in Sudan.

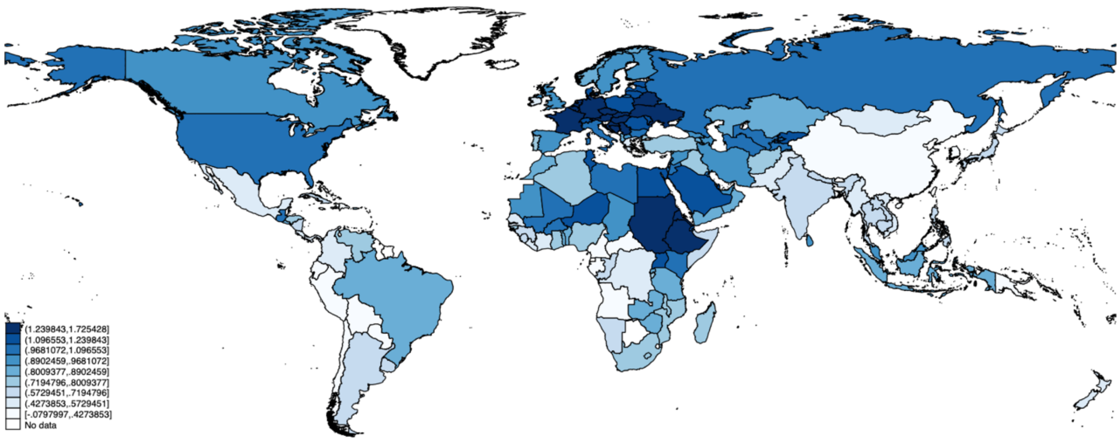
Figure 3: Global mean national level temperatures, 1965-2015



Note: The figure shows mean annual temperature across all countries in our sample in degrees Celsius, for each 5-year period from 1965-2015. The series used here is (area-weighted) temperature for each country, aggregated from monthly observational data to 5-year averages, using gridded weather data from CRU TS v4.03 (Harris et al. 2014).

[11] See also https://earthobservatory.nasa.gov/world-of-change/global-temperatures for a discussion of how global warming does not mean temperatures rise everywhere at the same rate.

Figure 4: Change in population-weighted temperature, 1965-2015



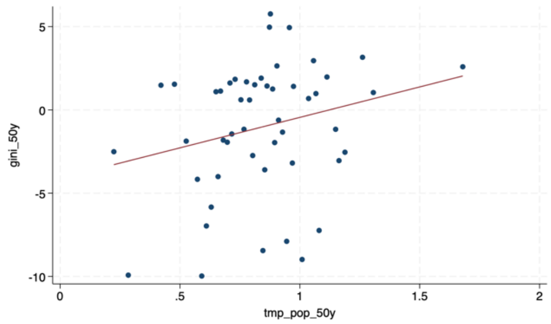
Note: The map shows changes in temperature (in degrees Celsius), by country, 1965-2015. The series used here is population-weighted temperature for each country, aggregated from monthly observational data to 5-year averages, as described in the text. (Sources: Author calculations based on gridded weather data from CRU TS v4.03 (Harris et al. 2014), and gridded population data from the Global Population of the World v4 dataset).

Warming and increasing inequality

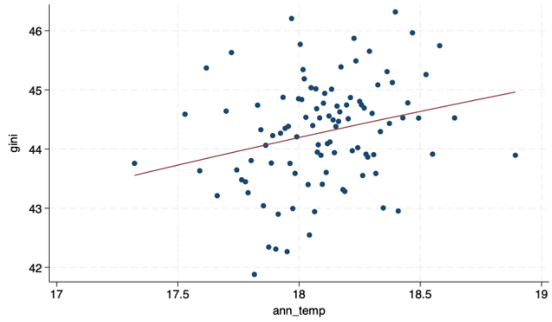
Figure 5 shows the association between average temperatures and income inequality (as measured by the Gini coefficient). We consider both a long-run and a medium-term association. For the long-run association, we look at changes in temperatures over 50 years (1965-2015) and changes in inequality over the same period for our global sample. We compute these long-run changes using average temperature in the most recent five-year period with those same averages 50 years previously. By doing so, we reduce potential noise introduced by particularly hot and cold years. For inequality, being highly persistent, we just compute the difference between inequality levels in 2015 with those of 1965. Panel A shows the association for these long differences, controlling for regional fixed effects. For a more medium-term association, we look at 5-year periods using our full panel data. Panel B presents this association, controlling for country and time fixed effects. In this way, panel B captures the connection between temperatures and inequality considering only the within-country evolution over time (what we are after). Both figures suggest a clear association between higher temperatures and increases in income inequality within countries over medium to longer time scales.

Figure 5: Mean temperatures and income inequality

Panel A: Long differences, 50-year changes (1965-2015)



Panel B: 5-year panel



Note: Figures show binscatters. In Panel A, controlling for region fixed effects, where each point represents 3 observations in the dataset. Temperature is the 50-year change in (population-weighted) national level mean temperature, averaged over a 5-year period. Similarly, the Gini is the 50-year change 1965-2015 for each country. In Panel B, controlling for country- and time-specific fixed effects, where each point represents 40 observations in the dataset. Temperatures here are measured in the preceding 5-year period compared to inequality.

4. Changing climatic conditions and the evolution of inequality: econometric analysis

Long-run warming and inequality

To study the association between climatic conditions and the evolution of inequality, we begin by looking at long-run changes in our key variables for our global sample. Table 1 presents results of a simple *Deep First Difference* specification, where we regress the 50-year change in inequality on a 50-year change in climatic conditions, as in Equation (1):

$$\Delta Inequality_i = \alpha_1 + \beta_1 \Delta Climate_i + \epsilon_i \qquad (1)$$

where $\Delta Inequality_i$ is the 50-year Change in the Gini coefficient and $\Delta Climate_i$ is the 50-year change in average temperatures for country *i*.

Results in Table 1 show a positive and statistically significant coefficient for the 50-year change in temperatures, suggesting that countries that have experienced more warming are, on average, also those where inequality has increased the most.

An obvious concern here might be that differences in warming over the past 50 years are not randomly assigned across countries. As is clear from the map in Figure 4, warming has been more pronounced in northern latitudes (in line with the predictions of climate models). Simple balance tests on key development outcomes confirm that at a global level, countries that experienced higher warming over the past 50 years had higher incomes, were more urbanised, had lower fertility rates and lower shares of agriculture-to-GDP at the beginning of our sample period (see Table B.1 in the Appendix). However, within regions, warming does appear to have been more varied. In Column (2) of Table 1, we show that the association between long-run warming and increasing inequality is robust to the inclusion of region fixed effects; i.e. the results are not driven by a particular world region.

The positive association between increasing temperature and increasing inequality is also robust to controlling for changes in average rainfall and initial climatic conditions (column 3) as well as controlling for economic growth over the 50-year period and several country-specific socio-economic characteristics (column 4). Results in Table 1 suggest that a 1-degree Celsius increase in average temperatures over a 50-year period has translated into a 3.5-4.3 point increase in the Gini coefficient over the same period, a non-negligible increase, relative to an average decrease of 1.04 points in the Gini index across the countries in our sample over this period. A similar pattern of results is reported in Appendix Table B.2, where the outcome *Top10* is the 50-year change in concentration of income amongst the Top 10% of earners.

Table 1: Warming and inequality, Deep First Difference (Deep FD) specification

	(1) Deep FD	(2) Deep FD	(3) Deep FD	(4) Deep FD
Dependent variable: Gini (50y change)				
Temperature	3.782**	3.737*	3.559*	4.237*
(50y change)	(1.475)	(1.968)	(2.010)	(2.159)
Region FE	NO	YES	YES	YES
Initial climate	NO	NO	YES	YES
Controls	NO	NO	NO	YES
Observations	143	143	143	133

Note: This table reports results of deep first difference specifications as in Equation (1). Variables are calculated as the change over a 50-year period (1965-2015). Initial climate includes average annual temperature and rainfall at the beginning of our sample (1960-1964). Controls include changes in average rainfall and GDP per capita growth over the 50-year period, as well GDP per capita, export share and agricultural valued added (to GDP) in levels (each lagged one period). Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Warming and inequality: panel results

In this section we turn to our global panel data in 5-year periods, exploiting the random variation in weather conditions over time, to examine short to medium-term effects on inequality. We now consider a panel-data model as specified in Equation (2):

$$Inequality_{it} = \alpha_1 + \beta_1 Climate_{it} + \gamma_t + \theta_i + \epsilon_{it} \quad (2)$$

where $Inequality_{it}$ is one of the different dimensions that we consider for income inequality within countries. $Climate_{it}$ is our climatic variable, capturing the country's average in temperature over the preceding 5 years. Our panel specification also allows us to include period fixed effects, γ_t, which control for common global shocks in the evolution of inequality, and country fixed effects, θ_i, which control for country-specific time-invariant characteristics of countries. Standard errors are clustered by country. In addition, in some specifications we add several time-varying socio-economic variables as controls.

As we include country-specific fixed effects, our panel-data specification exploits the within-countries evolution over time, controlling for time-specific fixed effects. Our identification of β_1 rests on the assumption that inter-temporal variation in our climate measure is exogenous with respect to the evolution of within-country inequality, conditional on country and period fixed effects. As clearly stated by the climate literature, variation in climatic conditions for each country depend on the impact of a myriad of global phenomenon, including changes in oceanic and wind changes, atmospheric pressure and more, making it exogenous to the evolution of country-level inequality.[12]

Table 2 presents our main results. Column 1 omits time and country fixed effects, therefore considering all the variation in our panel data, and considers our climatic variables without weighting by population. We find a positive and highly significant coefficient for temperatures. In column 2, we consider population-weighted temperatures. The coefficient for temperature continues to be positive and significant and increases in value, pointing to the relevance of weighting by population. In column 3, we include time effects, while in column 4 we include time and country fixed effects. The coefficient for temperatures continues to be positive and highly significant.

Results in Table 2 suggest a significant role of rising temperature in explaining the evolution of inequality within countries. The coefficient on temperature in column (4) can be interpreted as indicating that a 1-degree Celsius increase in average temperatures over a 5-year period is associated with a 1.3-point rise in the Gini coefficient.

Table 2: Warming and income inequality, panel results

Dependent variable:	Gini	Gini	Gini	Gini
Temperature	0.898***	1.006***	1.008***	1.265**
	(0.0901)	(0.0986)	(0.0992)	(0.526)
Year FE	NO	NO	YES	YES
Country FE	NO	NO	NO	YES
Observations	1,859	1,859	1,859	1,859
No. of countries	143	143	143	143

Note: This table reports results of specifications based on Equation (2) and as described in the text. The dependent variable is the Gini coefficient (as reported by WIID). Temperature is average temperature in degrees Celsius over the preceding 5-year period. Columns 2 onwards weight climate variables by population. All specifications control for average rainfall. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In Appendix B, we perform a range of robustness tests on our main panel results. Appendix Figure B.1 shows the results of a simple event-style analysis, where we estimate β_1 from equation (2) for the first lead of our climate variables (a temporal placebo), as well as for the contemporaneous effect and up to 5 lags (the figure only reports the estimated coefficients on temperature, but the regressions also control for rainfall during the same period in each case). As expected, temperatures at time *t* have no effect on the Gini at time *t-1*. Interestingly, the event study suggests that the effects of temperature on inequality, reported above in Table 2, are compounded over time, peaking at *t+1*, or up to 10 years after the temperature shock.[13]

In Table B.3, we check the robustness of our results to alternative time periods and panel specifications. First, we perform a falsification (see column 1). For falsification, we consider a simple temporal placebo test. If the temperature-inequality link was driven by internal trends, we would still

[12] To see how changes in climatic conditions at the country level are determined globally, not locally, and therefore exogenous to national socio-economic outcomes, see for instance: https://www.climateandweather.net/global-warming/factors-that-influence-climate/
https://www.americangeosciences.org/education/k5geosource/content/climate/what-factors-determine-climate

[13] The coefficient on temperature continues to be positive and statistically significant at the 5% level at t+2, and at the 10% level at t+3 and t+4, before returning close to zero at t+5. A linear combination of coefficients on temperature from a regression with the contemporaneous and lagged temperature included together, shows an estimated cumulative coefficient of 5.44 (p-value 0.014). This is notably quite similar in magnitude to the estimate from our long-differences specification reported in Table 1, reinforcing our argument of a long-run impact of (gradually) increasing temperatures.

find a positive coefficient if we assigned the change in temperatures in the following period to the increase in inequality in the preceding period. However, as expected, we find no significant coefficient for temperatures. This result reinforces the idea that it is the changing climatic conditions of each country, in particular higher temperatures, which is significantly associated with increases in inequality in that country. Second, we restrict our sample to data either post 1980 or, alternatively, post 1990. This reduces our sample size but restricts our data to more recent, and more reliable, inequality data. In both cases, we still find significant coefficients for temperatures (see columns 2 and 3). In terms of alternative specifications, we include region- or country-specific time trends (see columns 4 and 5) and consider a dynamic model by including the lag of inequality as a regressor (see column 6). The coefficient for lagged inequality is positive and significant, reflecting the high degree of persistency of inequality over time. Nevertheless, in all cases, our main results of an inequality-increasing role of rising temperatures remains statistically significant.[14]

In Table B.4, we test our results to the inclusion of several time-variant country characteristics potentially relevant to explain the evolution in inequality. These include income per capita, and its square, total population size, fertility rates, and urban rates. The coefficient for average temperature remains significant. One notable result here is in Column (5) of Table B.4, where we add urban rate as an additional control. The estimated coefficient on temperature here drops in magnitude by almost a third (from 1.44 in column 5 to 1.01 in column 6), albeit remaining positive and statistically significant (at the 5% level). This finding suggests that urbanization could be a potential mechanism linking warming and inequality (as shown in Castells-Quintana et al. 2022). We further investigate this here by estimating the relationship between temperatures and spatial inequality (proxied by inequality in lights) as discussed further below.

In Table B.5, we consider a first-difference specification. When working with highly persistent dependent variables, as inequality, it has been suggested to use first differences rather than fixed effects (see Woolridge 2010). Our main results for temperature remain significant.

In Table B.6, we allow for more flexible specifications allowing the coefficient for temperature to vary based on potentially relevant country characteristics: First, we allow the coefficient to vary by income per capita levels, and second by the initial share of agriculture in total employment. We find no evidence of significant heterogeneity of effects across these two dimensions, at least in the cross-section. We also allow for the effect of temperature on inequality to vary as incomes rise, or as agricultural share shifts over time for a given country, finding that the positive temperature-inequality association is weaker as income per capita rises over time. This is expected as richer countries have higher resilience and adaptation capacity. However, unlike the findings in recent papers that focus on short run associations between climate and inequality (see for instance Palagi et al, 2022), the longer-term relationship between higher temperatures and inequality that we document appears to be independent of agricultural share.

Finally, in Tables B.7 and B.8, we look at distributional dynamics at a finer spatial scale by looking at inequality within subnational units. Subnational data on income inequality are scarce, but are available for some countries over relatively limited time periods. In Table B.7, we exploit sub-national inequality data, based on official national statistics from the US, Russia and Spain, as three different countries for which there is subnational inequality data.[15] For the US, we look at state-level as well as county-level Gini coefficients, while for Russia and Spain we look at regional estimates of

[14] Interestingly, including country-specific trends (in column 5) also results in a negative and statistically significant coefficient on average rainfall (at the 10% level), suggesting that, controlling for country-specific trends, higher rainfall is associated with less inequality. Or, in other words, particularly excessive drying is associated with more inequality, in line with recent results in the literature (see Palagi et al, 2022).

[15] The literature has shown that warming has strong effects not only among poorer countries but also among richer ones. Chisadza et al. (2023) have recently provided some insights suggesting that the climate–inequality nexus is not limited to developing countries, but also existent in developed countries such as the U.S. Liang et al. (2017) have shown how different changes in climatic conditions can explain differentiated trends in agricultural productivity within the US, with potential distributional consequences.

income inequality. In each case, our results suggest an association between higher temperatures and inequality even at a subnational level – when pooling observations together (with or without time fixed effects), and when controlling for higher level fixed spatial effects. For example, for the US data, higher temperatures at a county level are associated with higher income inequality, controlling for year and State fixed effects.[16] Given data limitations here, these results should be treated as exploratory in nature, but are nevertheless suggestive of patterns that merit further research using richer local or subnational level datasets than those available for this study.

In Table B.8, we rely on data from night-time lights to build measures of spatial concentration of economic activity. Results show that rising temperatures are associated not only with interpersonal concentration of income, but also with higher spatial concentration of economic activity (as measured by nightlights). The effects appear to be stronger when using larger subnational units (global administrative level 1), in line with our results for the US (where we see stronger effects for state rather than county level inequality). These findings underline again the idea that higher temperatures will lead to a change in how economic activity is distributed across space.

Warming and concentration of income and wealth

If rising temperatures have the potential to increase income inequality, do they also change the pattern of inequality? Or, similarly, do rising temperatures affect different parts of the income distribution differently? And, if so, increase the concentration of income and wealth? To answer these questions, we explore how rising temperatures affect different parts of the distribution of income. The WIID dataset includes several variables that allow us to explore the climate-inequality relationship along the income distribution (as well as check our results to different inequality measures). In particular, we focus on three complementary income inequality measures: the concentration of income at the Top 10% (*Top10*), the concentration at the Middle 50% (*Middle50*) and the concentration at the Bottom 40% (*Bottom40*). Results for these alternative measures and dimensions of inequality are presented in Table 4. We find that higher temperatures are associated with more concentration of income at the top of the income distribution (column 1), and less concentration at the middle and bottom of that distribution (see columns 2 and 3). This pattern of results for concentration at the top and at the bottom remain significant after controlling for country-specific trends (see Appendix Table C.1). Together, these results would suggest that the inequality-increasing role of rising temperatures is associated with increasing (relative) concentration of income at the top (i.e., the rich) at the expense of the middle and bottom part of the distribution (i.e., the middle class and the poor).

[16] Given the relatively short panels and limited number of observations available here, as well as the relatively modest variation in Gini values over time (within units), in these subnational specifications we include spatial fixed effects at a higher level of aggregation, rather than unit fixed effects. Interestingly, for Russian regions, where average temperatures are very low (see summary statistics in Appendix Table A.3), we find that higher temperatures – which in this context may be productivity enhancing – are associated with lower income inequality. If we restrict the sample to relatively warmer Russian regions, the coefficient on temperature turns positive, as in results elsewhere.

Table 4: Warming and concentration of income

	(1)	(2)	(3)
Dependent variable:	Top10	Middle50	Bottom40
Temperature	1.276***	-0.812***	-0.464*
	(0.406)	(0.265)	(0.271)
Year FE	YES	YES	YES
Country FE	YES	YES	YES
Observations	1,859	1,859	1,859
No. of countries	143	143	143

Note: This table reports results of specifications based on Equation (2) and as described in the text. Temperature is average temperature in degrees Celsius over the preceding 5-year period. All specification control for rainfall and its lag. Robust standard errors (clustered by country) in parentheses. p<0.01, p<0.05, p<0.1

If there is a long-run impact of higher temperatures on the concentration of income, we could expect that will eventually reflect in effects on the concentration of wealth. To assess this, we draw on data from the World Inequality Data (WID), which provides data on concentration of wealth at the country level every ten years from 2000 to 2020. We find a positive and significant association between temperatures and wealth concentration, robust to several time-variant controls, including income inequality (see Table C.2). The results suggest a delayed effect from higher temperatures to concentration of wealth. This income- and wealth-concentrating impact of rising temperatures is in line with, and reinforces, previous findings suggesting that, globally, while the poor are getting poorer, the rich are getting richer under climate change (see Diffenbaugh and Burke 2019).

Warming and inequalities in life expectancy

Finally, we consider the possibility of rising temperatures affecting distributional dynamics beyond income and wealth. If international comparable data on income inequality is scarce, data availability for other dimensions of inequality is even more limited. However, the United Nations Development Program (UNDP) provides data on several development outcomes, including inequality in life expectancy in 5-year intervals from 2010 to 2020. Life expectancy is not just a key dimension of development, but also a long-run one that depends on income as well as other non-economic factors. Focusing on (inequality in) life expectancy allows us to explore the role of rising temperatures on inequality dynamics beyond income. As explained in Section 2, deteriorating climatic conditions have been associated with socio-political instability and conflict (see for instance Burke et al. 2015), as well as worse health conditions and higher mortality (see for instance Hondula et al. 2015; Ebi et al. 2022). In Tables D.1 and D.2, in Appendix D, we explore these potential impacts of rising temperatures. In Panel A of Table D.2, considering several proxies for instability and conflict, including *government stability*, *corruption* and *internal conflict*.[17] In Panel B of Table D.2 looking at several variables for health conditions and mortality, including *undernourishment*, *infant mortality*, *mother mortality*, and the incidence of widespread diseases like *tuberculosis* and *malaria*.[18] In all cases, we find a significant coefficient for average temperatures.

[17] For this, we rely on data from the International Country Risk Guide (ICRG) from the PRS group. The ICRG evaluates several dimensions of political, economic and financial risks for some 150 countries over several decades. See Table A.1 in Appendix A for definition and sources. See Table D.1 in Appendix D for pairwise correlations between our alternative outcomes and inequality. Most alternative outcomes are highly correlated with inequality levels.

[18] Here we rely on data from UNDP and for World Bank – World Development Indicators.

These potential wide impacts of rising temperatures are likely to affect disproportionally the most vulnerable and thus likely to have unequal consequences (see insights in Cramer 2003). Consequently, as temperatures rise, we could expect to see not only more instability and conflict, worse health conditions and higher mortality, but also higher inequality in life expectancy. Column 1 of Table 5 shows a significant connection between temperatures and inequality in life expectancy, controlling for time- and country-fixed effects, while column 2 shows that this result also holds when controlling for several time-variant factors (including income, population, fertility and urbanization). As shown in column 3, this result is not driven by income dynamics; controlling for income inequality (as measured by the Gini coefficient) hardly affects the magnitude and significance of the coefficient for temperatures. By contrast, as shown in column 4, introducing proxies for (in)stability and conflict and for health conditions and mortality yields highly significant coefficients, and makes our coefficient for temperatures nonsignificant. In other words, the connection between rising temperatures and inequality in life expectancy seems relate to higher instability and conflict and worse health conditions than to merely income inequality dynamics.[19]

Table 5: Warming and inequality in life expectancy

	(1)	(2)	(3)	(4)
Dep. variable:	IneLifExp	IneLifExp	IneLifExp	IneLifExp
Temperature	1.497*	1.461**	1.443**	0.103
	(0.791)	(0.716)	(0.721)	(0.741)
Gini			0.029	0.007
			(0.065)	(0.052)
Stability&Conflict				0.674**
				(0.266)
HumanHealth				4.652***
				(1.330)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Controls	NO	YES	YES	YES
Observations	282	280	280	133
No. of countries	141	140	140	67

Note: This table reports results of specifications based on Equation (2) and as described in the text. Gini is income inequality (lagged). Temperature is average temperature in degrees Celsius over the preceding 5-year period. Stability&Conflict is the principal component of *government stability*, *corruption* and *internal conflict*. HumanHealth is the principal component of *undernourishment*, *infant mortality*, *mother mortality*, *tuberculosis* and *malaria*. All specification control for rainfall. Controls include GDPpc and its square, total population, fertility and urban rate. Robust standard errors (clustered by country) in parentheses. p<0.01, p<0.05, p<0.1

5. Conclusions

In this paper, we have empirically explored the connection between climate change and distributional dynamics within countries. To do so, we first built a global panel dataset combining gridded data on climate variables with gridded population data, country-level data on a range of several inequality measures and data on several development outcomes. For inequality, we looked at the (interpersonal) distribution of income, using traditional Gini coefficients, but also at indices of

[19] All these results are exploratory and should not be interpreted in causal terms. It is also worth noting that, given data limitations, introducing proxies for stability, conflict and health factors significantly reduces sample size.

concentration of both income and wealth, proxies of inequality in the spatial distribution of economic activity (relying on night-time lights), and measures of inequality in life expectancy. Using panel-data econometric techniques, and exploiting random variation in weather conditions over time, we have found a positive and statistically significant role of rising temperatures on the evolution of within-country inequality. This role of rising temperatures is robust to several controls and different specifications and estimation techniques. Exploiting data at the state and county level for the US, and regional data for Russia and Spain, we have shown that the climate-inequality connection also seems to hold at the subnational level.

Our findings suggest a non-negligible impact of rising temperatures on the evolution of income inequality: a one-degree Celsius increase in average temperatures over a 5-year period is associated with a 1.3-point rise in the Gini coefficient. Moreover, we have shown that rising temperatures may be connected not only with higher income inequality, but also higher concentration of wealth and economic activity in space. Finally, we have shown that given the multiple impacts of climate change, rising temperatures can also affect other distributional dynamics beyond income, like inequalities in life expectancy. This distributional impact of climate change, beyond income dynamics, is something, to the best of our knowledge, novel in the literature, and worthy of further research.

By looking at several complementary outcomes, including measures of economic, social, political, and human development, our research points towards the high social relevance of our findings. As we have shown, the connection between changing climatic conditions (i.e., rising temperatures) and the evolution of inequality is likely to relate not only to income, wealth and economic activity, but also to political stability and internal conflict, as well as indices of human health. Understanding the socio-economic and political consequences of climate change, including the impact on distributional dynamics, is of first-order importance not just for informing climate change mitigation and adaptation strategies, but also for the design of development policies. Global average temperatures are expected to rise (even in the best-case scenario), along with an increase in the frequency and intensity of extreme weather events. For 2 degrees of warming, the frequency of droughts, for instance, will more than double. The frequency of a one-in-50-year extreme heat event will increase almost 14-fold (see IPCC 2021). All these climatic changes will have significant socio-economic impacts, including effects on distributional dynamics, which calls for urgent policy action. Further research to increase our understanding on the interplay between climatic trends and socio-economic and political dynamics will prove to be of utmost relevance.

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Appendix A: Data overview

Table A.1: Overview of main variables and sources

Variable	Definition	Time Span	Source
I. Climatic variables			
Temp_50y_change	Long-run (50-year) change in mean temperature	1965-2015	Constructed using data from the World Bank Climate Change Knowledge Portal (CCKP) and the UEA's CRU-TS data. (See below for more detail)
Rain_50y_change	Long-run (50-year) change in mean rainfall	1965-2015	
Temperature	Mean annual average temperatures (in degree Celsius) over preceding 5 years	1955-2020	
Rainfall	Mean annual average rainfall (in mm per year) over preceding 5 years	1955-2020	
II. Inequality variables			
Gini	Gini coefficient for the income distribution	1950-2019	World Income Inequality Database (UNU-WIDER)
Top10	Share of income in the top 10 percentiles	1950-2020	
Middle50	Share of income between the 25th and 75th percentiles	1950-2020	
Bottom40	Share of income in the bottom 40 percentiles	1950-2020	
Top10_weatlh	Share of wealth in the 10 percentiles	2000-2020	World Inequality Database (WID)
SpatialGini	Spatial Gini coefficient, using alternative subnational divisions	1992-2013	Constructed using satellite data of night-time lights (NOAA) and maps from Global Administrative Areas (GADM). (See below for more detail)
IneLifeExp	Inequality in life expectancy (as measured by Gini coefficients)	2000-2020	United Nations Development Program (UNDP)
III. Other (control) variables			
GDPpc	Gross Domestic Product (GDP) per capita	1960-2020	Penn World Tables
Pop	Total population	1960-2020	World Development Indicators (World Bank)
Fertility	Fertility rate	1960-2020	
Urb	Urban rate	1960-2020	
AgriGDP	Agricultural share in GDP	1960-2020	
EmpAgr	Agricultural share in total employment	1960-2020	
Exports	Exports share to GDP	1960-2020	
IV. Other variables			
Undernourish	Undernourishment(prevalence)	2000-2020	World Development Indicators (World Bank)
InfMortality	Infant mortality	1960-2020	
Tuberc	Tuberculosis (incidence)	1990-2020	
Malaria	Malaria (incidence)	1990-2020	
Stability	Government Stability. Range of values between 0=min stability and 12=max stability	1985-2020	Constructed using data from International Country Risk Guide (ICRG-PRS)
Corruption	Corruption index.	1985-2020	
IntConflict	Internal conflict. We re-arrange so 0 is low risk and 12 is high risk.	1985-2020	

Climate data

Our climatic variables are based on historical weather data, including temperature and rainfall observations, and are derived from monthly global gridded data, which have been aggregated to country means. The simple area-weighted country-level averages for rainfall and temperature (as used in Column 1 of Table 1) were obtained from the World Bank's Climate Change Knowledge Portal (CCKP).[20] These data are in turn derived from the University of East Anglia's Climate Research Unit (CRU) time-series (TS) dataset of high resolution gridded monthly climatic observations (see Harris et al. 2014). However, most of our analysis uses population-weighted versions of these variables, which we construct by combining gridded weather data from the CRU TS version 4.03 dataset from the University of East Anglia (Harris et al. 2014) with gridded population data from the Global Population of the World v4 dataset.[21] As our focus is in long-run dynamics, in each case (for both area-weighted and population-weighted versions) we aggregate for every country in five-year periods from 1950-55 to 2015-20.[22]

Based on these data, we construct three distinct sets of climatic variables, as follows:

Long-run changes:

To begin with, we construct measures of long-run changes in temperature and rainfall, measured as the 50-year (1965-2015) change in average temperature or average rainfall. We label these as *temp_50y_change* and *rain_50y_change*. We compute this long-run changes using average temperature and rainfall in the last five years with those same averages 50 years ago. By doing so, we reduce potential noise introduced by particularly hot (wet) and cold (dry) years.

5-year averages:

The variables *Temperature* and *Rainfall* measure mean average temperatures (in degree Celsius) and rainfall (in mm per year), at the national level, over 5-year time periods. Given that our regressions include country fixed effects, when we include *Temperature* or *Rainfall* as explanatory variables, estimation is based on the temporal variation in these measures for each country, i.e., the variation relative to that country's long-run average climate. Average annual temperatures and rainfall have been used in global analyses of the economic effects of weather variation for example in Dell et al. (2012). As noted, we have two versions of these average variables based on different methods for aggregating from gridded observations to national averages; area-weighted and population-weighted. In most of our analysis we rely on the population-weighted versions as better representing the weather experienced by the average person for a given country-time period observation in our data.

Each of our set of climatic variables thus captures distinct aspects of weather variation; for the long-run changes, the 50-year change in climatic conditions; and for 5-year averages, medium-term time scale variation in the levels of temperature and rainfall.

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[20] Available at http://sdwebx.worldbank.org/climateportal/index.cfm?page=downscaled_data_download&menu=historical (last accessed on 7 November 2018).

[21] The data are available from https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-adjusted-to-2015-unwpp-country-totals-rev11/data-download (last accessed June 2020). We use the version of the population data adjusted to match UN country totals, and we take population estimates for the earliest available year in the data (2000).

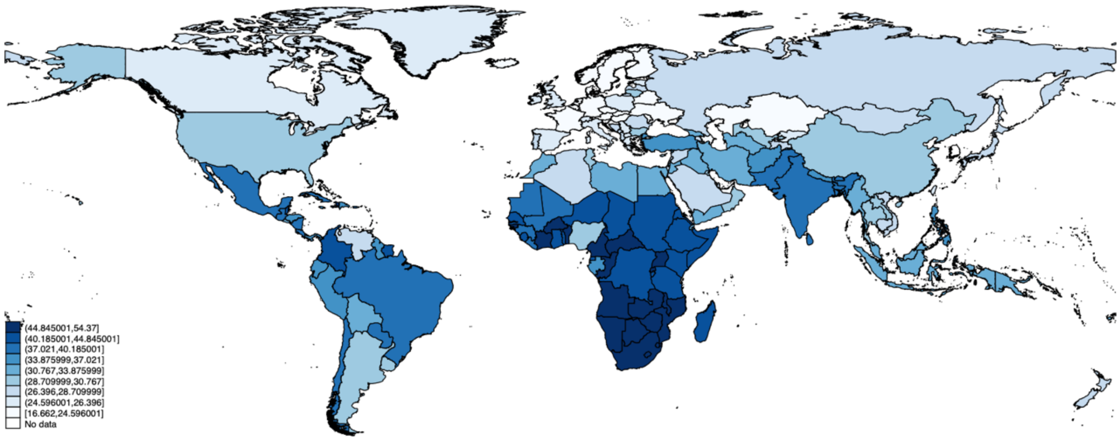
[22] Our 5-year aggregates are constructed to be backward looking, such that an observation of temperature in 2015 is actually the mean temperature in the preceding 5-year period (i.e., 2010-2014). This is so that outcomes in our analysis are always related to weather over the preceding period.

Constructing measures of spatial concentration of economic activity

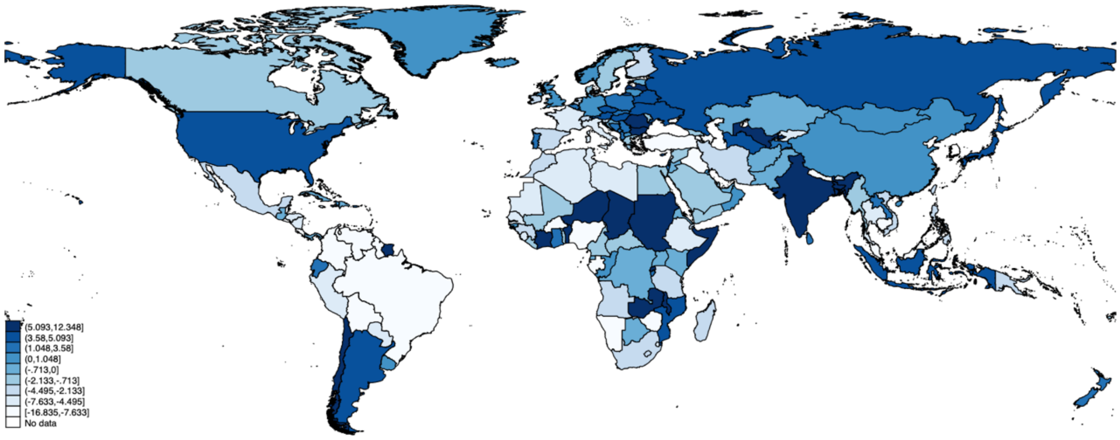
To construct measures proxying for the spatial concentration of economic activity, we rely on satellite data on night-time lights. In particular, we use data from the Defence Meteorological Satellite Program's Operational Linescan System, operated by the National Oceanic Administration Agency, and available at the pixel level (30 arc seconds, corresponding to <1 square kilometer at the equator) as a yearly panel from 1992 to 2013. These data have become established as a proxy for local economic activity in recent years (see Henderson et al., 2012; Donaldson and Storeygard, 2016). We rely on the top-coding correction applied by Bluhm and Krause (2022) to adjust for maximum brightness in cities. Using this data, we compute Gini coefficients in lights across spatial units. We do this aggregating night-time lights at two different spatial levels relying on maps from the Database of Global Administrative Areas (GADM): we use the first subnational division in GADM (*gadm1*) or, alternatively, the second subnational division (*gadm2*). To calculate the Gini coefficients across spatial units, we either weight by the area of each spatial unit (*area-weighted ginis*), or, alternatively, weighting by the population of each unit (*population-weighted ginis*). Because of their gradual changes, we assign the first year of the lights data, 1992–1990 as well as the last year, 2013–2015, to match the quinquennial structure of our data (1990, 1995, 2000, 2005, 2010, 2015). These measures have also been used in Castells-Quintana et al. (2021).

Figure A.1: Top10

Panel A: 2015



Panel B: 1965-2015 change



Note: Panel A shows the concentration of income at the 10% richest by country in 2015, according to data from WIID. Panel B shows the change in this concentration by country over a 50-year period (1965-2015).

Table A.2: Main variables, descriptive statistics (Global panel, national level data)

Panel A: Climatic variables

	Obs.	Mean	Std. Dev.	Min	Max
5-year panel:					
Temperature (area-weighted)	1,859	18.10	8.42	-7.38	29.14
Temperature (pop-weighted)	1,859	18.36	7.48	-2.26	29.34
Rainfall (area-weighted)	1,859	1015.54	735.18	27.35	3331.46
Rainfall (pop-weighted)	1,859	1027.94	661.45	31.17	3361.95
50-year changes:					
Temp 50-y	143	0.84	0.34	-0.08	1.73
Rain 50-y	143	-8.27	107.96	-383.00	437.00

Panel B: Income inequality variables

	Obs.	Mean	Std. Dev.	Min	Max
5-year panel:					
Gini	1,859	44.28	11.84	15.16	77.09
Top10	1,859	34.99	10.00	16.66	68.77
Middle50	1,859	50.12	5.26	28.11	60.30
Bottom40	1,859	14.90	5.32	1.95	30.55
50-year changes:					
Gini 50-y	143	-0.90	7.07	-21.76	15.71
Top10 50-y	143	-1.37	5.68	-16.84	8.96

Panel C: Inequality in Life Expectancy

	Obs.	Mean	Std. Dev.	Min	Max
5-year panel:					
IneLifeExp	282	16.41	12.15	2.72	48.62

Notes: Temperatures here are in degrees Celsius, and rainfall in mm. 50-year changes are calculated as the change from 1965-2015 (change in 5-year averages for climatic variables). Variables in Panel B are from the WIID data, while Inequality in Life Expectancy (Panel C) is from the UN's HDR data, as described elsewhere.

Table A.3: Descriptive statistics, additional datasets

Panel A: Sub-national data

	Obs.	Mean	Std. Dev.	Min	Max
US – state level (2010, 2015, 2020)					
Temperature	147	12.07	4.60	-0.50	23.60
Gini	147	46.06	1.90	41.90	51.38
US – county level (annual: 2010-2019)					
Temperature	2,440	13.51	4.47	-2.64	25.47
Gini	2,440	44.62	3.57	32.88	60.11
Russia – region level (2010, 2015, 2020)					
Temperature	241	3.72	4.97	-11.05	12.43
Gini	241	38.05	2.72	32.80	50.50
Spain – region level (2000, 2006, 2010, 2015, 2020)					
Temperature	75	14.78	2.27	11.57	19.26
Gini	75	31.13	4.05	23.00	44.80

Panel B: Wealth inequality

Top 10 wealth (WID)	680	63.23	7.43	40.84	81.71

Panel C: Spatial inequality (nightlights)

SpatialGini1sqkm	810	0.51	0.21	0.05	0.94
SpatialGini1pc	810	0.30	0.16	0.03	0.90
SpatialGini2sqkm	738	0.67	0.19	0.16	0.96
SpatialGini2pc	738	0.41	0.14	0.09	0.88

Notes: In Panel A, the inequality data are based on official national statistics of each country. In Panel B, wealth inequality is from WID, while in Panel C the spatial inequality measures are constructed using night lights data, as described in Appendix A above.

Appendix B

Table B.1: Balance tests, Global Sample (N=143)

	Low Warming (1)	High Warming (2)	Difference (1) – (2)	t-stat
Log(GDPpc)	7.86	8.55	-0.69***	4.12
Urb Rate %	27.46	42.08	-14.61***	4.11
Fertility rate	6.03	4.81	1.22***	4.15
Agri Share %	30.23	19.53	10.70***	3.47

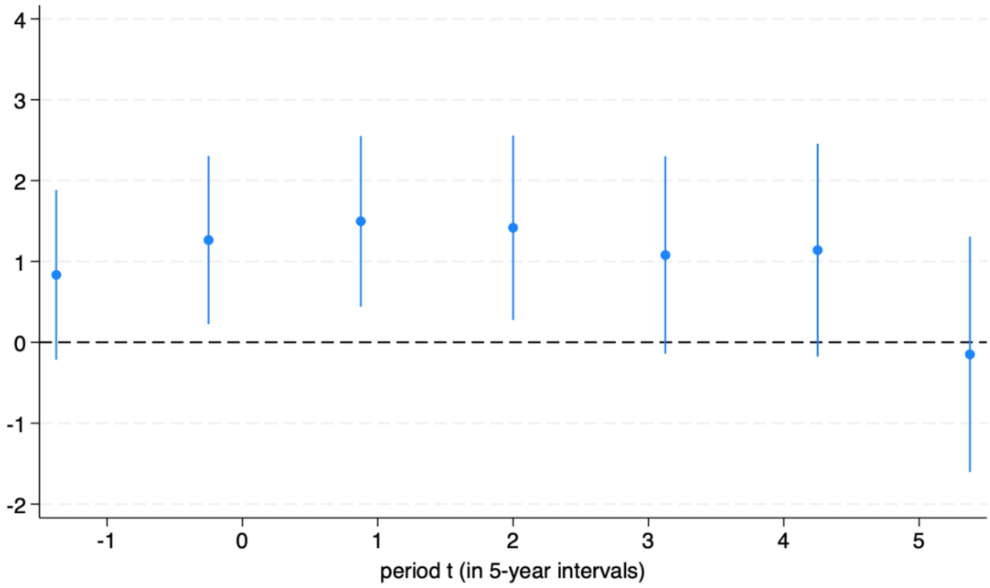
Note: The table shows the mean value (in columns 1 and 2) of each variable for the earliest observation in the data, across countries with above and below median warming over 1965-2015 in our data.

Table B.2: Robustness to Long-difference results

	(1) Deep FD	(2) Deep FD	(3) Deep FD	(4) Deep FD
Dependent variable: Top10 (50y change)				
Temperature	3.963***	3.638**	3.453*	4.173**
(50y change)	(1.282)	(1.805)	(1.828)	(1.930)
Region FE	NO	YES	YES	YES
Initial climate	NO	NO	YES	YES
Controls	NO	NO	NO	YES
Observations	143	143	143	133

Note: This table reports results of deep first difference specifications as in Equation (1). Variables are calculated as the change over a 50-year period (1965-2015). Initial climate includes average annual temperature and rainfall at the beginning of our sample (1960-1964). Controls include changes in average rainfall and GDP per capita growth over the 50-year period, as well GDP per capita, export share and agricultural valued added (to GDP) in levels (each lagged one period). Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure B.1: Event-style analysis for temperature and Gini



Note: The figure shows estimated coefficients (and 95% confidence intervals) on temperature from separate regression estimates of equation (2) for the first lead, contemporaneous and up to five lags of temperature. In each regression we control for average annual precipitation, and include country and year fixed effects. Standard errors are clustered by country in each case.

Table B.3: Alternative time periods and panel specifications

	(1) Temporal placebo	(2) 1980+	(3) 1990+	(4) Region-specific trends	(5) Country-specific trends	(6) Dynamic Model
Dependent variable:	Gini	Gini	Gini	Gini	Gini	Gini
Temperature	0.834	1.495**	1.261**	0.948**	0.922***	0.647**
	(0.531)	(0.591)	(0.606)	(0.448)	(0.332)	(0.253)
L.Gini						0.835***
						(0.0224)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Time-trends	NO	NO	NO	YES	YES	NO
Observations	1,716	1,144	858	1,859	1,859	1,716
Countries	143	143	143	143	143	143

Note: This table reports results of specifications based on Equation (2) and as described in the text. The dependent variable in each column is the Gini coefficient. Temperature is average temperature in degrees Celsius over the preceding 5-year period. All specifications control for average rainfall. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.4: Robustness to different time-varying controls

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Gini	Gini	Gini	Gini	Gini
Temperature	1.280**	1.294**	1.305**	1.444***	1.014**
	(0.534)	(0.531)	(0.529)	(0.491)	(0.473)
L.GPDpc	0.586	1.089	0.464	5.536	5.303
	(0.528)	(3.007)	(3.247)	(3.665)	(3.743)
L.GPDpc^2		-0.0285	0.00378	-0.261	-0.234
		(0.166)	(0.179)	(0.203)	(0.207)
L.Pop			2.62e-09	6.13e-09**	5.52e-09*
			(3.13e-09)	(3.06e-09)	(3.18e-09)
L.Fertility				0.994***	0.889***
				(0.285)	(0.289)
L.Urb					-0.107**
					(0.0461)
Year FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Observations	1,716	1,716	1,716	1,566	1,551
No. of countries	143	143	143	143	141

Note: This table reports results of specifications based on Equation (2) and as described in the text. The dependent variable in each column is the Gini coefficient. Temperature is average temperature in degrees Celsius over the preceding 5-year period. All specifications control for average rainfall. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.5: Panel First-Difference (FD) specification

	(1) FD	(2) FD	(3) FD
Dependent variable:	Gini_g	Gini_g	Gini_g
Temperature	1.731***	2.156***	2.494***
	(0.451)	(0.523)	(0.620)
Time FE	NO	YES	YES
Controls	NO	NO	YES
Observations	1716	1716	1400
No. of countries	143	143	140

Note: This table reports results first-difference specifications. All variables are defined as changes over 5-year periods. Temperature is average temperature in degrees Celsius over the preceding 5-year period. All specifications control for (changes in) average rainfall. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.6: Warming and income inequality, heterogeneity

	(1)	(2)	(3)	(4)
Dependent variable:	Gini	Gini	Gini	Gini
	Cross-section		Dynamic	
Temperature	-0.300	0.905	1.856***	1.503**
	(3.672)	(0.875)	(0.709)	(0.708)
Temperature*GDPpc	0.182		-0.088	
	(0.417)		(0.056)	
Temperature*Agr		-0.0194		0.001
		(0.025)		(0.005)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	1859	715	1716	572
No. of countries	143	141	143	143

Note: The dependent variable in each case is the Gini coefficient (as reported by WIID). Temperature is average temperature in degrees Celsius over the preceding 5-year period. In columns (1) and (2) we allow for cross-sectional differences in the temperature-Gini relationship by interacting temperature with initial (earliest available) value of *GDPpc,* GDP per capita in logs, for each country in the data (in column 1) and with initial employment share in agriculture *Agr*, again taking the initial (earliest available) value for each country in the data (in column 2). In columns 3 and 4, we allow for dynamic differences in temperature-inequality relationship over time by interacting temperature with lagged values of *GDPpc* and *Agr*. In columns 3 and 4, the lagged values of *GDPpc* and *Agr* are also included as separate controls. All columns control for rainfall. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.7: Warming and income inequality, subnational results

Panel A: US (state-level)

Dependent variable:	Gini	Gini	Gini
Temperature	0.236***	0.234***	0.281***
	(0.0305)	(0.0307)	(0.0463)
Year FE	NO	YES	YES
Region FE	NO	NO	YES
Observations	147	147	147
No. of FE units			4

Panel B: US (county-level)

Dependent variable:	Gini	Gini	Gini
Temperature	0.185***	0.184***	0.198***
	(0.0216)	(0.0217)	(0.0749)
Year FE	NO	YES	YES
State FE	NO	NO	YES
Observations	2,440	2,440	2,440
No. of FE units			49

Panel C: Russia (region-level)

Dependent variable:	Gini	Gini	Gini
Temperature	-0.132***	-0.125***	-0.163*
	(0.0440)	(0.0445)	(0.0939)
Year FE	NO	YES	YES
Fed District FE	NO	NO	YES
Observations	241	241	239
No. of FE units			8

Panel D: Spain (region-level)

Dependent variable:	Gini	Gini	Gini
Temperature	0.885**	0.737***	0.717*
	(0.313)	(0.230)	(0.382)
Year FE	NO	YES	YES
NUTS 1 FE	NO	NO	YES
Observations	75	75	75
No. of FE units			7

Note: This table reports results of specifications based on Equation (2) and as described in the text. The dependent variable in each case is the Gini coefficient (based on official national statistics of each country). US county level inequality data are an annual panel (2010-2019), but for the purposes of the analysis here we only use the observed values in 2010, 2015 and 2019. Russian data are for administrative regions. These and the US state-level data include observations for three periods (2010, 2015, 2020). The Spanish data are for autonomous regions and include five periods (2000, 2006, 2010, 2015 and 2020). Temperatures are measured in degrees Celsius. Weather data for the US are from NOAA, based on county level data, available here: https://www.ncei.noaa.gov/pub/data/cirs/climdiv/, while regional weather data for Russia and Spain are from the World Bank's Climate Change Knowledge Portal (based on original data from CRU). As usual, we aggregate the weather data to the preceding 5-year period: i.e. we match 2010 inequality with average weather conditions for 2005-2009, 2019 inequality (US counties) is matched to weather from 2015-2018, while 2006 inequality (Spanish regions) is matched to weather data from 2001-2005. Robust standard errors (clustered by spatial unit) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.8: Warming and spatial concentration of economic activity

	(1)	(2)	(3)	(4)
Dependent variable:	SpatialGini1sqkm	SpatialGini1pc	SpatialGini2sqkm	SpatialGini2pc
Temperature	0.020**	0.032**	0.004	0.018*
	(0.009)	(0.013)	(0.008)	(0.011)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	816	816	744	744
No. of countries	136	136	124	124

Note: In columns 1 and 2 the spatial gini is calculated using first-level subnational divisions (i.e., gadm1 maps), while in columns 3 and 4 using second-level subnational divisions (i.e., gadm2 maps). In columns 1 and 3, we use area-weighted spatial ginis, while in columns 2 and 4 we use population-weighted spatial ginis. Temperature is average temperature in degrees Celsius over the preceding 5-year period. All columns control for rainfall. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix C

Table C.1: Warming and concentration of income (controlling for country-specific trends)

	(1)	(2)	(3)
Dependent variable:	Top10	Middle50	Bottom40
Temperature	0.527**	-0.00412	-0.523***
	(0.259)	(0.180)	(0.175)
Year FE	YES	YES	YES
Country FE	YES	YES	YES
Country-specific trends	YES	YES	YES
Observations	1,859	1,859	1,859
No. of countries	143	143	143

Note: This table reports results of specifications based on Equation (2) and as described in the text. Temperature is average temperature in degrees Celsius over the preceding 5-year period. All specification control for rainfall and its lag. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.2: Warming and wealth inequality, panel results

Panel A:

Dependent variable:	Top10_wealth	Top10_wealth	Top10_wealth	Top10_wealth
Temperature	0.382***	0.457***	0.479***	0.652
	(0.065)	(0.073)	(0.073)	(0.525)
Year FE	NO	NO	YES	YES
Country FE	NO	NO	NO	YES
Observations	680	665	660	660
No. of countries	136	133	132	132

Panel B:

Dependent variable:	Top10_wealth	Top10_wealth	Top10_wealth	Top10_wealth
Temperature	-0.336	-0.201	-0.342	0.504
	(0.466)	(0.304)	(0.306)	(0.537)
L.Temperature	0.716	0.682**	0.835***	1.576***
	(0.457)	(0.296)	(0.296)	(0.539)
Year FE	NO	NO	YES	YES
Country FE	NO	NO	NO	YES
Observations	678	663	660	660
No. of countries	136	133	132	132

Note: This table reports results of specifications based on Equation (2) and as described in the text. The dependent variable is the concentration of wealth (as reported by WID). Temperature is average temperature in degrees Celsius over the preceding 5-year period. Columns 2 onwards weight climate by population. All specifications control for average rainfall. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix D

Table D.1: Pairwise correlations, inequality and alternative development outcomes

	gini	stability	iconflict	unempl.	undernur	inf_mort	tubercu
stability	**-0.15**						
iconflict	**0.41**	0.38					
unemployment	**0.09**	-0.06	-0.06				
undernur	**0.53**	0.02	-0.38	0.01			
inf_mortal~y	**0.51**	-0.28	-0.50	-0.08	0.73		
tubercu	**0.45**	0.09	-0.19	0.22	0.44	0.55	
malaria	**0.41**	0.12	-0.10	-0.21	0.32	0.69	0.13

Table D.2: Warming and alternative outcomes

Panel A:

Dependent variable:	Stability	Corruption	IntConflict
Temperature	-0.523**	0.4000***	1.012***
	(0.222)	(0.137)	(0.313)
Year FE	YES	YES	YES
Country FE	YES	YES	YES
Controls	YES	YES	YES
Observations	830	830	830
No. of countries	121	121	121

Panel B:

Dependent variable:	Undernurish	InfMortality	MotherMortality	Tuberc	Malaria
Temperature	1.724*	7.061***	37.988**	19.818*	44.092**
	(1.008)	(2.524)	(18.151)	(11.079)	(21.878)
Year FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	381	1436	840	564	359
No. of countries	127	140	140	141	91

Note: This table reports results of specifications based on Equation (2) and as described in the text, but changing the outcome variable. *Stability* and *IntConflict* here go from 0 (low) to 12 (high). Temperature is average temperature in degrees Celsius over the preceding 5-year period. Controls include rainfall, GDPpc and its square, total population, fertility rates and urban rates. Robust standard errors (clustered by country) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0$.

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