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# Climate impacts on material wealth inequality: Global evidence from a subnational dataset

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**Abstract**

Worsening climatic conditions are a significant threat to livelihoods, health and well-being worldwide. In this paper, we estimate the impact of temperature and precipitation anomalies on inequality and poverty using a dataset combining comprehensive climatological data with subnational regional wealth and inequality measures derived from the Demographic and Health Surveys for 52 countries and 453 regions. Using the International Wealth Index as a comparative measure of material wealth, we find a significant impact of temperature anomalies on the distribution of material wealth. We estimate that an average temperature anomaly of one standard deviation in the past 4 years increases the regional Gini coefficient by 0.018 points and increases the share of extremely poor households by 4.1 percent. The impacts are stronger in rural areas. We find that temperature anomalies affect inequality through multiple channels, including agricultural employment, the deterioration of assets, decreased economic activity, higher unemployment and worsened access to healthcare. The impacts of precipitation anomalies on inequality, on the other hand, are more ambiguous.

**Keywords** Environment, Inequality, Regional Development

**JEL codes:** Q56, I31, R11

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# 1 Introduction

Climate change will exacerbate the frequency, intensity, duration, and spatial extent of environmental hazards (Cramer et al., 2018; Field et al., 2012). This will affect populations worldwide with major implications for health, food, water security, jobs, productivity and well-being. These impacts are obviously not distributed equally across space and populations. Less developed regions are typically more exposed to hazards and more vulnerable because they lack the adaptive capacity to adequately prepare for and cope with the consequences. Within these regions, it is often the poorest parts of the population that suffer the most (Tol, 2018). Previous research has shown that environmental hazards can have important impacts on resource allocation within households (Doss, 1996; Hadley et al., 2008) and on the wealth distribution between households in a community (Reardon and Taylor, 1996; Thiede, 2014; Sedova et al., 2019). Higher levels of inequality can increase social tensions and result in conflict (Cramer, 2003; Lessmann, 2016), further destabilizing affected regions.

However, little is known about the effects of climatic events on inequality on a wider geographical scale and over time (Islam and Winkel, 2017). It is crucial to gain a better understanding of these processes as these relationships are central to estimating the damage function of current and future climate change. Our study explores the impact of temperature and precipitation anomalies on material wealth inequality within regions across a large set of countries. Our analysis exploits the Demographic and Health Surveys (DHS), a standardized survey framework which disproportionately samples the poorest countries of the world, but also includes observations on lower middle-income and middle-income countries in Africa, Latin America, South and Southeast Asia and Eastern Europe. Our approach produces comparable estimates for a sample covering the earliest stages of development up through to the lower middle range of the world income distribution. We construct a subnational panel dataset that allows us to test for the effects of anomalies on the wealth distribution within regions. In total, we obtain data for 453 subnational regions with information on more than 3.5 million households. DHS surveys are collected every three to six years[1] from 1990 to 2019 depending on the country, resulting in an unbalanced time series covering a period of 30 years.

DHS surveys collect rich data on households and their individual members. Based on this information, we construct a material wealth index at the household level that captures a level of material assets that allow for a decent living. We use information on household

[1] This rule can be broken in some rare cases with a maximum variation of one year.

assets following a methodology developed for the International Wealth Index (IWI), which is comparable across countries and over time (Smits and Steendijk, 2015). Based on the information on material household wealth, we calculate inequality measures (e.g., Gini coefficient) at the regional level that reflect the material wealth distribution within regions in our sample. The material wealth indices constructed based on DHS surveys focus on household consumption. Important assets such as homeownership or financial holdings are not included, as they are not available at the household level.

We use high-resolution, high frequency climate data from the Climate Research Unit of the University of East Anglia (Harris et al., 2014) to calculate the occurrence and intensity of temperature and precipitation anomalies for each region. Combining the regional climate and inequality data, we analyze the extent to which changes in material wealth inequality are driven by climate anomalies that have occurred in the period prior to a DHS survey. The extensive microdata provided in the DHS allow us to explore the underlying mechanisms influencing the direction and size of the relationship.

We find that temperature anomalies increase both inequality and the share of poor households within regions. A temperature anomaly of one standard deviation in the previous 4 years leads to an increase in the regional Gini coefficient by 0.018 points and an increase in the share of the poorest households by 4.1 percent. The effects on inequality are found to be stronger for climate anomalies that persist over longer time windows, including for 60 months (0.018 points), 72 months (0.031 points) and 84 months (0.048). In rural regions, households are particularly vulnerable to temperature anomalies, leading to an increase in material asset-based wealth inequality of 0.039 points, a decrease in mean wealth by 0.019 points, and an increase in the share of the poorest households by 6.7 percent. Poorer, more equal and colder regions tend to be more affected by temperature anomalies. Distributional impacts increase over time, with the strongest inequality-enhancing effects observed in the last two decades.

We test multiple channels for these results. We test the socioeconomic channel and decompose the wealth effects into different asset subcategories to understand which assets are most likely to be affected by climatic events. Our analysis shows that temperature anomalies affect inequality through multiple channels, including decreased economic activity, higher unemployment, and worsened access to healthcare. Decomposing the wealth effects into different asset subcategories also shows that temperature anomalies affect households' material assets and diminish resilience. They lead to a reduction in electronic assets (in particular cheap electronics, such as telephones) and to a deterioration in housing facilities. These assets could be either directly affected through long periods of heat, not renewed

or maintained due to income shocks, or sold by households for consumption smoothing. Individuals employed in agriculture are more affected by temperature anomalies, seeing a larger decline in their wealth. Thus, selling assets to compensate for an income shock and to smooth consumption seems to be a likely scenario.
We also test for migration by checking whether weather anomalies lead to compositional demographic changes according to gender, education and age. We find evidence that a small part of the population seems to be responding to temperature shocks by migration: temperature anomalies do not seem to impact the educational and gender composition of a region but do seem to affect the age composition by a small amount. When controlling for these compositional changes, the main results are consistent and barely change in size.
We also rule out conflict as a mechanism through which climate affects inequality: while recent work has argued that climate affects conflict (Burke et al., 2015), we find no evidence that conflict is driving our results.
The remainder of this paper is structured as follows. In Section 2, we provide an overview of the previous literature and discuss our conceptual framework. Section 3 introduces the data and measures used in our analysis. Section 4 presents our research design and estimation strategy and we present our results in Section 5.

## 2 Literature

The literature on the distributional effects of environmental hazards has grown over the past years. Papers have studied the impacts of different hazards on inequalities mostly between countries. The findings show contrasting climatic effects on inequality depending on local contexts and the measure of wealth used.
At the national level, climatic changes and extreme events have been shown to exacerbate global inequality between rich and poor countries as measured through GDP per capita (Mendelsohn et al., 2006) and economic output (Diffenbaugh and Burke, 2019). Using a panel of countries from 1992 to 2018, Cappelli et al. (2021) find that higher levels of income inequality, as measured with the Standardized World Income Inequality Database (SWIID), are associated with a greater number of people affected by disasters and of fatalities. Limited evidence exists as to changes in inequality at the subnational level.
Within countries, it is often the poorest that suffer the most (Tol, 2018). Poor households are more likely than richer households to be located in disaster-prone areas due to lower housing costs, greater accessibility of jobs, and the importance of social networks in the choice of relocation following a disaster (Patankar, 2015). In addition, poor households

are more vulnerable to disasters and have a reduced ability to cope with and recover from losses (Hallegatte et al., 2016, 2018, 2020).

At the micro-level, environmental hazards have important distributional impacts on the resource allocation within and between households in a community (Doss, 1996; Hadley et al., 2008). Most studies focus on one catastrophic event and assess whether the related damages widen inequality (Baez and Santos, 2007; Belasen and Polachek, 2009; Mottaleb et al., 2013; Sakai et al., 2017; Thiede, 2014). Given the unreliability of income data, especially in developing countries, alternative measures have been utilized to assess wealth disparities like nightlight satellite data or composite wealth indices derived from asset ownership (Narloch and Bangalore, 2018).

The development of wealth indices only started in the late 1990s when systematic surveys were carried out by large organisations like the World Bank. These indices are based on the notion that the possession of assets reflect a household's material and physical wealth and wellbeing. Filmer and Pritchett (1999, 2001) were the first to use principal component analysis of assets to create country-specific wealth indices. Studies using these methods yield mixed findings: while some papers find that disasters decrease inequality in income as poorer households sell assets, recording a temporary increase in earnings (Reardon and Taylor, 1996; Keerthiratne and Tol, 2018), other studies find no effect (Thiede, 2014) or a positive effect on inequality (Gilli et al., 2024; Palagi et al., 2022; Dang et al., 2023; Castells-Quintana and McDermott, 2023). Climatic hazards can affect the level and distribution of asset-based wealth outcomes in various ways: households can choose to sell non-productive assets for consumption smoothing in times of distress (De Waal, 2005; Watts and Bohle, 1993). Assets can also be directly affected or damaged by a hazard, for example through destructions of properties. While wealthier households may be relatively worse affected by the latter effects in absolute terms, as they are more often houseowners and have a higher income (Hallegatte et al., 2020), poorer households are more vulnerable and hence suffer more from the impacts in relative terms. Hazards may also prevent affected poor households from expanding their asset-based wealth (e.g., by restricting their access to credit) further contributing to an increase in inequality (Patankar and Patwardhan, 2016). These ambiguous results highlight the need for more investigations into the distributional impact of climatic events and their relevance across different populations within countries (Kousky, 2014).

A more limited body of work has analysed the persistence of the effects of climatic shocks. Sustained anomalies, including long-lasting droughts, have been shown to lead to shocks in the agricultural sector and to damage cropland and animals in North Brazil (Piedra-Bonilla et al., 2021). Studies have shown that climatic hazards can have lasting negative effects on economic output, labour productivity and asset growth for more than five years (Acevedo et al., 2020; Donadelli et al., 2017).

Using data from Ethiopia and Honduras, Carter et al. (2006) find a drop in disposable income in the short run after a disaster event due to crop failures, increased medical expenditure and assets or land being destroyed. In the medium run, they find that climate shocks increase asset inequality in Honduras, with the poor struggling to rebuild their assets while richer households are better at protecting their assets during a shock or selling assets to smooth consumption. The extent of the asset loss depends on whether affected households can engage in other coping strategies as well as changes in asset prices over time (Carter et al., 2006). When looking at assets, we would therefore expect to see an effect over the medium to long run once households have used up their disposable income or savings. More frequent, persistent and long-lasting shocks would further decrease households' ability to exploit other coping mechanisms and exacerbate the impact on assets.

In addition to directly reducing asset-based wealth, climatic hazards can also exert an indirect effect on wealth inequality, through the out-migration of affected households. This is particularly problematic if migration depends on the wealth of the household, thereby changing the composition of the population in a region. This would in turn bias the econometric estimation of climatic impacts on wealth and inequality over time. Studies interested in the socio-economic impacts of hazards therefore need to test and account for such migration patterns (Bohle et al., 1994; Watts and Bohle, 1993). Indeed, several studies find that environmental hazards affect migration, although a decline in migration has been reported in some studies (Cattaneo, 2019; Berlemann and Steinhardt, 2017; Borderon, 2019). Hoffmann et al. (2020) quantitatively analyse the influence of environmental factors on migration through a meta-analysis of country-level studies and find that a one standard deviation change in the environmental conditions leads to an increase in migration by 0.021 standard deviations. They find that migration is primarily internal, or occurs within neighbouring low- and middle-income countries.

Our study employs the asset-based International Wealth Index (Smits and Steendijk, 2015) which employs principal component analysis to make wealth levels comparable across countries and time. We provide novel evidence that temperature anomalies impact material wealth assets and housing characteristics through multiple channels, which increases the difficulty for households to posses assets that allow for a decent living. Regional economic output, agricultural employment, unemployment and access to healthcare are affected by temperature anomalies. We also look at migration by studying regional composition changes. We find evidence that supports a story of migration among the young, but our main results hold when accounting for these changes. Our study also contributes to the literature on the duration of climatic shocks. Our paper adds to this literature and finds that the effects of temperature anomalies on inequality are found to be stronger for anomalies that persist over longer time windows (60 months or longer). We find evidence for agricultural employment, effects on economic output, unemployment and access to healthcare.

# 3 Data and Measurement

We combine asset and wealth data from the Demographic and Health surveys (DHS), GDP data from satellite date (Kummu et al., 2018) and environmental hazards data from the Climate Research Unit gridded data. We describe these datasets below.

## 3.1 Asset and wealth data

We measure the material and physical well-being of households using the household level Demographic and Health surveys (DHS). Rolled out by USAID, these surveys cover more than 90 low- and middle-income countries representing about 23% of the world population (Croft et al., 2018). We use data for those countries for which longitudinal information covering several time periods is available. In total, the data employed covers 52 countries (see the Summary Statistics Table 9) with 453 subnational regions.

DHS surveys are repeated cross-sectional surveys every 3 to 6 years from 1988 until 2017 resulting in a repeated cross-section. They provide nationally representative and standardized data on health, population and several socioeconomic variables in low- and middle-income countries. DHS also includes a limited set of household characteristics including the size of the household (number of occupants) and whether or not the household is located in an urban or rural setting.

DHS surveys also contain a geographic identifier, which provides the approximate coordinate location of the survey cluster. There are typically 500–1000 survey clusters in a country, with each cluster containing around 25 households.[2]

Based on the DHS data, we construct two datasets for our analysis. First, we build a macro-level dataset at the subnational regional level. For this, we use harmonized regional iden-

[2] To guarantee the anonymity of the interviewed households, the geographical locations of the clusters are randomly allocated by DHS within a radius from the real location of a maximum of 2km for urban areas, and 5km for rural areas. One limitation of the DHS dataset for our analysis is that large cities usually form one unit, while smaller cities are combined with rural areas. If weather shocks impact large cities less, and if large cities have a higher Gini coefficient, this might bias our effects downwards.

tifiers to study regional observations over time, even if regions' boundaries have changed (Belmin et al., 2021). Using the harmonized region IDs, we aggregate the DHS micro household data to the subnational regional level obtaining aggregate measures on overall wealth and its distribution. Combining this data with the information on climatic impacts prior to the DHS using harmonized regional boundary shapefiles allows us to test to what extent changes in environmental conditions and anomalies have influenced wealth and inequality within the regions over time and to explore heterogeneity by regions' characteristics.

Second, in addition to the regional database, we also make full use of the DHS micro data at the individual level to explore some of the underlying mechanisms. As shown in the previous literature, population groups are impacted differently by extreme events with implications for the wealth distribution in an area. Using the detailed DHS microdata on household and individual characteristics, including socioeconomic status, agricultural dependency, and household composition, allows us to test not only whether climatic shocks have an impact on wealth and its distribution, but also for whom and where.

## 3.2 Wealth Index construction

To measure the level of inequality within a region, we first construct a composite wealth measure at the household level, which allows us to determine the wealth distribution between households. For this, we rely on the methodology of the International Wealth Index (IWI) (Smits and Steendijk, 2015). The index expands the standard DHS household level wealth index and makes it comparable over time and across countries.

The IWI was developed with the idea that wealth can be defined by global material requirements needed for living a decent life. It is based on each household's possession of a standard set of assets such as housing construction materials, quality of water access and sanitation facilities, consumer durables, cheap utensils that reduce the workload, electricity and more. In total, twelve assets are used to create a wealth score for each household, grouped into three categories: consumer durables, housing characteristics and public utilities.

The selection of the twelve assets is a function of the availability, clumpiness, and dimensionality of the data. Each indicator is assigned a weight derived from a principal component analysis in Smits and Steendijk (2015). The weights reflect the possibility that a household that owns one specific asset also owns other selected assets. By summing up the differently weighted assets and items, a household wealth score can range between 0 and 100.[3] Not all DHS surveys contain information for all the selected asset classes, so we normalize the index by dividing it by the maximum possible value the wealth index could take given the indicators available in a given country survey. We do this by summing up the positive weights derived from the principal component analysis, which gives us the denominator of our wealth index (the weights are shown in the Appendix Figure 6). We run robustness tests on the sample of countries for which we have at most one missing asset item across every survey year and our results are not sensitive to this restriction (see Table 17).

The first factor loading of the IWI explains 30 percent of the variation in assets, which is higher than the percentages generally obtained using country-specific indices (26% Filmer and Pritchett (2001); 27% McKenzie (2005); 24–27% Córdova (2009)). The principal component analysis can also be country-specific if we consider that the dimensionality and underlying understanding of wealth are not universal. For our analysis, comparability over time and across countries is derived from using the weights from the International Wealth Index. In addition, we run a region fixed-effects model that accounts for time-invariant region-specific characteristics.

Based on the index of household assets, we create aggregate regional measures of inequality. Our main outcome, the Gini coefficient of material wealth, is based on the Lorenz curve, which plots the cumulative percentage of income (of the wealth index) over the cumulative percentage of the population, and compares it with a uniform distribution. The Gini coefficient has a number of weaknesses often highlighted in the inequality literature, two of them are of importance to our study. The main weakness of using the Gini as a measure of inequality is that it describes the whole distribution in one number and tends to be more sensitive when it comes to changes in the middle of the distribution (Sen, 1997). In order to improve on this limitation and understand what parts of the wealth distribution are affected, we additionally create measures that describe the share of households below a certain cutoff point, e.g. below 0.2. This describes the share of households below a wealth index score of 0.2, the tail of distribution, which serves as a poverty measure. In order to uncover what happens to the material distribution of wealth when the Gini coefficient increases, we investigate micro-level asset data in Section 5.5. The second main limitation of applying a Gini-like inequality measure to our index are comparability issues (Young,

[3] For example, the weight assigned to owning a car is lower than the weight assigned to a television or a refrigerator. This is explained by the fact that the probability for a household to own a car once they own a television and a refrigerator is high, hence the car does not provide more information about the wealth of the household. On the other hand, the ownership of a television and a refrigerator is more discriminatory between income groups

2013). This would be a greater concern if we used principal components analysis, however we construct an index that applies the weights of a PCA to a basket of assets so the inequality measure is calculated off a weighted average rather than a principal component. We then apply the same weights across all regions to ensure the orders of magnitude are comparable between regions. The fact that we standardise the index by the number of available assets introduces some noise, as we apply a distribution based measured to different standardised distributions but we consider this a worthwhile trade-off to capture as many assets available in the surveys.

The asset-based wealth indices constructed from DHS surveys have several limitations. The index of wealth is truncated, to the extent that there is nothing to discriminate between wealthy households who own all assets of the highest quality. While assets such as 'expensive utensils', defined as the possession of expensive (roughly over 250 US dollar) items - e.g. a washer, dryer, computer, motorbike, motorboat, air conditioner, or generator - are meant to create more discriminatory power at the upper end of the wealth distribution, the discriminatory power is still limited. Financial assets or loans are not captured in the DHS surveys and one of the key assets, home ownership, is not recorded in a systematic way in the DHS surveys.[4] As the impact of environmental hazards has been shown to impact property values, our results on inequality are downward biased, as we would expect hazards to decrease the values of properties for homeowners and leave renters' wealth the same.

At its inception, the index was reported to have had low discriminatory power at the bottom of the wealth distribution (Rutstein, 2008). As a result, cheaper assets - e.g. chair, table, fan or mixer - were included in later surveys to be able to better differentiate among the poorest groups. These were used in the International Wealth Index.

We present the summary statistics of the data in Table 9, Figure 7, Figure 8 and Figure 9.

## 3.3 Further socioeconomic data

We use gridded data on regional GDP per capita and human development derived from Kummu et al. (2018) to capture the additional impact of anomalies on the mean distribution of wealth in a subnational region. This dataset comes with certain limitations. Temporal coverage of the national and subnational data varied between countries so they use temporal interpolation and extrapolation approaches to fill the missing values. They also had to make assumptions to translate national data sources to regional level data. To estimate the total

[4]Note that the Gini coefficient was designed to characterise a distribution of wealth over the cumulative population, and that if our wealth index is truncated at the top, our measure of inequality represents how equal that truncated distribution of wealth is. In addition, wealthier households might use financial assets such as insurance products to mitigate and adapt to environmental hazards and these will not be captured in our data.

GDP (PPP) of each grid cell, Kummu et al. (2020) multiply the GDP per capita (PPP) by grid specific population data using two different spatial resolutions, from HYDE 3.2 and from GHS population grid. The additional assumptions and methods used to produce this dataset can be found in Kummu et al. (2018). In addition, as the data covers only the period 1990-2015, we are missing data for the most recent DHS observations. Our results using GDP per capita as an outcome are shown in the Table 6.

### 3.4 Environmental hazards: climate anomalies

In the last decade, studies have exploited high-frequency (e.g., month to month) changes in temperature, precipitation, and other climatic variables to identify the causal short-term economic impacts of weather shocks using panel methodologies. We follow best practice in measuring environmental hazards causally (for a full review, see Dell et al. (2014) exploiting exogenous variation in climatic shocks over time within a given spatial area, on regional inequality).

The most standard type of climate data are sourced from ground stations, which usually directly observe temperature, precipitation, and other weather variables. One important challenge posed by ground station data is incomplete coverage, particularly in low-income countries or in areas with sparse population density. As a result, climate scientists have developed a variety of gridded data products, which interpolate ground station data over a grid.[5]

We use the Climate Research Unit (CRU TS 4.05) gridded data[6]. The data are provided in a raster format covering all land areas at a 0.5° spatial and monthly temporal resolution[7]. From this dataset, we create a balanced panel on temperature and precipitation levels at the subnational regional level from 1900 to 2020.[8] The spatial coverage of precipitation data is limited and more time-dependent so the temporal and spatial aggregation and interpolation is noisier than it is for temperature anomalies (CRU TS 4.05).

[5]As gridded data interpolates ground station data, it suffers from similar limitations in areas where ground station data are sparse (e.g. some developing countries). Interpolation methods uses distance-weighting from weather stations and do not use elements of wealth or built-up areas, removing concerns that predictions might bias our estimation strategies. Precipitation has a greater spatial variation than temperature, especially in rugged areas, so the interpolation introduces more measurement error.

[6]Of the University of East Anglia and of Willmott, Matsuura at the University of Delaware (UDEL)

[7]While satellite data can provide complementary climate data for areas with a limited ground network, satellite data were introduced more recently and ground station is more accurate than the satellite data (Houghton et al., 2001; Karl et al., 2006)

[8]While satellite data can provide complementary climate data for areas with a limited ground network, satellite data were introduced more recently and ground station is more accurate than the satellite data (Houghton et al., 2001; Karl et al., 2006)

Our study considers climate anomalies, where the climate variable is calculated as its level difference from the within-region mean and divided by the within-region standard deviation.

The nominator — the difference in mean - is partly captured by the panel model. The denominator scales the difference by the historical standard deviation of that climate variable for that month. This follows the underlying "climate-economy model" (Dell et al., 2014) where level changes matter not in an absolute sense but relative to an area's usual variation. Due to the standardization, the order of magnitude of these anomalies can be compared across countries and regions. In addition, they reflect climatic impacts that are relevant to local populations as they accurately reflect deviations and extremes on the ground (Hsiang and Jina, 2014; Dell et al., 2014; Hoffmann et al., 2021).

Based on this data, we calculate for each region $r$ for a given month $m$ deviations in temperature and precipitation ($X_{rmy}$) from the long-term monthly mean over the reference period 1900-2020 ($\overline{X}_{r,m_{1900-2020}}$). We then calculate for each month in a year $y$ the long run standard deviation $SD_{rm_{1900-2020}}$ for the entire reference period and standardise our mean deviations using the following formula:

$$Anomaly_{rmy} = \frac{X_{rmy} - \overline{X_{rm}}_{1900-2020}}{SD_{rm_{1900-2020}}} \tag{1}$$

Our main independent anomaly variable then sums these monthly standardised mean anomalies (of temperature and precipitation) over the 48 months prior to the survey date. There are two main reasons to focus on the four year window. We assume that permanent decisions to do with purchasing or selling material goods are more likely to be based on average recent experience rather than one good or bad year, following Henderson et al. (2017). Furthermore, we would like to use the average period between two surveys. The median period between surveys is 60 months, but as the survey collection takes multiple months to complete, we take the anomalies over a period of 48 months. This ensures that we capture the period between surveys that do not overlap with previous survey collection, on average. To determine the accurate date for the data collection, we rely on information provided by DHS on the respective interview dates in the regions, using the first month of data collection.

The mean temperature anomaly can be positive or negative, as shown in Table 9. For temperature, an anomaly over the last 48 months tends to be positive on average, referring typically to higher temperatures than its long-run mean. In contrast, for precipitation, the mean anomaly is negative.

# 4 Estimation Strategy

Large cross-sectional correlations exist between a country's climate and its socioeconomic outcomes, posing well established challenges in identifying causality.

This paper follows the new wave of empirical research that use panel methodologies, exploiting high-frequency (e.g., year-to-year) changes in temperature, precipitation, and other climatic variables to identify the economic effects of these shocks. To the extent that climatic shocks are exogenously determined, reverse causation is unlikely to be a major concern (Dell et al., 2014). Many controls are endogenous to the weather variation. We follow best practice, which only include either no controls or credibly exogenous controls (Dell et al., 2014).

Following the literature, our estimation strategy tests the causal effects of regional climate anomalies on regional wealth inequality using fixed effects panel models with region and year fixed effects. We include no additional controls to mitigate the issue of bad controls in climate models (Baquie and Foucault, 2023; Dell et al., 2014):

$$\mathrm{Y}_{r,y} = \alpha + \beta S_{r,p} + \mu_y + \eta_r + \varepsilon_{r,y} \tag{2}$$

Our main outcome of interest $Y_{r,y}$ is inequality, calculated as the Gini coefficient of the material wealth index in region r at survey year y. We also estimate the impacts of climate anomalies on economic outcomes, as well as on the percentage of households possessing specific assets.

$S_{r,p}$ are climate anomalies summed in a region $r$ over a time period $p$ of 12 to 84 months. We test for temperature and precipitation anomalies. As described earlier, our preferred specification tests for anomalies summed over 48 months. We include year fixed effects ($\mu_y$ the survey year) and region fixed effects ($\eta_r$) to control for unobserved heterogeneity and common time trends. All standard errors are clustered at the region level. We also study the impact of weather anomalies on the mean wealth of a region to complement the picture on inequality.

We test for the heterogeneity of environmental hazards on inequality considering a range of regional characteristics. We distinguish regions by income level (measured by GDP per capita), their baseline temperature and their initial inequality level.

Migration is important for the interpretation of the results. We worry about asymmetric migration by household wealth in response to climatic shocks. The departure of households and individuals that might be disproportionately wealthy or poor will change the composition of the population in a region. The empirical issue we face is the degree to which the location of poorer and richer households is endogenous to anticipated shocks. The failure to account for sorting likely leads us to under-estimate the impact of climatic shocks on inequality (bias $\beta$ downwards) if the hardest hit populations from climatic shocks are the poorest, or if the least affected are the wealthiest who might nonetheless update their preferences and decide to migrate away from risky areas. Conversely, if poor households sort into areas prone to climatic shocks after a shock because rent or housing is now cheaper, then we would be over-estimating $\beta$ – as it would capture the impacts of climatic shocks on households that overcame the disaster, and capture the migration of poor households into the region due to lower house or rental prices.[9] Equally, we would over-estimate $\beta$ if the richest households decide to migrate to an area following or in anticipation of climatic shocks because they might see an economic opportunity. Ultimately, we need to formally test for migration to better understand the impacts of weather shocks on regional inequality. The survey data used is repeated cross-section rather than panel data, we thus test for sorting by studying changes in the composition of the population over time (Table 7).

# 5 Results

## 5.1 Descriptives

Figure 1 shows the distribution of the Gini index globally, revealing substantial differences in the level of wealth inequality between and within countries. Regions with particularly high levels of inequality can be found in Central America, the Sahel region, Central Africa, and the Horn of Africa (Figure 1 Panel A). Countries with relatively higher wealth levels, such as Turkey or Egypt, are characterized by relatively low levels of inequality. This is due to the particular nature of the dataset used to capture inequality, which is better suited to capture the inequality at the lower end of the wealth distribution.

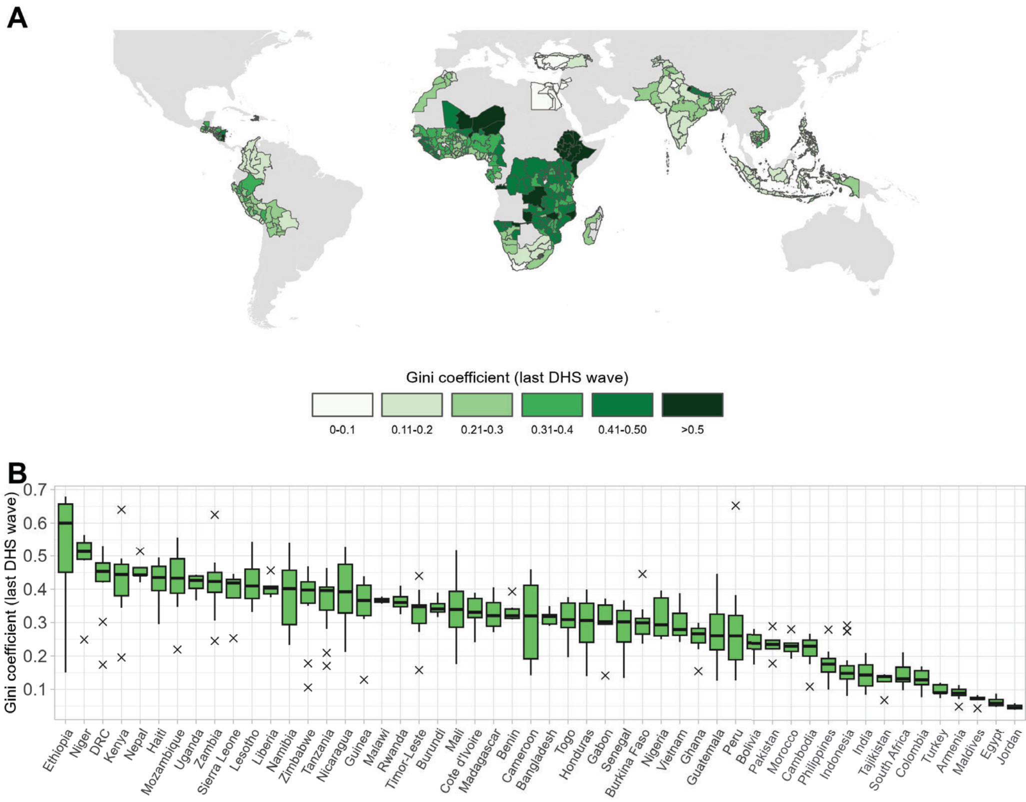
Major differences in inequality are not only observable between but also within countries (Figure 1, Panel B). The boxplots show a wide span in the levels of regional inequality for countries like Ethiopia, Namibia, Mali, and Cameroon. These findings highlight the importance of taking a subnational perspective when considering inequalities in wealth levels.

In our empirical analysis, we combine the information about changes in the wealth distribution at the regional level over time with information on temperature and precipitation anomalies. The temperature anomalies employed increase over time (Appendix Figure 8),

[9] Cappelli et al. (2021) find evidence in favor of a vicious cycle between disasters and inequality.

while the precipitation anomalies do not (Appendix Figure 9).

Figure 1: Distribution of the Gini index at the subnational level globally




Notes: The figure shows information for the most recent DHS wave for each country

## 5.2 Baseline models: Impacts of anomalies on inequality

Our baseline results are presented in Table 1, where we regress the regional wealth Gini coefficients on different climate indicators. Our main independent variable is the average temperature or precipitation anomaly within the 48 months prior to a DHS survey. In our main specifications, we control for region and year fixed effects. Standard errors are clustered at the region level.

We estimate a significant impact of temperature anomalies on material wealth inequality. Specifically, we find that an increase of one standard deviation in the average temperature anomaly in the past 48 months increases the regional material wealth Gini coefficient by 0.018 points (SE 0.007).

In addition, we find a significant negative effect of -0.011 (SE 0.005) of temperature anomalies on regional mean wealth levels. The combined effects of a widening of the wealth distribution and of a reduction in overall wealth levels suggests that selected population groups in the sample are particularly affected by temperature anomalies whereas others are less impacted leading to a reduction in mean wealth levels contributing to the observed increase in inequality.

The relationship between extreme temperatures and inequality also holds when we control for precipitation anomalies. We do not find an impact of precipitation anomalies on inequality or on mean wealth levels, but find some impacts of precipitation on individual assets (Appendix Figure 10). However, as stated above, caution is warranted when interpreting the effects of precipitation anomalies as the temporal and spatial aggregation and interpolation is noisier than it is for temperature anomalies (CRU TS 4.05).

Various robustness tests were performed to test for the sensitivity of our findings. First, our model estimates are not sensitive to different inequality measures (Appendix Table 16), which likewise confirm a positive relationship between temperature anomalies and wealth inequality. We test whether the effects on inequality might be driven by outlier events in regions such as conflicts. Our results are not sensitive to the exclusion of countries affected by conflict during the observation period, as shown in Appendix Table 17. We also test whether the availability or missing data on assets in the DHS surveys affects our findings by removing countries from the sample that have assets that are missing. Similarly, the results are robust to this additional check and confirm the positive, even larger, effect of temperature anomalies on material wealth inequality (see Table 17). In further extended models, we consider GDP per capita as an outcome using an alternative dataset to confirm the negative wealth impacts observed with the DHS data (Table 6). In line with our main results, we find that temperature anomalies over the last 48 months are associated with a significant negative impact on regional GDP per capita.[10]

[10] This result confirms that GDP per capita would be a 'bad control' (Angrist and Pischke, 2009, 2014) in our main regressions. Note that our measure of GDP per capita might underestimate yearly fluctuations due to the interpolation and extrapolation methods used (see Data section).

Table 1: Temperature & precipitation anomalies over 48m on regional Gini and wealth

| Dependent Variables: | Gini | | | Wealth mean | | |
|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| Tmp anom | 0.016** | | 0.018** | -0.012*** | | -0.011** |
| | (0.007) | | (0.007) | (0.005) | | (0.005) |
| Pre anom | | 0.012 | 0.014 | | 0.014* | 0.012* |
| | | (0.009) | (0.009) | | (0.007) | (0.007) |
| *Fixed-effects* | | | | | | |
| Region | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | |
| Observations | 1,829 | 1,829 | 1,829 | 1,829 | 1,829 | 1,829 |
| $R^2$ | 0.87094 | 0.87048 | 0.87120 | 0.96944 | 0.96939 | 0.96952 |
| Within $R^2$ | 0.00486 | 0.00133 | 0.00686 | 0.00518 | 0.00366 | 0.00796 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Anomalies can exert cascading influences on populations, where the experience of environmental stress in one period affects the likelihood and severity of a household being affected again. In additional analyses, we explore temporal dynamics of the effects (see Table 12) using distributed lag models (Gasparrini et al., 2010) to analyze how impacts of temperature and precipitation anomalies evolve over time.[11] For temperature anomalies, we find some evidence for short-term impacts, 24 months prior to the DHS surveys, but mostly longer-term impacts of anomalies occurring in the period of 36 to 72 months. This suggests that effects of temperature anomalies are complex and characterized by different underlying processes affecting wealth levels and inequalities.

The DHS data employed covers 30 years allowing us to analyse how anomaly impacts differed by time periods in the data. For this, we interacted the anomaly measures with a factor variable capturing the decades when the DHS data were collected (see Table 13).

[11] By simultaneously estimating lagged impacts, we can explore how anomalies in different time periods have affected the outcomes and explore cumulative effects.

We find particularly strong effects of temperature anomalies in the 2000s and 2010s, suggesting an increasing impact of temperature anomalies on the distribution of wealth over time. Climate change has led to an increase in the intensity of anomalies observed in many regions of the world. These larger anomalies may have disproportionate effects on wealth levels and distributions explaining the larger effects observed in latter periods (Schlenker and Roberts, 2009). The existing literature has also tested for non-linear damage functions of climatic shocks (Cui et al., 2024). However, the climatic shocks we study are standardised mean temperature and temperature anomalies so we do not expect to see strong non-linearities in the shocks. We test for quadratic versions of our climatic shocks and our results are not significant (Appendix Table A.6).

## 5.3 Distributional impacts

While our baseline models consider changes in the overall wealth distribution and mean levels, Table 2 provides detailed analysis of the impacts of anomalies on the wealth distribution. For this, we create a series of variables that measure for each DHS data collection the share of the population in a subnational region that falls into fixed wealth bins.[12] We study shifts in the population share between wealth bins (e.g., wealth index $<0.2$) and analyze how the relative population in each bin changes over time. All models control for region and year fixed effects to rule out confounding effects of unobserved heterogeneity on underlying time trends.

[12] We split the wealth index into 5 bins (0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1) and study how population shares swicth between them over time)

Table 2: Distributional impacts of Temperature & precipitation anomalies over 48m

| Dep. Var.: | Wealth <0.2 | Wealth 0.2-0.4 | Wealth 0.4-0.6 | Wealth 0.6-0.8 | Wealth >0.8 |
|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Tmp Anom | 0.041*** | -0.032*** | -0.009 | 0.0007 | 0.007 |
| | (0.010) | (0.009) | (0.007) | (0.008) | (0.006) |
| Pre Anom | 0.016 | -0.012 | -0.041*** | -0.036*** | -0.033*** |
| | (0.013) | (0.014) | (0.010) | (0.014) | (0.009) |
| *Fixed-effects* | | | | | |
| Region | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 1,829 | 1,829 | 1,829 | 1,829 | 1,829 |
| $R^2$ | 0.93102 | 0.73555 | 0.83406 | 0.95138 | 0.92039 |
| Within $R^2$ | 0.01108 | 0.00826 | 0.01641 | 0.00893 | 0.01948 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

While we find that temperature anomalies affect the entire wealth distribution, particularly strong effects are observed for the lowest wealth bin which is estimated to grow by 4.1% with a one standard deviation increase in temperature anomalies in the past 48 months. All other wealth bins are estimated to shrink in size with particularly strong negative effects observed for the second lowest wealth quintile. This suggests that climatic shocks particularly affect those with already limited resources further pushing them into even greater poverty. No significantly negative effects are observed for the population shares in the wealthiest quintile, underscoring that temperature anomalies mostly affect the poor, with no evidence of wealthier parts of the population being affected.

Ultimately, it is the stark increase in the poorest wealth quintile that drives the spread in wealth in response to temperature anomalies and the resulting increase in inequality. By increasing the share of the extremely poor, temperature anomalies contribute to a reduction in the mean wealth level and an increase in the Gini coefficient as observed in Table 1. This underpins the finding established in the literature that climatic stress can have particularly adverse consequences for the lower end of the wealth distribution, leading to an exacerbation of poverty in affected areas.

Temperature anomalies could affect the tail of the wealth distribution by reducing the number of assets, forcing households to use cheaper materials for housing construction, or destroying water access and sanitation facilities. These results are in line with the literature, which shows that extreme weather events are associated with diminishing resilience and wealth in the short-term (Jones and Ballon, 2020). While we remain cautious about the results on precipitation anomalies, as discussed earlier, we observe that they affect the wealth distribution in different ways, and seem to have shifted the distribution of wealth from the middle of the distribution to the top.

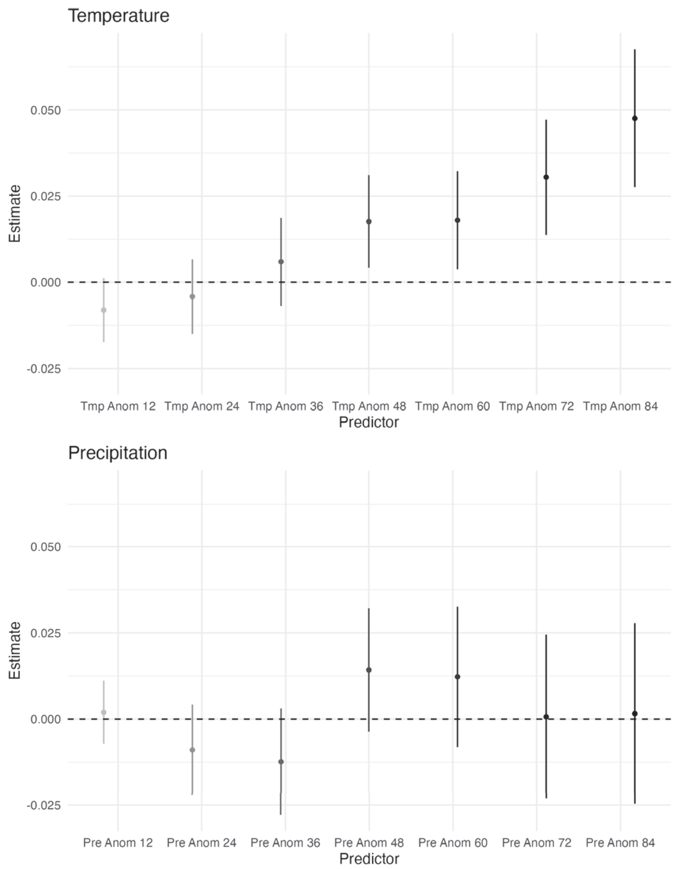
## 5.4 Duration of Climate Anomalies

Our baseline results show that unusually high temperatures have a significant impact on regional inequality. We next test the effect of environmental shocks over different time periods. How does the duration of climate anomalies impact inequality?

We present our results in Figure 2. We find that temperature anomalies in the last 12 months have no significant effect on inequality. However, once we extend the period to consider the number of months over 48 months and over 84 months before the survey, the impact steadily increases. At the same time, temperature anomalies have a significant negative effect on mean wealth of a region as shown in Figure 3. The weather anomalies thus increase inequality and bring down the distribution of material wealth, meaning the poor get poorer, rather than the rich richer.

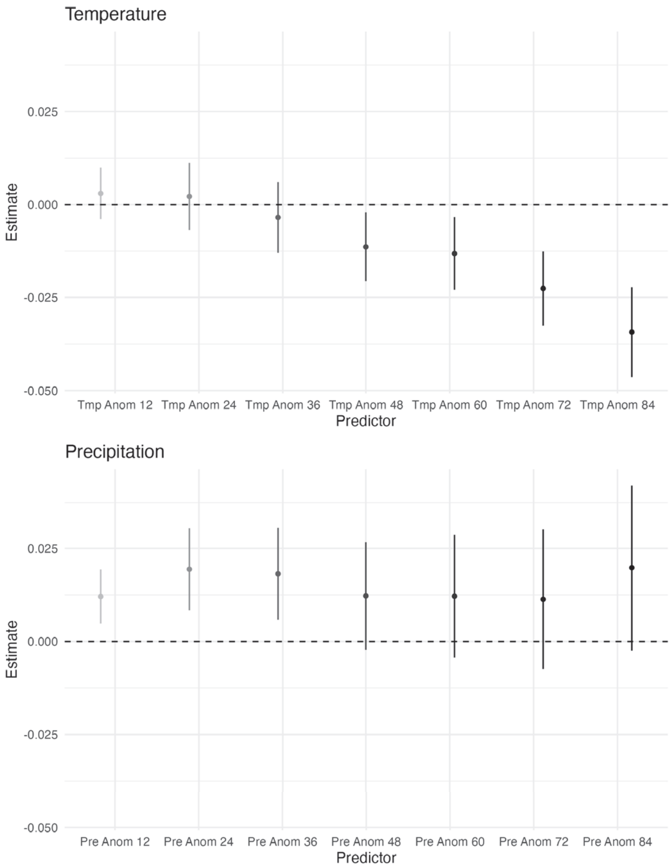
These results suggest that impacts of anomalies increase with their prolonged duration. Accordingly, household assets are only affected if climatic shocks last over a longer period. The distinct adaptation mechanisms available to poor and rich households following shocks may translate into regional inequality only over longer time horizons explaining the observed temporal pattern. The results are robust to changes in mean temperature and precipitation levels over a time period of 48, 60, 72 or 84 months (Figure 2). We see the same patterns of positive temperature anomalies on the wealth distribution: it reduces mean wealth and the effect increases over time.

Figure 2: Mean temperature and precipitation Anomalies on regional Gini: different Time Periods




Notes: 'Tmp' stands for temperature. 'Pre' for precipitation. The bars represent the 95% confidence interval.

Figure 3: Mean temperature and precipitation Anomalies on regional mean wealth: different Time Periods




Notes: 'Tmp' stands for temperature. 'Pre' for precipitation. The bars represent the 95% confidence interval.

## 5.5 Heterogeneity by Regional Characteristics

Anomalies can exert differential effects on wealth depending on local contexts and economic conditions. We test how the effect differs by development level, mean temperature and inequality levels and present the results in Table 3.

First, we look at the differences in effects by GDP per capita. We interact temperature anomalies with GDP per capita, displaying the results in Column 1. We find a negative interaction effect, indicating that the effect of temperature anomalies on inequality is less pronounced for regions with higher development level, and stronger in poorer regions. In line with the previous results, we find a positive impact of positive temperature anomalies on the Gini coefficient. Also, regions with higher GDP are linked to lower inequality, which is in line with the Kuznets curve (Kuznets, 1955).

Second, we also test how hot and cold regions are differentially impacted. We interact the baseline temperature mean over 48 months with temperature anomalies and the results are shown in Column 2. Surprisingly, regions with a higher baseline temperature experience less pronounced effects of temperature anomalies on material wealth inequality. Thus, temperature shocks have a more pronounced effect on inequality in colder regions. One potential explanation could be adaptation. While we would have expected a stronger effect in warmer regions, households might already have adopted measures or strategies to deal with pronounced heatwaves. In contrast, households in colder regions might lack experience and infrastructure to cope with severe heatwaves, explaining why we observe stronger effects in colder regions.

Third, we look at differences by baseline inequality levels. In Column 3, we focus on the baseline inequality measure and interact it with temperature anomalies to understand whether equal and unequal regions experience stronger effects. We find that the effect of temperature anomalies is less pronounced in regions with a higher initial inequality level. Temperature anomalies exacerbate inequality in more equal regions. Similar to the previous results, this could be as more unequal regions might have been more affected by temperature shocks and adapted, in contrast to regions with lower inequality. We also find a positive effect of positive temperature anomalies on the Gini coefficient in Column 2 and 3, which is consistent with the previous results. In summary, our findings suggest that local contexts and economic conditions shape the relationship between climate anomalies and inequality, as poorer regions with lower baseline temperature and lower inequality levels tend to be more affected by temperature shocks.

Table 3: Regional Heterogeneities: Temperature and precipitation anomalies over 48m on Gini

| Dependent Variable: | | Gini | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| Tmp anom | 0.133** | 0.078*** | 0.055*** |
| | (0.060) | (0.026) | (0.017) |
| Log(GDP pc) | -0.005 | | |
| | (0.010) | | |
| Pre anom | 0.009 | 0.016* | 0.015* |
| | (0.009) | (0.009) | (0.009) |
| Tmp anom × log(GDP pc) | -0.014* | | |
| | (0.007) | | |
| Tmp anom × Baseline Tmp | | -0.003** | |
| | | (0.001) | |
| Tmp anom × Baseline Gini | | | -0.099** |
| | | | (0.047) |
| *Fixed-effects* | | | |
| Region | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 1,618 | 1,829 | 1,829 |
| $R^2$ | 0.86576 | 0.87179 | 0.87178 |
| Within $R^2$ | 0.01366 | 0.01130 | 0.01143 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

## 5.6 Differences by Urban, Rural and Agricultural Dependency

The literature has documented significant heterogeneity in climate impacts between rural and urban areas (Henderson et al., 2017). In line with these results, we find particularly pronounced effects of temperature anomalies on the wealth distribution and wealth levels in rural areas, which experience a decrease in wealth of 1.9 percent, and an increase in the Gini coefficient of 0.039. Urban regions experience a substantially smaller effect on material wealth inequality or mean wealth, which is not statistically significant. We also observe a stronger increase in the share of poor households in rural areas, with the share of household in the lowest wealth quintile increasing by 6.7 percent in rural areas, whereas the effect is smaller and not significant in its urban counterpart (Appendix Table 14).

Table 4: Temperature and precipitation anomalies over 48m on regional Gini and Mean Wealth in urban and rural areas

| Dependent Variables: | Gini Urban | Wealth Mean Urban | Gini Rural | Wealth Mean Rural |
|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Tmp anom | -0.0009 | -0.002 | 0.039*** | -0.019*** |
| | (0.005) | (0.006) | (0.010) | (0.006) |
| Pre anom | -0.012** | 0.035*** | 0.022* | 0.005 |
| | (0.006) | (0.010) | (0.013) | (0.009) |
| *Fixed-effects* | | | | |
| Region | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 1,824 | 1,824 | 1,759 | 1,759 |
| $R^2$ | 0.87961 | 0.91851 | 0.78596 | 0.95192 |
| Within $R^2$ | 0.00226 | 0.01102 | 0.01964 | 0.00995 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

To explore this relationship, we investigate what might cause the rural-urban differences. Previous studies have shown that climatic anomalies can destroy cropland and negatively affect agricultural livelihoods, forcing affected households to sell assets thereby increasing material inequality. To test whether agriculture is one of the mechanisms through which environmental anomalies affect inequality, we use DHS microdata on agricultural employment and land. Agricultural employment describes whether an individual is currently employed in agriculture, which refers to work related to agriculture in the previous 7 days. Agricultural land measures whether a household owns land that can be used for agriculture.[13]

We present the results in Table 5. We find that individuals that are employed in agriculture tend to suffer more from wealth shocks following a temperature anomaly relative to individuals in non-agricultural jobs. There are many possible explanations for this effect: income losses forcing households to sell assets, or loss of employment. We test for the latter channel in Column 2 where we regress individual unemployment on the anomaly measures. While the coefficient is negative, it is insignificant, suggesting that the negative anomaly effects may not be driven by affected individuals losing their job, but rather by them experiencing reductions in their income (e.g., because of destroyed agricultural production).

In contrast, we do not find any negative effects on wealth stemming from temperature anomalies for households that own agricultural land, as shown in Columns 3. One explanation might be that households owning land might possess assets less affected by climate anomalies. Another explanation is that they might not need to sell them as a response to a temperature shock. Interestingly, we do find a positive effect of temperature anomalies on livestock. This could be part of an adaptation strategy: households might diversify their agricultural portfolio by investing into livestock that is more resilient to high temperatures. Column 5 shows that households in urban areas are more likely to buy livestock, possibly because wealthier urban households can afford to diversify and adapt to changing climatic conditions.

Summing up these results, this section shows that rural areas are more affected by anomalies, which could be explained by the higher agricultural dependency of their inhabitants. Inhabitants that are employed in agriculture tend to suffer more from wealth shocks, which is not the case for households that own agricultural land. Urban households are wealthier and more resilient to shocks, likely because cities possess better adaptive infrastructure on average[14]. In rural areas, different channels can explain the relatively stronger impacts experienced, which we cannot perfectly distinguish in our analysis. These include reductions in overall wealth due to a decrease in agricultural output, the direct destruction of assets, out-migration of richer households, or in-migration of poorer households (see Table 6.3 on migration and composition effects below).

[13] Agricultural employment is provided by the DHS at the individual level, while the measure of agricultural land is available at the household level.

[14] This is not the case for informal settlements in cities

Table 5: The effects of temperature and precipitation anomalies over 48m on agriculture: Agricultural Employment, Agricultural Land and Livestock

| Dependent Variables: | Wealth | Agric. emp. | Wealth | Livestock | |
|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Tmp anom | -0.017** | -0.004 | -0.006 | 0.060*** | 0.033 |
| | (0.008) | (0.005) | (0.010) | (0.020) | (0.021) |
| Agric. emp. | 0.044*** | | | | |
| | (0.009) | | | | |
| Pre anom | 0.023** | 0.010* | -0.0002 | -0.126*** | -0.110*** |
| | (0.011) | (0.006) | (0.013) | (0.029) | (0.027) |
| Tmp anom × Agric. emp. | -0.018** | | | | |
| | (0.008) | | | | |
| Agric. land | | | -0.075*** | | |
| | | | (0.017) | | |
| Tmp anom × Agric. land | | | 0.019 | | |
| | | | (0.018) | | |
| Urban | | | | | -0.398*** |
| | | | | | (0.015) |
| Tmp anom × Urban | | | | | 0.084*** |
| | | | | | (0.020) |
| *Fixed-effects* | | | | | |
| Region | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 2,635,392 | 2,635,392 | 2,531,092 | 1,266,576 | 1,266,576 |
| $R^2$ | 0.43943 | 0.13733 | 0.39377 | 0.16136 | 0.24821 |
| Within $R^2$ | 0.00159 | $6.55 \times 10^{-5}$ | 0.02006 | 0.00140 | 0.10481 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

# 6 Exploring underlying mechanisms

In this section, we explore different mechanisms that could explain the observed effects of temperature anomalies on inequality. In a first step, we test the extent to which different socio-economic channels explain the observed temperature effects. In a second step, we decompose the wealth effects into different asset subcategories to understand which assets are most likely to be affected by climatic events. In a third step, we analyze the role of population composition in influencing the results reported.

## 6.1 Socio-economic Effects

The observed effects of temperature anomalies on wealth inequality and overall wealth levels might be explained through changes in other affected variables. Here, we explore four possible channels of influence testing for climatic impacts on regional GDP per capita, unemployment, undernourishment, and healthcare access. All of these are theoretically relevant in explaining the observed relationship between inequality, wealth, and anomalies. While we obtain information on regional GDP from external data sources, we rely on the rich DHS individual level data to explore the role of the other characteristics. Table 6 shows the results of models that regress the four variables on the occurrence of temperature and precipitation anomalies in the regions. A temperature anomaly is estimated to reduce regional income levels, which is in line with a large literature on the economic impacts of weather shocks using panel data, e.g. Hsiang (2010); Dell et al. (2012); Linsenmeier (2023); Kotz et al. (2024). Further negative effects of temperature anomalies are found for unemployment and the accessibility of health care services. Temperature anomalies of one standard deviation increase the likelihood that an individual is unemployed by 6.4 percent and that they do not have access to health care by 6.0 percent. We do not find any significant effect for food security. The effect for an individual to be unemployed is substantially higher in rural areas, as shown by a negative coefficient of the interaction term with the urban dummy in Model 3. For access to healthcare, we do not find any significant differences for urban vs. rural areas. These results are estimated using linear probability models as well as in the form of logistic regressions (Appendix Table 15). The results of the logistic regressions confirm a negative relationship for an individual being unemployed and not having access to healthcare. Overall, these findings show substantial and consistent effects of temperature anomalies on respondents' livelihoods and well-being with potential implications for their wealth and the inequality observed in the subnational regions.

Table 6: Temperature and precipitation anomalies impacts on GDP pc, unemployment, food security and health

| Dep. Var.: | Log(GDP pc) | Unemployed | | Healthcare | | Undernourished | |
|---|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Variables* | | | | | | | |
| Tmp anom | -360.4** | 0.064*** | 0.082*** | -0.060*** | -0.052*** | 0.008 | 0.005 |
| | (176.3) | (0.017) | (0.018) | (0.016) | (0.016) | (0.008) | (0.008) |
| Pre anom | -26.9 | -0.045** | -0.046** | -0.011 | -0.014 | -0.017** | -0.017** |
| | (305.3) | (0.023) | (0.022) | (0.019) | (0.019) | (0.008) | (0.008) |
| Urban | | | 0.065*** | | 0.064*** | | -0.045*** |
| | | | (0.009) | | (0.009) | | (0.010) |
| Tmp anom × Urban | | | -0.041*** | | -0.016 | | 0.002 |
| | | | (0.010) | | (0.010) | | (0.009) |
| *Fixed-effects* | | | | | | | |
| Region | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | |
| Observations | 1,618 | 2,878,725 | 2,878,725 | 1,690,633 | 1,690,633 | 2,535,857 | 2,535,857 |
| $R^2$ | 0.95413 | 0.22564 | 0.22709 | 0.09109 | 0.09322 | 0.10598 | 0.10882 |
| Within $R^2$ | 0.00650 | 0.00108 | 0.00294 | 0.00059 | 0.00293 | $6.49 \times 10^{-5}$ | 0.00324 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

## 6.2 Affected Assets

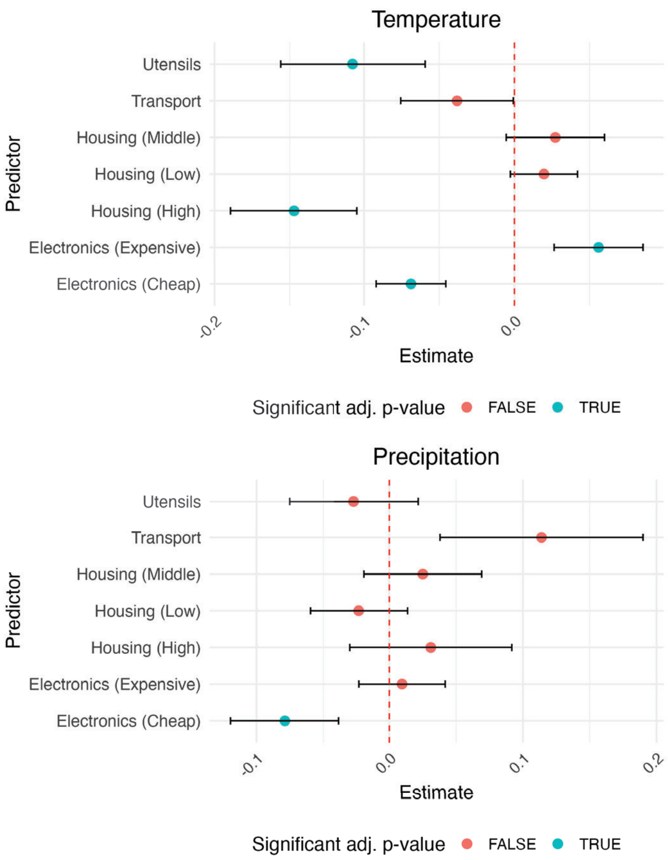
In the next step, we turn to the impacts of weather anomalies on different subcategories of material assets as reported in the DHS (for more details see Appendix Figure 10). The outcome variable describes the percentage of households possessing a specific asset within a region. We create categories for assets and housing characteristics.[15] We then aggregate these statistics at the regional level and get the share of households possessing at least one of the assets in the category. We show the results in Figure 4 below, exhibiting not only the standard regression results, but also the results corrected for multiple hypotheses testing to reduce the probability of a type I error. As we test a large number of hypotheses at once, we

[15]Transport includes bicycle, motorcycle and car. Expensive electronics refer to computers, televisions, or fridges, while cheap electronics include radios, watches and telephones. Housing includes toilet, floor, water and rooms. We assign a value of 1 to a household if it possesses at least one element of each category.

show the initial p-value as well as the Bonferroni adjusted p-values, which are calculated when running the regressions for all 54 assets. The results of all other models are shown in the Appendix Figure 10, Figure 11 and Figure 12.

We find that temperature anomalies affect different assets and housing characteristics that are relevant for a decent living. Anomalies have a particularly strong effect on the possession of cheap electronics and utensils (watch, radio and telephone). These could either be directly damaged by the climate anomalies, not renewed or maintained due to income shocks, or sold by households for consumption smoothing. We show the impacts across the individual assets, the asset categories by education level and by urban and rural regions in the Appendix Figure 11 and Figure 12. Households affected by anomalies are particularly less likely to possess a telephone. We observe this effect in urban as well as rural areas, with the effects being more pronounced in rural regions. Surprisingly, we find a positive effect on expensive electronics. This effect likely stems from wealthier households, proxied by secondary education levels, which see a positive (though insignificant) effect as a response to temperature anomalies, whereas households with no secondary education show a negative coefficient. This could be explained that due to pronounced heatwaves wealthier households spend more time indoors and thus are more likely to invest in a computer, television, or fridge. In addition, temperature anomalies decrease the share of households with high-quality housing. This is more likely for households without secondary education and for households in rural areas. Again, this could result from direct damages to the households or failure to maintain or improve their housing.

Figure 4: Mean temperature and precipitation anomalies over 48m on regional share of households owning assets




Notes: 'Tmp' stands for temperature. 'Pre' for precipitation. The bars represent the 95% confidence interval. P-values adjusted to multiple hypotheses testing using Bonferroni adjustment. Cheap electronics refer to three assets: watches, radios and telephones. Expensive electronics refer to three assets: computers, televisions and fridges.

## 6.3 Population Composition Effects

The occurrence of climatic anomalies can affect migration patterns. The out-migration of households from an area could affect our estimation if specific wealth groups are systematically more or less likely to leave in response to a shock in an area. (Bohra-Mishra et al., 2014) show that climate-induced migration is more often triggered by long-term increases in temperature or precipitation rather than by short-term catastrophic events. In line with this finding, recent evidence has shown that affected populations tend to move back into risky areas after large one-off weather shocks such as floods (Kocornik-Mina et al., 2020).

In this section, we test the magnitude of the migratory response to anomalies, and discuss whether migration may have affected our findings. DHS data are repeated cross-sectional so it is impossible to follow individuals and households over time. In addition, no information on migration patterns is available in the data. Other studies, such as Cattaneo and Foreman (2023); Mueller et al. (2020), do not provide migration data that could be applied in our context. Thus, we indirectly explore migration patterns and consider how the demographic composition of households has changed over time considering changes in time-invariant characteristics: educational attainment, gender and age.

The DHS describes educational attainment using six categories: no education, incomplete primary, complete primary, incomplete secondary, complete secondary and higher education. Although education composition is an imperfect variable, given that education levels have been rising across the world over the past 30 years, it allows us to proxy for changes in socioeconomic status controlling for time and region fixed effects. The composition of households is described by the share of households with at least one member having completed secondary education, at the regional level. For gender, we use the share of men within a region, calculating the share of male members within a household and then aggregating the weighted average at the regional level. Across the specifications, we do not find any evidence that temperature anomalies have affected population composition by education level and gender with regions experiencing anomalies showing no changes in their composition by these two variables. As a third characteristic, we consider the age distribution in the subnational regions and changes over time. Given that younger individuals are more likely to migrate (Bailey, 1993), we use the share of individuals between the age 18 and 35 within a region as the main outcome variable. We calculate the share of individuals in a region that are aged between 18-35 by first calculating the share of members between 18 and 35 within a household and then aggregating the weighted average at the regional level. Regressing the share of young adults on the temperature anomaly measure, we find a significant negative effect on the age composition suggesting an out-migration of younger individuals in response to temperature anomalies. Given the small size of the changes in the age distribution and given that the educational composition as main socioeconomic status indicator is not affected by anomalies, we do not consider these minor migration effects to lead to biases in our main results. To explicitly account for migration in our estimation, column 4 additionally controls for the share of individuals in a region that are aged between 18-35 to account for changes in the population composition. Even including this measure as an additional control, we find a significant impact of temperature anomalies on asset-based wealth inequality, with the coefficient remaining robust to our baseline model results. Thus, while we find evidence for systematic out-migration by age as a response to the anomalies considered, the migration responses is weak and does not systematically affect our estimation of the effects of anomalies on the wealth distribution. Instead, our findings suggest that households become poorer due to the anomalies, leading to an overall widening of the wealth distribution and an increase in the Gini coefficient.

Table 7: Compositional change: share of households with secondary education, share men and share of household members aged 18-35

| Dependent Variables: | Second. educ. | Men | Age 18-35 | Gini |
|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Tmp anom | 0.007 | 0.002 | -0.005*** | 0.018** |
| | (0.007) | (0.004) | (0.002) | (0.007) |
| Pre anom | -0.041** | 0.007 | -0.002 | 0.014 |
| | (0.017) | (0.005) | (0.002) | (0.009) |
| Age 18-35 | | | | 0.038 |
| | | | | (0.092) |
| *Fixed-effects* | | | | |
| Region | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 1,829 | 1,829 | 1,829 | 1,829 |
| $R^2$ | 0.94143 | 0.61826 | 0.89597 | 0.87122 |
| Within $R^2$ | 0.01175 | 0.00254 | 0.00557 | 0.00698 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

# 7 Discussion and Conclusion

Although it has long been recognized that climatic shocks can have differential impacts on different population groups, there is a dearth of evidence related to their distributional impacts at the regional level. In this paper, we build a unique panel dataset at the sub-national regional level combining high-frequency data on temperature and precipitation anomalies with information on the distribution of a material asset-based wealth index based on the Demographic and Health Surveys. To the best of our knowledge, our study is the first to analyse intra-regional distributional effects of climatic anomalies using asset-based inequality measures. Our paper contributes to the literature by showing how anomalies increase asset-based wealth inequality.

We estimate that an average temperature anomaly of one standard deviation increases material wealth inequality by 0.018 points and increases the share of poorest households by 4.1 percent. The distributional effects vary across periods and regions: they increased over time and rural areas tend to be more affected. Areas with higher agricultural dependency, lower levels of development and lower levels of inequality experience the strongest impacts of temperature anomalies. In rural areas, asset-based wealth inequality is estimated to increase by 0.039 points and the share of the poor population by 6.7 percent with a one standard deviation anomaly in temperature.

We explore the mechanisms driving these results and find that temperature anomalies affect inequality through multiple channels, including decreased economic activity, higher unemployment and worsened access to healthcare. Temperature anomalies also reduce the amount of households' material assets. Our results show that temperature anomalies impact assets and housing characteristics through multiple channels, which increases the difficulty for households to posses assets that allow for a decent living. Given the expected environmental changes in many regions of the world, this study generates important insights with implications for both academic research and policy.

We also test for migration and find evidence that a small part of the population may be responding and adapting to temperature shocks by migrating: temperature anomalies do not seem to impact the educational and gender composition of a region, but do seem to affect the age composition by a very small amount. When controlling for these compositional changes as proxy for migration, the main results are consistent and barely change in size. Future research could explore this issue further by studying the topic using panel data, which is currently unavailable in our setting but has been studied with other data (Mueller et al., 2020).

Climatic shocks are found to particularly affect the wealth of the poor highlighting the need for targeted interventions protecting the most vulnerable communities from the adverse effects of climate change. Policymakers should prioritize the development and implementation of climate adaptation strategies that specifically address the challenges faced by rural areas with high agricultural dependency, lower levels of development, and elevated inequality. These strategies could include investments in resilient agricultural practices, improved infrastructure for rural communities, and targeted poverty alleviation programs. Furthermore, recognizing the differential impacts of climatic shocks on wealth distribution, there is a pressing need for social safety nets that can mitigate the negative implications of climatic shocks. In particular, as climate change is expected to exacerbate the frequency and intensity of temperature anomalies, it will likely decrease households' ability to cope with these shocks even further. Using a material wealth index also speaks to the questions of persistence, indicating that the effects are long-lasting, rendering it even more difficult for (poorer) households to have the minimum standards that allow for a decent living. Our results highlight a need for an integration of long-term climate resilience measures into development plans, focusing on building adaptive capacity in regions where the distributional impacts of climate change are most severe.

Our findings also underscore the importance of justice considerations in climate mitigation and adaptation policy. It is the poor who have contributed the least to the climate crisis, but are the most severely affected. Their losses in wealth ultimately drive the increases in inequality observed in this study. Policies should therefore prioritize the most vulnerable and marginalized communities disproportionately affected by climatic shocks. International adaptation and resilience funds discussed at COP28 can play a crucial role in ensuring that the most affected regions receive assistance in adapting to and protecting themselves from the impacts of climatic shocks.

# A Appendix

## A.1 Precipitation and temperature data

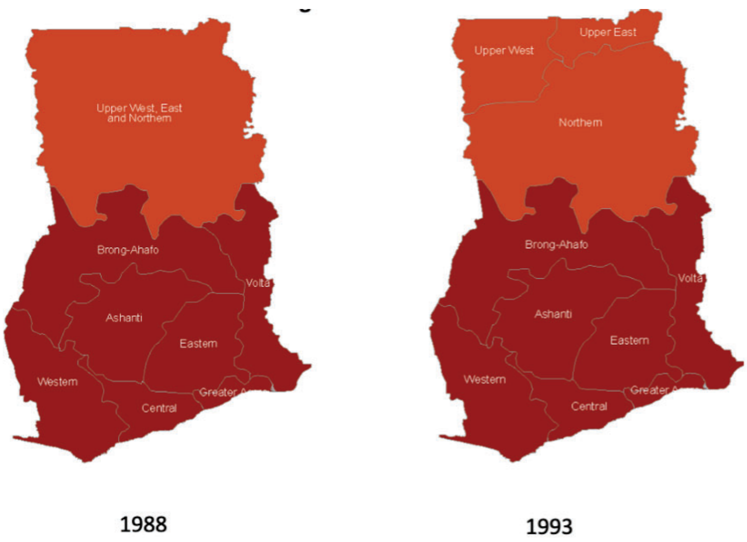
Monthly precipitation and temperature is pulled from the Climate Research Unit (TS4.04) at the University of East Anglia. Indicators of environmental and climatic conditions in a region are derived from the CRU TS (4.05) monthly high-resolution gridded multivariate climate dataset (Harris et al., 2014). We first derive gridded information on monthly average temperatures (in °C and precipitation in mm). We then use the information on the spatial boundaries of the regions to crop the gridded climate data and calculate mean monthly temperature and precipitation levels per region. The resulting dataset is a long time series with climate information from 1900 to 2020.

## A.2 Harmonised regions - common denominator geography

As some regions have split over time, we define a common denominator geography. This involves alternatively aggregating or disaggregating regions to ensure consistent common geography across survey waves. We review an example of this geography using the case study of Ghana. As shown in Figure 1, in Ghana, the northernmost region of Upper West, East and Northern split into three regions in 1988. In this case, we can aggregate our measures of inequality and weather shocks to ensure consistency. We can weight our inequality measure by employment and use the weather anomaly average for the common denominator geography.

For a few exceptions, regions have split in a way that is inconsistent with a common denominator geography approach. This might happen if regions extend or break up following new boundaries that our datasets do not cover. In such cases, we approximate geographies to the best of our ability using geographical areas or other national surveys.

Figure 5: Common denominator geography




Notes: The northernmost region is split into three between 1988 and 1993. The common denominator geography consists in aggregating the data back to one region to ensure it is considered as one region over time

## A.3 Surveys included in the analysis

Table 8: DHS Survey Waves included in the sample

| Country | Years available |
|---|---|
| Armenia | 2000, 2005, 2010, 2016 |
| Bangladesh | 1994, 1997, 2000, 2004, 2007, 2011, 2014, 2017 |
| Benin | 1996, 2001, 2006, 2012, 2017 |
| Bolivia | 1998, 2003, 2008 |
| Cambodia | 2000, 2005, 2010, 2014 |
| Cameroon | 2004, 2011, 2018 |
| Colombia | 1990, 1995, 2000, 2005, 2010, 2015 |
| Congo Democratic Republic | 2007, 2013 |
| Cote d'Ivoire | 1994, 2012 |
| Egypt | 1992, 1995, 2000, 2003, 2005, 2008, 2014 |
| Ethiopia | 2000, 2005, 2011, 2016 |
| Gabon | 2000, 2012 |
| Ghana | 1993, 1998, 2003, 2008, 2014 |
| Guinea | 2005, 2012, 2018 |
| Guatemala | 1995, 1999, 2015 |
| Haiti | 2000, 2006, 2012, 2016 |
| Honduras | 2005, 2011 |
| India | 1993, 2006, 2015, 2020 |
| Indonesia | 1994, 1997, 2003, 2007, 2012, 2017 |
| Jordan | 1997, 2007, 2009, 2012 |
| Kenya | 1993, 1998, 2003, 2008, 2014, |
| Lesotho | 2004, 2009, 2014 |
| Madagascar | 1992, 1997, 2004, 2008 |
| Mali | 1996, 2001, 2006, 2012, 2018 |
| Malawi | 1992, 2000, 2004, 2010, 2015 |
| Morocco | 1992, 2003 |
| Mozambique | 1997, 2003, 2011 |
| Namibia | 2000, 2006, 2013 |
| Nepal | 1996, 2001, 2006 |
| Nicaragua | 1998, 2001 |
| Niger | 1992, 1998, 2006, 2012 |
| Nigeria | 2003, 2008, 2013, 2018 |
| Pakistan | 1991, 2006, 2012, 2017 |
| Peru | 1996, 2000, 2004, 2007, 2009, 2010, 2011, 2012 |
| Philippines | 2003, 2008, 2013, 2017 |
| Rwanda | 2008, 2010, 2015 |
| Senegal | 1993, 1997, 2005, 2010, 2012, 2014, 2015, 2016, 2017, 2018, 2019 |
| Sierra Leone | 2008, 2013, 2019 |
| South Africa | 1998, 2016 |
| Tajikistan | 2012, 2017 |
| Tanzania | 1996, 1999, 2004, 2010, 2015 |
| Timor-Leste | 2009, 2016 |
| Togo | 1998, 2013 |
| Turkey | 2003, 2008, 2013 |
| Uganda | 2000, 2006, 2011, 2016 |
| Vietnam | 1997, 2002 |
| Zambia | 1992, 1996, 2002, 2007 |
| Zimbabwe | 1994, 1999, 2005, 2010, 2015 |

## A.4 International Wealth Index weights

Figure 6: Weights International Wealth Index, from Smits and Steendijk (2015)

| | Mean | SD | Raw indicator weight | IWI formula weight |
|---|---|---|---|---|
| *Consumer durables* | | | | |
| Television | 54.25 | 49.82 | 0.798552 | 8.612657 |
| Refrigerator | 36.99 | 48.28 | 0.781531 | 8.429076 |
| Phone | 38.74 | 48.72 | 0.660869 | 7.127699 |
| Car | 11.68 | 32.12 | 0.431269 | 4.651382 |
| Bicycle | 29.12 | 45.43 | 0.171238 | 1.846860 |
| Cheap utensils | 74.48 | 43.60 | 0.381851 | 4.118394 |
| Expensive utensils | 28.16 | 44.98 | 0.603345 | 6.507283 |
| *Housing characteristics* | | | | |
| Floor material | | | | |
| Low quality | 34.97 | 47.69 | −0.700809 | −7.558471 |
| Medium quality | 36.08 | 48.02 | 0.113815 | 1.227531 |
| High quality | 28.95 | 45.35 | 0.566271 | 6.107428 |
| Toilet facility | | | | |
| Low quality | 40.13 | 49.02 | −0.689810 | −7.439841 |
| Medium quality | 17.57 | 38.06 | −0.101100 | −1.090393 |
| High quality | 42.29 | 49.40 | 0.754787 | 8.140637 |
| Number of rooms | | | | |
| Zero or one | 38.44 | 48.65 | −0.343028 | −3.699681 |
| Two | 32.64 | 46.89 | 0.035609 | 0.384050 |
| Three or more | 28.92 | 45.34 | 0.319416 | 3.445009 |
| *Public utilities* | | | | |
| Access to electricity | 62.30 | 48.46 | 0.747001 | 8.056664 |
| Water source | | | | |
| Low quality | 32.13 | 46.70 | −0.584726 | −6.306477 |
| Medium quality | 23.85 | 42.62 | −0.213440 | −2.302023 |
| High quality | 44.02 | 49.64 | 0.737338 | 7.952443 |

## A.5 Summary statistics

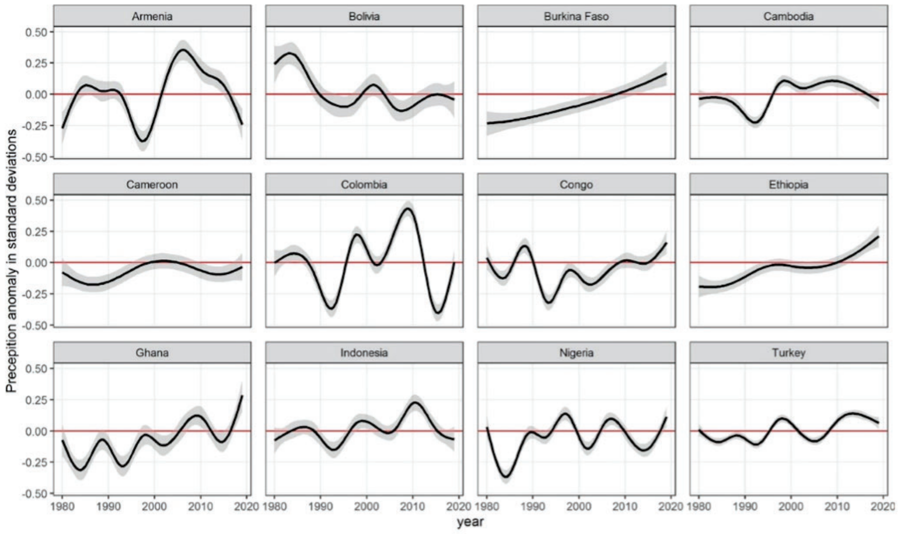
Table 9: Summary Statistics for regions, socioeconomic and climate variables

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| *Socioeconomic* | | | | | |
| Wealth mean | 1,869 | 0.383 | 0.197 | 0.062 | 0.889 |
| Gini | 1,869 | 0.319 | 0.131 | 0.040 | 0.800 |
| GDP pc | 1,573 | 4,100.950 | 3,998.069 | 259.569 | 37,156.630 |
| *Climate* | | | | | |
| Tmp anom mean 12 | 1,829 | 0.629 | 0.540 | −1.103 | 2.266 |
| Tmp anom mean 24 | 1,829 | 0.633 | 0.489 | −0.998 | 2.321 |
| Tmp anom mean 36 | 1,829 | 0.626 | 0.443 | −0.798 | 2.026 |
| Tmp anom mean 48 | 1,829 | 0.599 | 0.415 | −0.601 | 1.960 |
| Tmp anom mean 60 | 1,829 | 0.599 | 0.397 | −0.584 | 1.910 |
| Tmp anom mean 72 | 1,829 | 0.592 | 0.382 | −0.571 | 1.834 |
| Tmp anom mean 84 | 1,829 | 0.582 | 0.369 | −0.585 | 1.804 |
| Pre anom mean 12 | 1,829 | −0.032 | 0.372 | −1.183 | 1.229 |
| Pre anom mean 24 | 1,829 | −0.033 | 0.278 | −1.030 | 1.323 |
| Pre anom mean 36 | 1,829 | −0.038 | 0.241 | −0.988 | 1.278 |
| Pre anom mean 48 | 1,829 | −0.037 | 0.216 | −1.038 | 1.257 |
| Pre anom mean 60 | 1,829 | −0.037 | 0.205 | −0.852 | 1.118 |
| Pre anom mean 72 | 1,829 | −0.041 | 0.193 | −0.732 | 1.101 |
| Pre anom mean 84 | 1,829 | −0.038 | 0.185 | −0.744 | 1.027 |

‘Tmp’ refers to temperature, ‘Pre’ to precipitation. ’mean 12’ refer to the mean anomaly exactly 12 months before the survey.

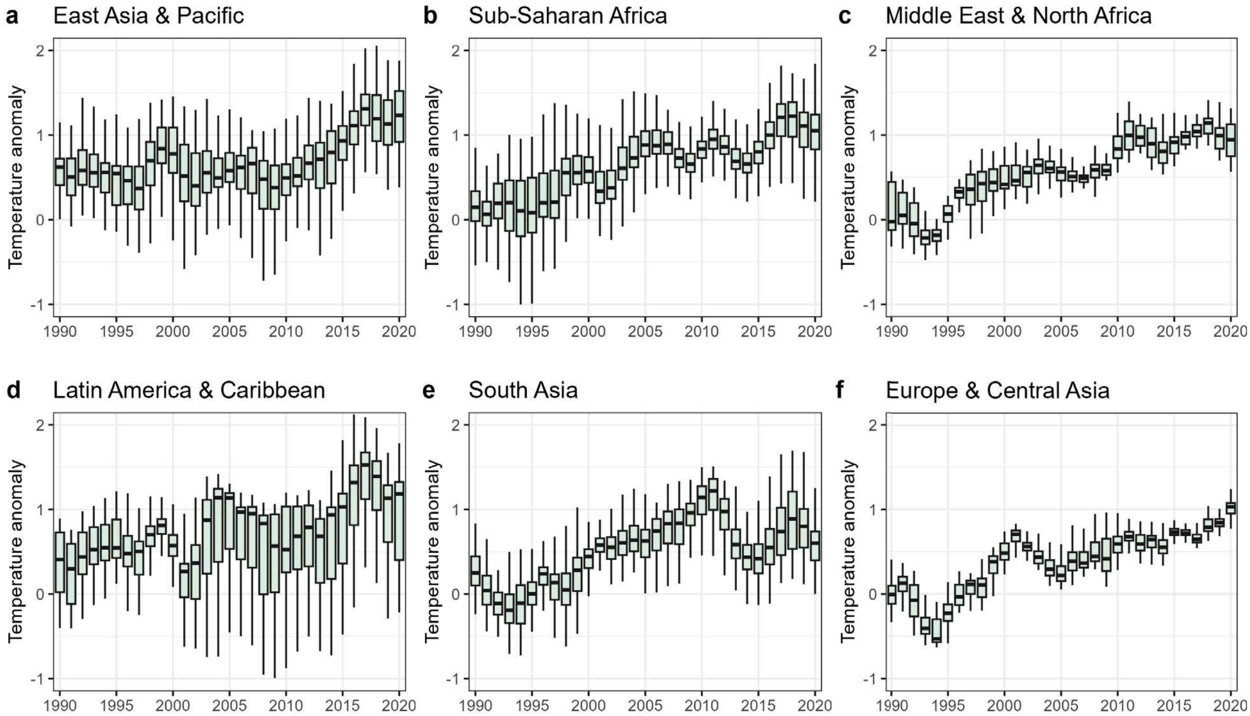
We present the variation of our independent variable of climate anomalies (Figure 7, aggregated at the country level). Precipitation anomalies do not seem to be systematically worsening over our time period. We also present the variation by different world regions, which are shown for temperature in Figure 8 and for precipitation in Figure 9. We assign each subnational region into one of the major world regions represented in our data: South Asia, Sub-Saharan Africa, the Middle East and North Africa, the Americas, and Europe and Central Asia. For each of them, we plot temperature anomalies in Figure 8, showing a substantial increase between 1990 and 2020. This is the case for all six world regions, indicating a steeper rise since the 2000s. When doing the same for precipitation anomalies, in contrast, we do not find any systematic increase or decrease over time.

Figure 7: Climate anomalies by country



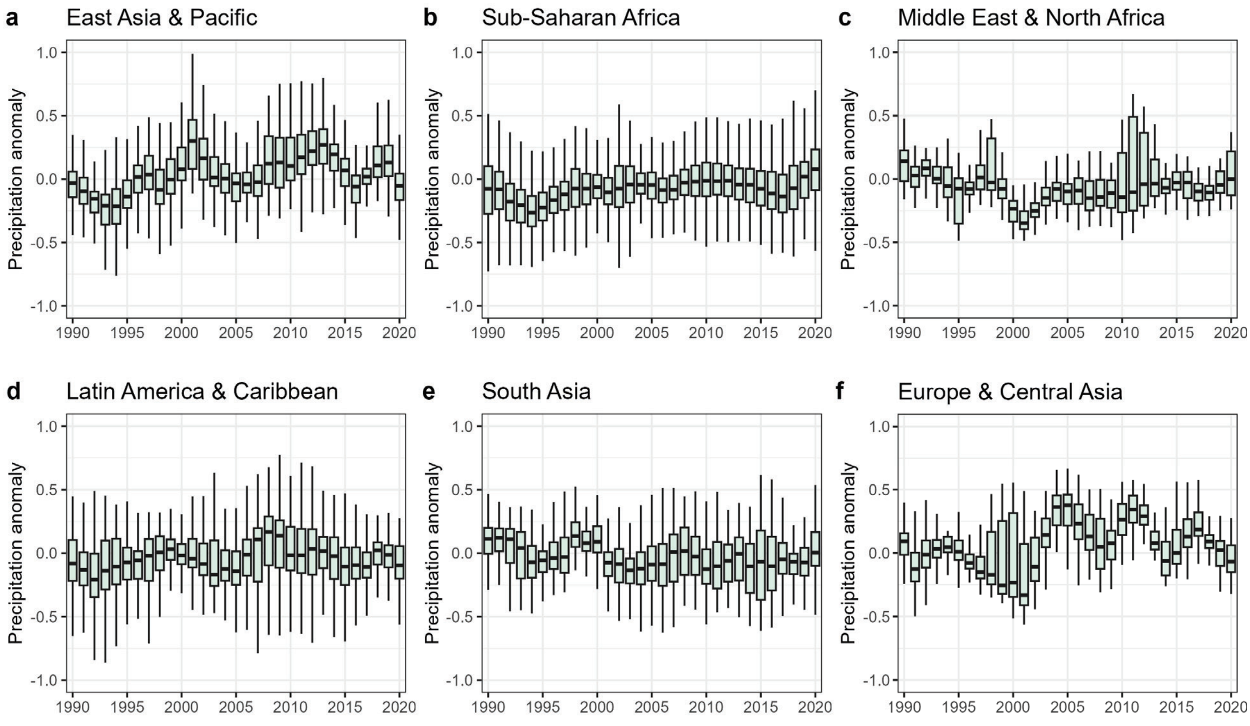

Notes: Precipitation anomalies from 1980-2020. Data from the Climate Research Unit (CRU TS 4.05) gridded data.

Figure 8: Temperature anomalies by world region




Notes: Temperature anomalies from 1990-2020. Data from the Climate Research Unit (CRU TS 4.05) gridded data.

Figure 9: Precipitation anomalies by world region




Notes: Precipitation anomalies from 1990-2020. Data from the Climate Research Unit (CRU TS 4.05) gridded data.

## A.6 Nonlinear Effects

Table 10: Nonlinear Effects: Mean temperature and precipitation Anomalies over 48m on wealth mean

| Dependent Variable: | Gini | |
|---|---|---|
| Model: | (1) | (2) |
| *Variables* | | |
| Tmp anom | 0.018 | 0.018 |
| | (0.011) | (0.011) |
| Tmp anom square | -0.0005 | -0.0005 |
| | (0.007) | (0.007) |
| Pre anom | 0.014 | 0.014 |
| | (0.009) | (0.009) |
| Pre anom square | -0.021 | -0.021 |
| | (0.013) | (0.013) |
| *Fixed-effects* | | |
| Region | Yes | Yes |
| Year | Yes | Yes |
| *Fit statistics* | | |
| Observations | 1,829 | 1,829 |
| $R^2$ | 0.87131 | 0.87131 |
| Within $R^2$ | 0.00770 | 0.00770 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

## A.7 Positive and Negative anomalies

In addition to looking at the effects of mean anomalies, we also show the effects of positive and negative temperature as well as precipitation anomalies of different intensities, including 1 and 1.5 standard deviations. We separate the mean anomaly into a positive and negative component where the climate has deviated from its long-run mean by different intensities. For example, a positive temperature anomaly of 1 standard deviation ("Tmp anom p1SD") refers to the number of months in 48 months with a positive temperature anomaly exceeding the threshold of 1 standard deviation.

Table 11 shows a positive and significant effect for positive temperature anomalies for 1 and 1.5 standard deviations. The coefficient for negative temperature anomalies is insignificant in both models. This clearly shows that the positive effect of mean anomalies on the Gini coefficient is driven by positive temperature anomalies.

Negative and positive precipitation have both a negative effect on the Gini coefficient. These findings are surprising given that we do not find any significant effects for the mean precipitation anomalies. A likely explanation is that the effects of precipitation are heterogeneous and depend on the region and its local conditions.

Table 11: Positive and negative temperature & precipitation anomalies 48 months for 1 and 1.5SD on inequality

| Dependent Variable: | Gini | |
|---|---|---|
| Model: | (1) | (2) |
| *Variables* | | |
| Tmp anom p1SD | 0.031** | |
| | (0.014) | |
| Tmp anom n1SD | 0.009 | |
| | (0.045) | |
| Pre anom p1SD | -0.046* | |
| | (0.026) | |
| Pre anom n1SD | -0.070** | |
| | (0.028) | |
| Tmp anom p1.5SD | | 0.053*** |
| | | (0.019) |
| Tmp anom n1.5SD | | -0.011 |
| | | (0.095) |
| Pre anom p1.5SD | | -0.061* |
| | | (0.033) |
| Pre anom n1.5SD | | -0.129** |
| | | (0.053) |
| *Fixed-effects* | | |
| Region | Yes | Yes |
| Year | Yes | Yes |
| *Fit statistics* | | |
| Observations | 1,829 | 1,829 |
| $R^2$ | 0.87180 | 0.87216 |
| Within $R^2$ | 0.01144 | 0.01422 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

## A.8 Distributed Lag Model

Table 12: Lag in Mean temperature and precipitation Anomalies on Gini: different Time Periods

| Dependent Variable: | Gini |
|---|---|
| Model: | (1) |
| *Variables* | |
| Tmp anom Lag 12 | 0.0003 |
| | (0.004) |
| Pre anom Lag 12 | -0.011** |
| | (0.005) |
| Tmp anom Lag 24 | 0.007* |
| | (0.004) |
| Pre anom Lag 24 | -0.007 |
| | (0.005) |
| Tmp anom Lag 36 | 0.012** |
| | (0.005) |
| Pre anom Lag 36 | 0.027*** |
| | (0.005) |
| Tmp anom Lag 48 | -0.009** |
| | (0.004) |
| Pre anom Lag 48 | -0.007 |
| | (0.005) |
| Tmp anom Lag 60 | 0.010** |
| | (0.005) |
| Pre anom Lag 60 | -0.010** |
| | (0.005) |
| Tmp anom Lag 72 | 0.026*** |
| | (0.004) |
| Pre anom Lag 72 | 0.008 |
| | (0.005) |
| *Fixed-effects* | |
| Region | Yes |
| Year | Yes |
| *Fit statistics* | |
| Observations | 1,829 |
| $R^2$ | 0.88362 |
| Within $R^2$ | 0.10264 |

*Clustered region standard-errors in parentheses. 'Tmp' stands for temperature. 'Pre' stands for precipitation. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

## A.9 Impacts over time

In Model 1 of Table 13 we show that relative to the period 1990-1999, the effects of temperature anomalies on regional wealth inequality are significantly larger in 2000-2009 and 2010-2019. Thus, the effects are increasing over time. Model 2 and 3 uses a subset including only regions that have participated at least once every decade in the DHS. The idea is to test whether the conclusion of Model 1, that the effect is increasing over time, still holds when accounting for changes in the composition of the sample. We therefore only keep regions that are observed over a long time and at least once in each decade. Model 2 shows the baseline results with this newly constructed sample, depicting an effect that is also positive, statistically significant and similar in size as in Table 1. Model 3 also shows the interaction effect, demonstrating that the effect in the last decade is positive and statistically significant, relative to the first period. This confirms that when accounting for compositional effects, the conclusion of the effects increasing over time still holds.

Table 13: Mean temperature and precipitation Anomalies over 48m on Gini for different time periods

| Dependent Variable: | Gini | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| Tmp Anom | -0.0152 | 0.0298*** | 0.0020 |
| | (0.0118) | (0.0085) | (0.0139) |
| Pre anom | 0.0115 | 0.0022 | -0.0011 |
| | (0.0090) | (0.0096) | (0.0099) |
| Tmp Anom × period 2000-2009 | 0.0373*** | | 0.0359* |
| | (0.0131) | | (0.0199) |
| Tmp Anom × period 2010-2019 | 0.0416*** | | 0.0349** |
| | (0.0127) | | (0.0145) |
| *Fixed-effects* | | | |
| Region | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 1,829 | 998 | 998 |
| $R^2$ | 0.87218 | 0.86134 | 0.86232 |
| Within $R^2$ | 0.01443 | 0.01503 | 0.02199 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

## A.10 Urban vs. rural: Households in extreme poverty

Table 14: Mean temperature and precipitation anomalies over 48m on Bottom of the wealth distribution

| Dependent Variable: | Urban Wealth <0.2 | Rural Wealth <0.2 |
|---|---|---|
| Model: | (1) | (2) |
| *Variables* | | |
| Tmp Anom | 0.011 | 0.067*** |
| | (0.010) | (0.013) |
| Pre anom | -0.030** | 0.036** |
| | (0.012) | (0.018) |
| *Fixed-effects* | | |
| Region | Yes | Yes |
| Year | Yes | Yes |
| *Fit statistics* | | |
| Observations | 1,824 | 1,759 |
| $R^2$ | 0.83408 | 0.91647 |
| Within $R^2$ | 0.00444 | 0.02183 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

## A.11 Socio-economic Effects: Logit Models

Table 15: Logit model: Temperature and precipitation anomalies impacts over 48m on unemployment, food security and health

| Dependent Variables: | Unemployed | Undernourished | Healthcare |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| Tmp Anom | 0.310*** | -0.254*** | -0.101 |
| | (0.081) | (0.069) | (0.062) |
| Pre anom | -0.242** | -0.040 | -0.084 |
| | (0.108) | (0.083) | (0.093) |
| *Fixed-effects* | | | |
| Region | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 2,878,725 | 1,690,633 | 2,535,857 |
| Squared Correlation | 0.22618 | 0.09158 | 0.11085 |
| Pseudo $R^2$ | 0.18162 | 0.06891 | 0.13475 |
| BIC | 3,111,962.3 | 2,180,889.0 | 1,858,556.1 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

## A.12 Other Inequality Measures

In addition to the Gini coefficient, we test the effect of environmental anomalies on different inequality measures. All three measures confirm a positive and significant relationship for temperature anomalies and inequality, but differ in effect size. For the Theil index we find an effect of similar size to the Gini coefficient. The coefficient for the Watts Poverty index is larger in size, showing that the poorest are particularly affected by temperature anomalies. The quantile share ratio at the top and tail of the distribution and shows a larger effect than the Gini coefficient and Theil index, but is smaller than poverty measures.

Table 16: Mean temperature and precipitation Anomalies over 48m on other inequality measures

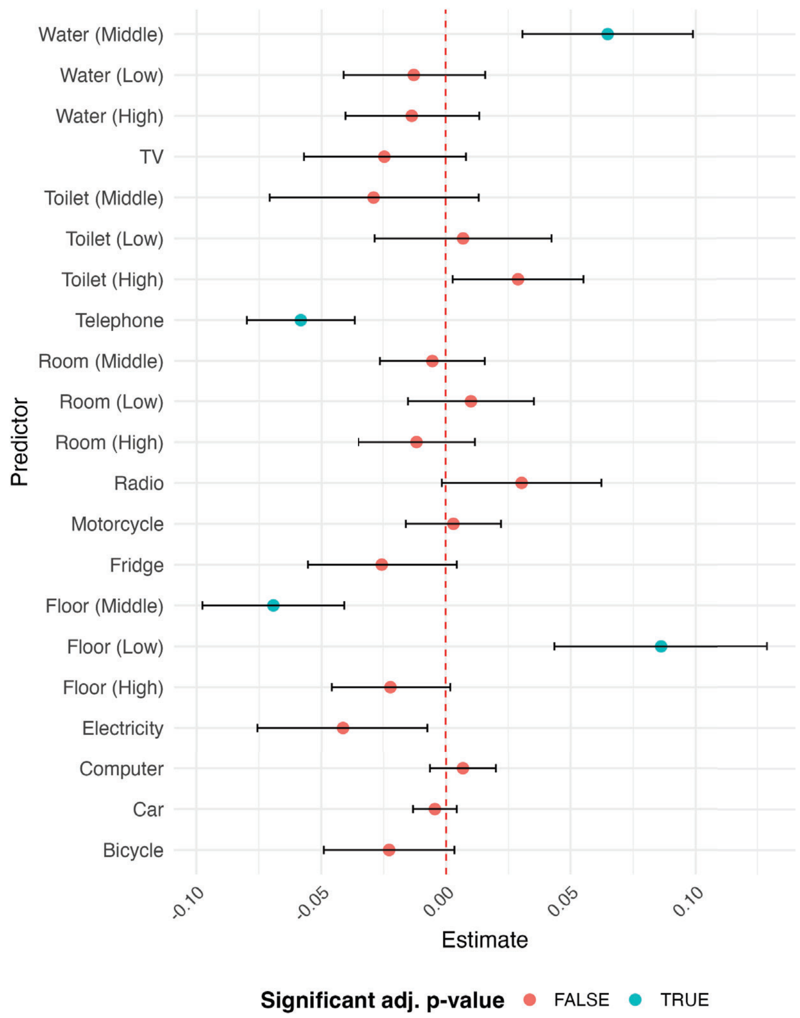
| Dependent Variables: | Theil | Watts Poverty | QSR Wealth 90/10 |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| Tmp anom | 0.015*** | 0.034*** | 0.024* |
| | (0.005) | (0.012) | (0.014) |
| Pre anom | 0.013** | -0.025 | 0.016 |
| | (0.006) | (0.016) | (0.018) |
| *Fixed-effects* | | | |
| Region | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 1,761 | 1,829 | 1,829 |
| $R^2$ | 0.66533 | 0.88977 | 0.69105 |
| Within $R^2$ | 0.01343 | 0.00727 | 0.00263 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

## A.13 Affected Assets

### All Assets

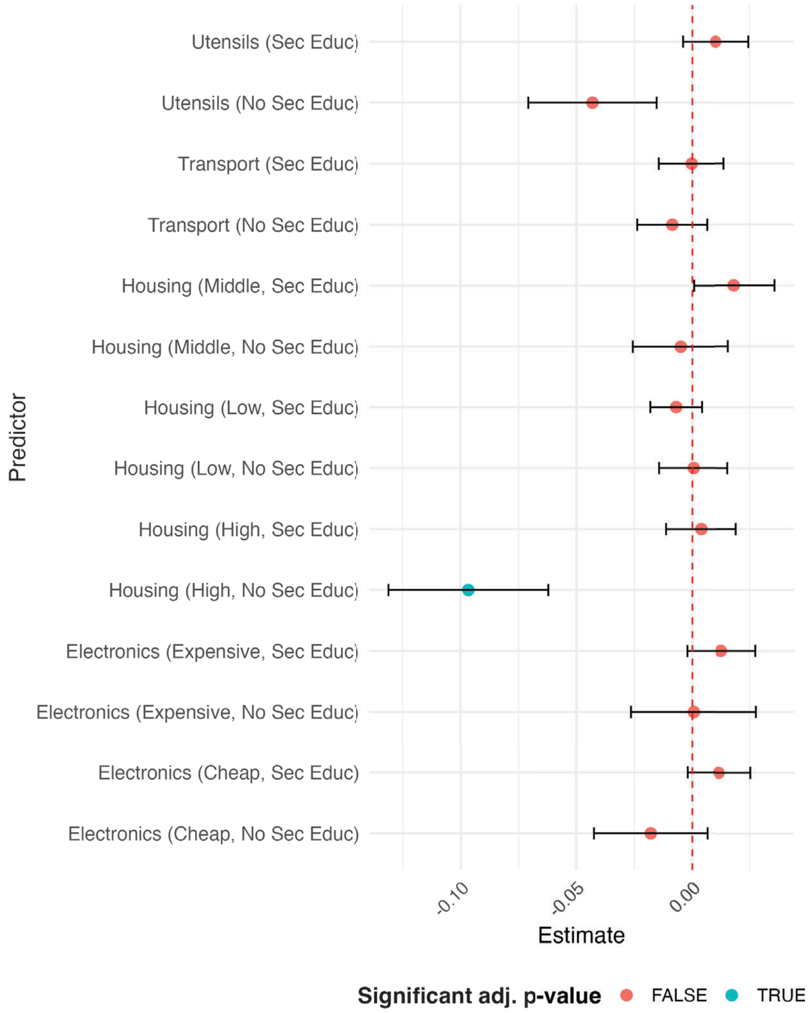
Figure 10: Mean temperature and precipitation anomalies over 48m on regional share of households owning assets




Notes: 'Tmp' stands for temperature. 'Pre' for precipitation. The bars represent the 95% confidence interval. P-values adjusted to multiple hypotheses testing using Bonferroni adjustment. Cheap electronics refer to three assets: watches, radios and telephones. Expensive electronics refer to three assets: computers, televisions and fridges.

### Asset Categories with or without secondary education

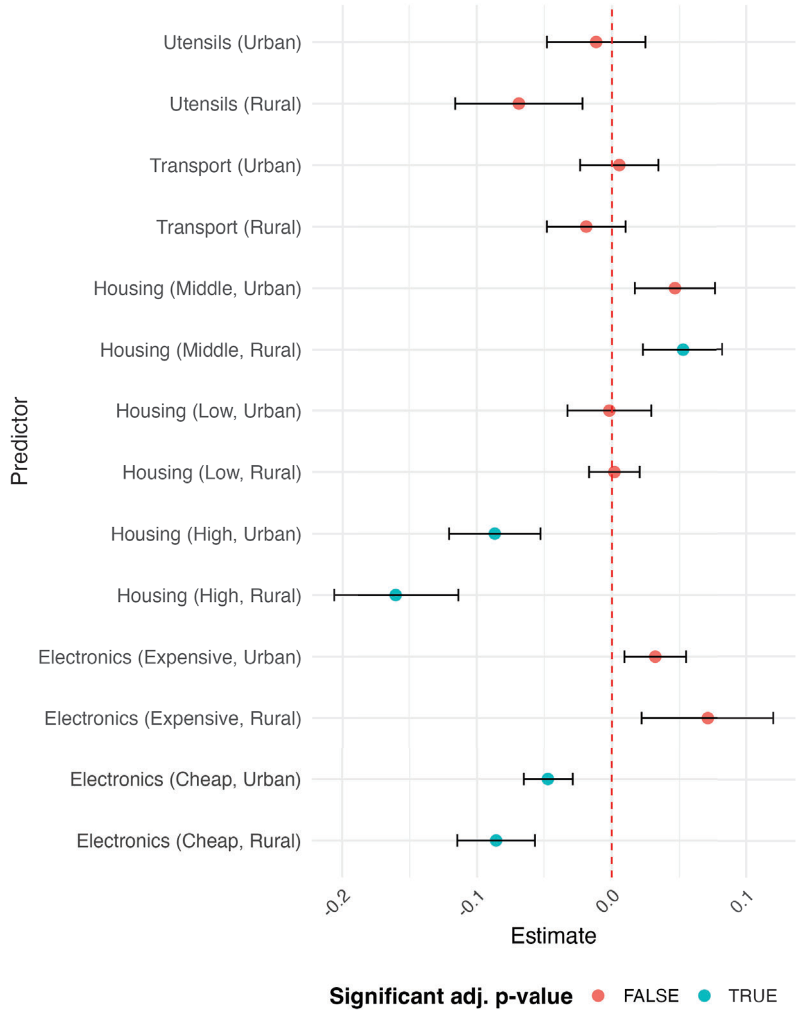
Figure 11: Second. Educ.: Mean temperature and precipitation anomalies over 48m on regional share of households owning asset categories




Notes: 'Tmp' stands for temperature. 'Pre' for precipitation. The bars represent the 95% confidence interval. P-values adjusted to multiple hypotheses testing using Bonferroni adjustment. Cheap electronics refer to three assets: watches, radios and telephones. Expensive electronics refer to three assets: computers, televisions and fridges.

## Asset Categories Urban. vs. Rural

Figure 12: Urban vs. Rural: Mean temperature and precipitation anomalies over 48m on regional share of households owning asset categories




Notes: 'Tmp' stands for temperature. 'Pre' for precipitation. The bars represent the 95% confidence interval. P-values adjusted to multiple hypotheses testing using Bonferroni adjustment. Cheap electronics refer to three assets: watches, radios and telephones. Expensive electronics refer to three assets: computers, televisions and fridges.

## A.14 Removing countries with missing assets and with conflict

We conduct two further robustness checks. First, we remove countries with missing assets. Missing assets refers to survey where more than one item was fully missing. While we normalize the index by dividing it by the maximum possible value the wealth index could take to ensure comparison over time, we aim to ensure that potential changes in wealth are not driven by items missing in a survey wave. Thus, we construct a sample only including countries with no more than one missing item in at least one survey wave. The results are presented in Model 1, showing a positive and significant effect, with an estimated size larger than the baseline effect. Therefore, we can conclude that missing assets are not a driver of the relationship, and our findings remain robust even when accounting for this potential source of bias.

Second, we are also concerned that conflict within a country could affect inequality. Recent work has argued that climate affects conflict (Burke et al., 2015), which is why we run further checks removing countries that have been affected by conflict during our observation period. This concerns the countries Egypt, Cote d'Ivoire, Mali and Nepal. Nepal, Mali and Cote d'Ivoire have experienced civil wars during the period and Egypt underwent a revolution followed by a substantial crisis between country surveys. We exclude these countries from our sample and present our results in Model 2. The results are consistent with the baseline effects shown in Table 1, indicating that conflict is not a significant factor driving our findings.

Table 17: Mean temperature & precipitation anomalies over 48m on Gini: missing assets and conflict

| Dependent Variable: | Gini | |
|---|---|---|
| Model: | (1) | (2) |
| *Variables* | | |
| Tmp anom | 0.0267** | 0.0185*** |
| | (0.0118) | (0.0067) |
| Pre anom | 0.0205* | 0.0140 |
| | (0.0114) | (0.0090) |
| *Fixed-effects* | | |
| Region | Yes | Yes |
| Year | Yes | Yes |
| *Fit statistics* | | |
| Observations | 1,222 | 1,752 |
| $R^2$ | 0.86735 | 0.87542 |
| Within $R^2$ | 0.01151 | 0.00760 |

*Clustered (region) standard-errors in parentheses*
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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