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Estimating Macro-Fiscal Effects of Climate Shocks From Billions of Geospatial Weather Observations

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ABSTRACT: A growing literature estimates the macroeconomic effect of weather using variations in annual country-level averages of temperature and precipitation. However, averages may not reveal the effects of extreme events that occur at a higher time frequency or higher spatial resolution. To address this issue, we rely on global daily weather measurements with a 30-km spatial resolution from 1979 to 2019 and construct 164 weather variables and their lags. We select a parsimonious subset of relevant weather variables using an algorithm based on the Least Absolute Shrinkage and Selection Operator. We also expand the literature by analyzing weather impacts on government revenue, expenditure, and debt, in addition to GDP per capita. We find that an increase in the occurrence of high temperatures and droughts reduce GDP, whereas more frequent mild temperatures have a positive impact. The share of GDP variations that is explained by weather as captured by the handful of our selected variables is much higher than what was previously implied by using annual temperature and precipitation averages. We also find evidence of counter-cyclical fiscal policies that mitigate adverse weather shocks, especially excessive or unusually low precipitation episodes.

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* We thank seminar participants at the IMF, the World Bank, and the EAERE 27th annual conference, for helpful comments and discussions.

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1. Introduction

Climate is changing and is expected to continue changing in the forthcoming decades even with sharp reductions in greenhouse gas emissions (IPCC, 2021b). In this context, economists and policy-makers are striving to better understand all the effects of climate on the economy.[1]

Studies of the macroeconomic impacts of weather and climate can be divided in two groups.[2] One strand of the literature estimates the effect of climate on the macro economy by aggregating impacts from sectoral studies in a reduced-form damage function that links global mean temperature to total output losses (e.g. Hope et al., 1993; Nordhaus and Yang, 1996; Tol, 1997; Christensen et al., 2012). Another strand of the literature uses econometric analysis to directly estimate the impact of random changes in temperature, and sometimes precipitation, on GDP per capita or Total Factor Productivity (Dell et al., 2012; Deryugina and Hsiang, 2014; Burke et al., 2015; Abatzoglou et al., 2018; Letta and Tol, 2019; Kalkuhl and Wenz, 2020; Tol, 2021; Newell et al., 2021; Abatzoglou et al., 2018; Kahn et al., 2021). Both strands of the literature have mostly focused on the effect of annual average weather on GDP and this contrasts with the public debate's main focus on extreme weather.

We fill this gap and contribute to the second strand of the literature along three dimensions. First, we leverage a global dataset of daily measurements of temperature and precipitation with high spatial resolution to construct a large array of weather variables which can capture all sorts of potentially relevant extreme events. However, the large number of potentially relevant weather variables creates a challenge for standard estimation techniques. Therefore, our second contribution is the use of the Least Absolute Shrinkage and Selection Operation (LASSO) to select the weather variables that contribute the most to explaining macroeconomic outcomes. Third, we look beyond the effect of weather on GDP and examine important fiscal aggregates. This extension relative to prior work is motivated by the fact that fiscal policy, if counter-cyclical, potentially absorbs and masks some of the macro effects of weather shocks.

In short, we find that focusing on GDP and weather averages misses most of the macro-fiscal impacts of climate shocks. The introduction of a small number of well-selected alternative weather variables goes a long way in improving our understanding of macro-fiscal variations.

Our study starts with the construction of a rich database of weather variables that can be used to conduct macro-fiscal analysis. We rely on dozens of billions of daily temperature and precipitation measurements on a global grid with a 30-Km resolution from the ERA5 dataset. There is an intractable number of ways to combine these daily geospatial measurements into country annual variables. Therefore, we rely on the

[1] IMF 9^{th} Statistical Forum: `www.imf.org/en/News/Seminars/Conferences/2021/11/17/9th-statistical-forum-measuring-climate-change`, IMF Climate Change Indicators Dashboard: `http://climatedata.imf.org`

[2] Climate is the long-run distribution of weather over several decades (Auffhammer et al., 2013). Weather varies continuously, but it is bounded by its long-term distribution. This distribution can be characterized using averages, but also higher-order moments. We refer to weather shocks or climate shocks to indicate short-term changes in a weather variable. Climate change is instead the long-run, slow-moving, change of the distribution of weather.

climate literature to guide the construction of potentially relevant weather variables. We obtain 164 variables that include, for example, the center and tails of the distribution of temperature and precipitation, heat and cold waves, droughts, and intense precipitation. Once merged with macro-fiscal outcomes, our dataset covers 199 countries annually over the 1979-2019 period.

Our weather dataset exploits the richness of daily geospatial measurements to capture local and infra-annual shocks. These variables can reflect weather events that are likely missed when averaging over space and time. For example, averages would fail to capture a local drought if it concurs with high precipitation later in the year or in other parts of the country. These variables also allow us to differentiate between the effects of duration and intensity. For example, the effect of extreme heat (short-lived extreme temperature) can differ from the effect of heat waves (prolonged periods with unusually high temperature). We can also measure shocks that are only relevant because they are deviations from local and seasonal norms (temperatures that can be normal in a country like India could be devastating in a country with a different climate like Mongolia). For each variable, we additionally consider an alternative aggregation over space using population weights.

We rely on a flexible empirical specification to relate weather shocks to macro-fiscal outcomes. In our baseline specification, we regress the first difference of the macro-economic variable of interest on the first difference of our selected weather variables including country and year fixed effects. We also add lags of all variables to allow for rich dynamic effects and control for auto-correlation. We also experiment with alternative controls considered in the literature to confirm the robustness of our results.

To select the variables that can best explain macro-economic outcomes, we use an algorithm based on the LASSO (Tibshirani, 1996; Belloni et al., 2014). Even after reducing the complexity of our weather data to only 164 variables, standard macro-economic regressions would quickly run into over-fitting and multi-collinearity issues, especially when adding multiple lags. The algorithm we use balances under and over-fitting issues. It relies on splitting our sample into training and test sets to select the variables that maximize the R-squared out of sample on the testing sets. Further, we follow the machine learning literature with an additional grid search to refine the selection and to obtain a robust and parsimonious set of relevant climate variables.

We find that a handful of weather variables have a significant impact on GDP per capita. Some of these variables capture droughts and very high temperatures. We estimate that an increase in the occurrence of such weather shocks has a detrimental effect on GDP. Conversely, we find that an increase in mild temperatures have beneficial effects. We additionally examine the persistence of these effects with impulse response functions estimated with the local projection method proposed in Jorda (2005). We find that these shocks have permanent effects on the level of GDP per capita. A shock of one standard deviation in the selected variables leads to impacts of around 0.2 percentage points of GDP that appear to be constant over time. This order of magnitude is similar to the effect of natural disasters measured in the literature (Cantelmo et al., 2019; IMF, 2020). We only find evidence that climate shocks have a persistent impact on GDP levels and no evidence of a persistent effect on growth.

We confirm the robustness of our results with a battery of alternative specifications and heterogeneity analysis. The heterogeneity analysis also highlights meaningful differences across country groups. Overall, we find that the effect of weather shocks is larger in countries that are more oriented towards agriculture and in countries that are poorer. The positive effects of more frequent mild temperatures are particularly relevant for agricultural and cold countries, possibly capturing the beneficial effect of fewer days with freezing temperatures. We find that sub-Saharan Africa is comparatively most affected by high temperatures while the Middle-East and Northern Africa is most affected by droughts.

One of our key results is that our selected climate variables perform much better in explaining GDP variations than the temperature and precipitation averages used in the literature. We confirm this result for a wide range of metrics by establishing comparisons with two central papers in the literature, Burke et al. (2015) and Kahn et al. (2021). For example, we measure the improvement of the within R-square that results from the introduction of climate variables relative to a specification without climate variables. We find that adding our selected climate variables in the GDP regression they consider can double or triple the increase in the within R-square. This result emphasizes that changes in weather extremes are more important than changes in average conditions.

Nevertheless, we find that the total amount of variation in GDP per capita attributable to weather is small. Our selection of climate variables can at most increase the within R-square by a few percents. This is an indication that weather is not the main driver of GDP variations globally on average.

Turning our attention to macro-fiscal outcomes, we consider government revenue, expenditure and debt, together with GDP, for a systematic analysis of the composition and cyclicality of fiscal responses. To keep our analysis compact, we use LASSO to select the most relevant climate variable for each of the three new dependent variables we consider. The procedure selects three new variables: the length of the longest dry spell, wetness intensity, and total precipitation in the longest period of continued intense precipitation. The last two variables are typically associated with flood-like conditions. We study their macro-fiscal implications jointly with the climate variables selected for GDP.

We find that weather shocks, especially excessive or unusually low precipitation episodes, also have significant and rich impacts on macro-fiscal aggregates. First, we find weak evidence that the new variables have a negative impact on GDP. Second, we find a counter-cyclical and often significant increase in government spending and debt in response to these shocks. These forms of fiscal response provide support to the economy and might explain why the negative effects on GDP are not significant. Conversely, revenue mostly responds significantly to high temperatures and we find that the response is pro-cyclical. The rich patterns we uncover suggest that the characteristics of the fiscal responses to weather shocks are complex and dependent on the characteristics of these shocks and the countries affected by them.

Our results suggest that weather shocks have causal effects on macro-fiscal outcomes. We do not have reasons to believe that our specification suffers from endogeneity. Our identification strategy relies on annual and infra-annual weather shocks. While there is strong evidence that climate change is the result of prolonged Greenhouse Gases emission-intensive GDP growth, there is no evidence to our knowledge that annual and infra-annual weather shocks are the result of annual shocks to economic activity. Therefore, we don't think that reverse causality is a concern. If anything, measurement errors would introduce an attenuation bias that does not undermine causality claims. Omitted variable bias remains a concern but we don't expect it to undermine causality claims substantially either. We are not aware of any variable that could simultaneously cause a weather shock and have a macro-fiscal impact.

Our identification strategy relies on random weather shocks that are not exactly like climate change (Mendelsohn and Massetti, 2017; Tol, 2021). In general, the effect of a transitory 1°C change in average annual temperature on the macro-economy is not equal to the effect of a slow but permanent 1°C increase of average temperature because short- and long-term elasticities are the same only under restrictive assumptions (Lemoine, 2018). Expected long-term climate change is also likely to induce unprecedented shocks, raising potential out-of-sample projection problems.[3] Therefore, extrapolating long-term impacts from our short-term responses requires caution and is an exercise we do not attempt.

The rest of the paper is organized as follows. The next section describes our empirical specification and the algorithm to select relevant climate variables. The third section explains how we construct the weather variables and summarizes the main characteristics of our dataset. The fourth and fifth sections present results, first for GDP per capita, and then for fiscal variables. The last section concludes.

2. Methods

2.1. Empirical model specification

Weather shocks can have potentially complex dynamic effects on GDP. We start by relating GDP per capita in country i at time t ($y_{i,t}$) to a vector of weather variables ($\boldsymbol{X}_{i,t}$) with a very flexible specification:

$$\ln y_{i,t} = \sum_{k=0}^{K} a_{k,i} t^k + \sum_{l=1}^{L} \theta_l \ln y_{i,t-l} + \sum_{p=0}^{P} \boldsymbol{\beta}'_p \boldsymbol{X}_{i,t-p} + \boldsymbol{c}' \boldsymbol{Z}_t + u_{i,t} \tag{1}$$

where $\sum_{k=0}^{K} a_{k,i} t^k$ are country-specific polynomial trends in weather patterns or economic activity, $\boldsymbol{Z}_t$ is a vector of variables capturing global shocks, and $\varepsilon_{i,t}$ is the error term. This specification encompasses various models estimated in the literature (Hsiang, 2010; Dell et al., 2012; Deryugina and Hsiang, 2014; Burke et al., 2015; Kalkuhl and Wenz, 2020; Kahn et al., 2021), potentially allowing weather variables to have persistent dynamic effects on GDP.

[3]For example, the standard deviation of average annual temperature is usually equal to about 0.5° C while even with strong mitigation it is possible to expect warming in the range of +2 to +4 °C in many countries.

To address serial-correlation and the fact that country GDP levels are non-stationary, we estimate equation (1) in first difference. It becomes a standard ARDL equation for GDP per capita growth:

$$\Delta \ln y_{i,t} = \sum_{k=0}^{K-1} \alpha_{k,i} t^k + \sum_{l=1}^{L} \theta_l \Delta \ln y_{i,t-l} + \sum_{p=0}^{P} \boldsymbol{\beta}_p' \Delta \boldsymbol{X}_{i,t-p} + \boldsymbol{c}' \Delta \boldsymbol{Z}_t + \epsilon_{i,t}. \tag{2}$$

We test alternative restrictions on the order of the polynomial and on the vector $\Delta \boldsymbol{Z}$. Note that very persistent effects of level shocks to weather variables on GDP growth can still be captured with a long trail of significant $\boldsymbol{\beta}_p'$.

We don't allow for a relationship between GDP growth and levels of the weather variables because GDP growth is stationary whereas many weather variables exhibit trends and are not stationary. Table A.2 in appendix presents evidence that average temperature and most variables built using temperature data are trended in most countries, as noted in the context of this literature by Kahn et al. (2021). This implies that GDP growth and these level variables cannot be related without additional manipulation (Tol, 2019; Kahn et al., 2021).

Climate variables can exhibit trends that are significant and different by country, requiring use of country fixed effects.[4] In our specification, country-specific trends imply that the country average of first differences in weather variables take different and significant values. If we did not include country fixed effects, we would fail to control for these country-specific averages.[5] Our specification is only valid if trends are constant over time. To handle time-varying trends, Kahn et al. (2021) subtract the 30-year moving average from each climate variable and take first differences. While effective, this would be very costly for us because our weather data starts in 1979 unlike their data that starts in 1960. Our method is not totally immune to bias from changes in trends but this does not seem to be a major problem in practice because many variables (Table A.2) and especially those used in our main specification do not show unambiguous evidence of a significant break in the past forty years (Table A.4 in appendix).

2.2. Local projection method

The complex dynamic effect of weather on GDP might not be immediately revealed by the estimation results from equation (2). There might be persistent weather effects because weather shocks themselves are persistent, because of feedback effects if current GDP per capita depends on past GDP levels, or because of a combination of both.

[4]For example, temperature trends range from 0.07 to 0.6 °C per decade across countries. The positive trend in the prevalence of days with maximum temperature above 35 °C is about four times larger than average in the country with the fastest trend, and is negative in some countries.

[5]To see this more clearly, consider a trended variable x evolving as $x_{i,t} = \theta_i t + v_{i,t}$, where θ_i is a time-invariant trend for country i, and $v_{i,t}$ is a random component with zero mean. The first difference is $\Delta x_{i,t} = \theta_i + \Delta v_{i,t}$. The panel average of first differences is $\overline{\Delta x_{i,t}} = 1/(T-1)\sum_t \Delta x_{i,t} = \theta_i + 1/(T-1)\sum_t \Delta v_{i,t}$. The joint use of first differences and fixed effects removes the trend from all weather variables, as $\Delta x_{i,t} - \overline{\Delta x_{i,t}} = \Delta v_{i,t} - \overline{\Delta v_{i,t}}$.

We use a local projection method following Jorda (2005) to estimate impulse response functions from a shock to one or more of our independent weather variables. As shown in Jorda's seminal paper, this procedure is more robust to misspecification than auto-regressions, easily accommodates flexible specifications, and allows for a simple visualization of the dynamic responses to weather shocks. We estimate variants of equation (2) where the dependent variables are long-differences between GDP per capita between time $t+h$ and time t:

$$\ln y_{i,t+h} - \ln y_{i,t-1} = \sum_{k=0}^{K-1} \alpha_{k,i}^{h} t^k + \sum_{l=1}^{L} \theta_l^h \Delta \ln y_{i,t-l} + \sum_{p=0}^{P} \boldsymbol{\beta}_p^{h\prime} \Delta \boldsymbol{X}_{i,t-p} + \boldsymbol{\gamma}^{\boldsymbol{h}\prime} \Delta \boldsymbol{Z}_t + \epsilon_{i,t}^h \tag{3}$$

where h indexes the estimation horizon measured in years. Equation (2) correspond to horizon 0 and coefficient estimates $\boldsymbol{\beta}^{0\prime}$ captures the contemporaneous effects of weather shock. We consider dynamics up to horizon 7 as in Acevedo et al. (2020). In case of growth effects, the coefficient $\boldsymbol{\beta}_p^{h\prime}$ would be expected to become increasingly large as time goes by. Alternatively, if the shock has a permanent level effect, we would obtain constant coefficient estimates. If instead the shock is mean-reverting, $\boldsymbol{\beta}_p^{h\prime}$ would be expected to converge to zero as time goes by.

2.3. Selecting relevant weather variables and estimating their effects

Our most important contribution to the literature is to study the effect of a wide set of climate variables. In total, we construct and examine 164 weather variables in $\mathbf{X}$, as described in Section 3.

If all the variables that we consider were entered simultaneously in equation (2), the model might still be estimated thanks to our large panel, but estimation would easily run into over-fitting issues. To avoid this problem, we use the Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani, 1996; Belloni et al., 2014) in a process where machine learning (ML) and expert judgement concur in selecting a parsimonious number of relevant variables.

The LASSO selects coefficients to minimize the sum of squared errors in equation (2) plus a weighted penalty term equal to the sum of the absolute value of each coefficient. The weight attributed to the penalty term is a hyper-parameter λ that needs to be selected before the minimization. Specifically, the LASSO solves the following problem:

$$\min_{\boldsymbol{\theta},\boldsymbol{\beta}} L(\boldsymbol{\theta},\boldsymbol{\beta}) + \lambda(||\boldsymbol{\theta}||_1 + ||\boldsymbol{\beta}||_1), \tag{4}$$

where

$$L(\boldsymbol{\theta},\boldsymbol{\beta}) = \left(\Delta \ln y_{i,t} - \sum_{k=0}^{K-1} \alpha_{k,i} t^k - \sum_{l=1}^{L} \theta_l \Delta \ln y_{i,t-l} - \sum_{p=0}^{P} \boldsymbol{\beta}_{\boldsymbol{p}}^{\prime} \Delta \boldsymbol{X}_{i,t-p} - \boldsymbol{\gamma}^{\prime} \Delta \boldsymbol{Z}_{i,t} \right)^2$$

$$\lambda(||\boldsymbol{\theta}||_1 + ||\boldsymbol{\beta}||_1) = \lambda \left(\sum_l |\theta_l| + \sum_{j,p} |\beta_{j,p}| \right)$$

Intuitively, the LASSO chooses coefficient estimates by comparing benefits measured by a reduction in the sum of squared errors in equation (2) with costs measured by the size of non-zero coefficients. When a coefficient $\beta_{j,p}$ is shrunk to zero, the variable is effectively omitted from the regression. The penalty term measures the costs associated with having a model with too many variables. The larger is λ, the smaller are coefficient estimates and the smaller the number of variables selected.

Before implementing the LASSO operator, we follow Belloni et al. (2014) and we impose that the model must use country fixed effects and in some specifications, year fixed effects or country quadratic trends. We do so in two stages, first by regressing all the dependent and independent variables on the selected fixed effects and trends, and second by applying the LASSO to the estimated residuals from the first stage (the "partialed-out" variables).[6]

As there is no universal "optimal" way to choose λ, the LASSO must be complemented by optimality conditions set by the analyst. In the ML literature, this is known as the "no free lunch theorem": there is no optimization algorithm that is capable of guiding the identification of a prior for the penalty weight when starting the analysis (Adebayo and Fokoue, 2019).

For the selection of the penalty weight, we rely on a two-stage process. In the first stage, we choose the value of λ that gives the highest R-square out-of-sample using k-fold cross validation. We start by dividing all our observations in a training set and in a test set. We run the LASSO on the training set for a randomly selected value of λ, use the selected variables to calculate the R-square in the test set and repeat this calculation many times. We choose the value of λ that maximizes the R-square in the test sets. This "random search" process is considered to be the most efficient in the ML literature (Bergstra and Bengio, 2012).[7]

The random search process leads to the selection of a very small value for λ with the effect of keeping about 20 variables or more. While this procedure helps with reducing over-fitting, many variables are not statistically significant in the OLS regression and are inter-correlated. Interpretation is the other important goal of our analysis in addition to out-of-sample accuracy. To preserve a compact number of variables whose effects can be easily interpreted, we refine further the choice of λ.

[6] We use the projection matrix $\left(I - T(T'T)^{-1}T'\right)$ where T is the matrix containing year dummies and I is the identity matrix. We then use Python's Scikit-Learn package (version 1.0.2) which uses coordinate-descent algorithm to run the LASSO on the partialed-out variables.

[7] More precisely, we start by randomly drawing a value of λ from a half normal distribution that starts from zero and has variance equal to 0.05. We then randomly divide (without replacement) the the whole panel data into five equal sets. We keep each of the five sets as a test set while using the union of the remaining four as training set. We apply the LASSO to the training sets and we calculate the R-square in the test sets. This leads to five estimates of out-of-sample R-square for each λ. We repeat this exercise using 200 randomly selected values of λ, for a total of 1,000 R-squared values. We select the λ that gives the largest R-squared on average.

In the second stage, we further select variables affecting GDP per capita by increasing the value of λ in small increments until no variable is dropped for three consecutive increments. When selecting variables affecting fiscal variables, we simply focus on the first selected variable for parsimony because we keep using the three variables selected for GDP. This second method, known as "grid search" in the ML literature, helps us both to refine the selection of a parsimonious model and to analyze the robustness of selection of climate variables. We also use the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) to assess the relative quality of the selected models.

The LASSO produces "biased" coefficient estimates because the penalty term shrinks them.[8] To estimate the "unbiased" effect of weather shocks, we finally re-estimate the model with the climate variables selected by the LASSO using standard OLS methods.[9]

3. Data

3.1. Weather data sources and aggregation over time and space

We use temperature and precipitation data from the ERA5 dataset compiled by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al., 2018). ERA5 provides hourly reanalysis weather data on a global grid from 1979 to 2019.[10] The grid resolution varies with latitude with cells of 30×30 km at most (at the equator).[11]

Weather data is available at a much higher spatial and temporal resolution than typical annual country macro-economic data. Our goal is to reduce the millions of weather measurements in every country and year to construct a manageable number of potentially meaningful climate variables. We aggregate raw ERA5 weather data over space and time to construct our variables using the cloud computing power of Google Earth Engine (GEE) (Gorelick et al., 2017).[12]

We can use the high spatial and temporal granularity to reveal weather events that would be lost when averaging weather variables over an entire country during a whole year. Country and year averages may bias estimates of weather impacts in at least three important ways.

[8] With "biased", we mean that the LASSO returns smaller coefficients compared to OLS. Alternatively, the literature sometimes uses the term "regularized" coefficients.

[9] For theoretical justification, see Belloni and Chernozhukov (2013).

[10] Reanalysis data is generated using models that combine a variety of weather observations and past short-term weather forecasts from different datasets (e.g., weather stations, satellites, ocean gauges, weather balloons) to remove biases in measurement and to create a coherent, long-term record of past weather into one regularly spaced grid. For more details, see `https://www.ecmwf.int/en/about/media-centre/focus/2020/fact-sheet-reanalysis`.

[11] See Section A.1 in appendix for more details.

[12] See `https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5` and `https://developers.google.com/earth-engine/datasets/catalog/ECMWF_ERA5_DAILY` for a detailed description of the datasets.

First, averages miss local and infra-year extreme weather events if events of opposite nature cancel out each other. For example, droughts in a specific region in summer can coincide with intense precipitation in another part of the country or in a different season. Country annual averages would then be unable to reflect these extreme events. Second, the relationship between a weather shock and the economy can be non-linear and dependent on duration, spatial coverage, and intensity. For example, both prolonged high temperatures (a heatwave) and short-lived but very high temperature could impact the economy in different ways. Even if average temperature might approximately reflect the occurrence of various hot weather events, it would fail to capture the different effects associated with the different characteristics of these events. Third, deviations from local seasons could be relevant even if they are not reflected in averages or as outliers in the full annual distribution. For example, unusually high precipitation in central Europe in summer could have an impact on the economy even if the same level of precipitation would be totally normal and irrelevant in another time of the year or in other regions that are more accustomed to heavy precipitation.

We build variables that describe the distribution of temperature and precipitation as well as notable extreme events following the climate literature (Kim et al., 2020; Perkins and Alexander, 2013). When the literature uses similar alternatives, we include all of them and let the LASSO select the most relevant option. While we could have used additional ML techniques to reduce the full matrix of weather measurements into country-year variables, we choose to start from definitions of weather events that are frequently used in the climate literature to obtain results that are easier to interpret and can be linked to other work.

When deriving country-level variables by aggregating grid-level information, we construct both unweighted and population-weighted variables. Unweighted variables do not introduce bias in the characterization of climate that could lead to miss impacts in areas with low economic and population density (Bandt et al., 2021). For example, droughts in agricultural areas may be more important for economic activity than droughts in urban areas. Lack of snow or rain in remote areas that supply water to economic centers may be missed completely using population weights. However, unweighted data may give excessive importance to weather, and particularly temperature, in areas with relatively little economic contribution to total output, especially in countries with large uninhabited regions. For these reasons, we construct both unweighted and weighted variables using year 2000 population weights.[13] We include both sets of variables in the LASSO exercise.[14]

[13] We obtain grid cell level population information by using Socioeconomic Data and Application Center's UN WPP-Adjusted Population count dataset. See `https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-adjusted-to-2015-unwpp-country-totals-rev11` for a detailed description.

[14] An interesting question for future applied research is to explore why our approach selects weighted variables in some cases and unweighted variables in others.

3.2. Variable definitions

This Subsection provides an overview of all the weather variables we construct from the raw data and of macro-fiscal variables. Appendix A.2 provides a complete description of definitions, exact formulas, and summary statistics for the selected variables.

Defining extreme weather. A practical problem for empirical research is the lack of unambiguous definitions of extreme weather. In general, a weather event is extreme if some of its characteristics exceed some thresholds. Specifically, definitions are ambiguous about the thresholds to use with respect to major characteristics, like intensity, frequency, or duration.

The literature has used both "relative" and "absolute" thresholds. In some cases, extreme weather is defined as weather "that is rare at a particular place and/or time of year" (Cubasch et al., 2013, p 134). This suggests the use of thresholds that are specific to locations and seasons ("relative thresholds"). For example, definitions can rely on the 90^{th} percentile of the local distribution of temperature at a certain time of the year. Relative thresholds account for the importance of adaptation to average conditions and emphasize the effects of deviations from local averages. In other cases, extreme weather is defined using thresholds that are constant across space and time ("absolute thresholds"). For example, maximum daily temperature greater than 40 °C are generally considered harmful everywhere. Absolute thresholds are better suited to capture physical limits beyond which weather causes damages, no matter when or where it occurs (e.g., IPCC, 2021a). We consider both "relative" and "absolute" weather extremes as they can both be relevant for the economy in different ways.

We typically capture extreme events at the country-year level by both counting their occurrences and measuring their intensity. To this end, we count the share of grid-cells and days with weather events that are defined for different thresholds. We also construct a wide range of variables that measure the average or maximum intensity of extreme events. We do so for temperature, precipitation and wetness/drought as detailed below.

Temperature variables. We consider average temperature, the variance of daily temperature, and the average diurnal temperature range (the difference between the minimum and maximum temperature in a day). We calculate the number of cold nights, cold days, warm nights and warm days using relative thresholds based on the 1979-2019 distributions for every 5-day window centered on each day of the year.

We build various heatwave and coldwave variables based on the climate literature.[15] We follow Perkins and Alexander (2013) and consider various thresholds to define heat and cold waves in daytime and nighttime. We then count the length of the longest wave, the number waves in a year, the number of days and the average maximum or minimum temperature during such waves. We also follow Kim et al. (2020)

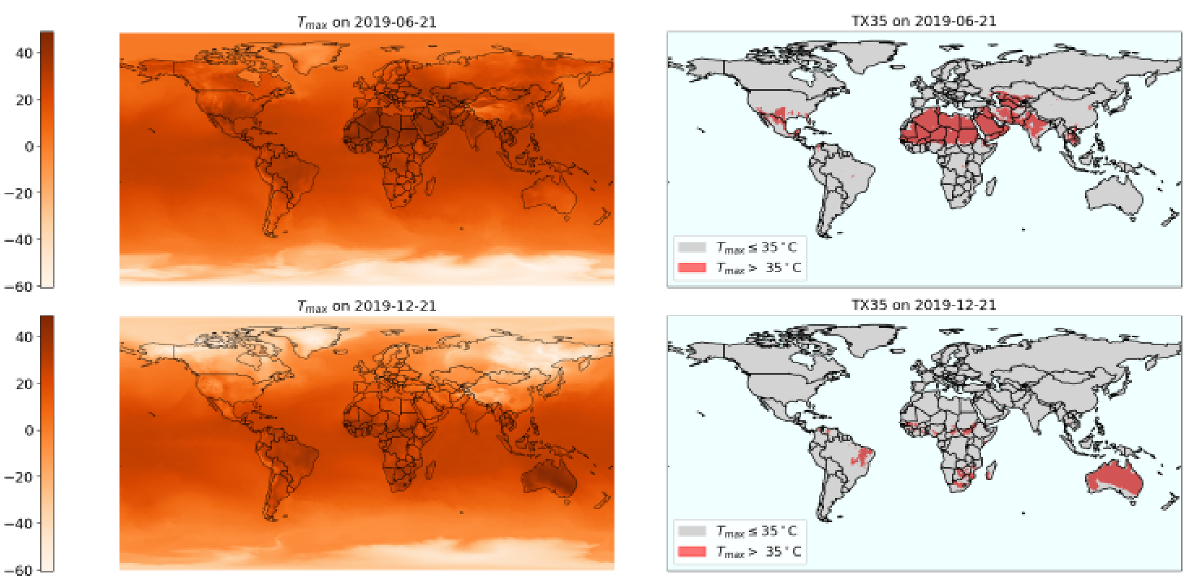
[15] "Heatwaves" and "coldwaves" are loosely defined as prolonged periods with unusually warm or cold temperatures (e.g., Perkins, 2015).

and additionally define the duration of cold and warm spells as the number of days exceeding alternative relative temperature thresholds for prolonged periods.

We use the fine spatial resolution of our data to define minimum and maximum variables that are used in the literature to capture local extremes. We compute the annual minimum of night temperatures and the maximum of daytime temperatures for every cell of a country's grid, and average them out over space.

We also define another set of extreme temperature variables using absolute temperature thresholds often used in the climate literature (e.g., IPCC, 2021a). With absolute thresholds, using the highest possible level of spatial resolution is essential to avoid missing the potentially meaningful events that would otherwise be averaged out. For example, Figure 1 illustrates how country averages can miss when maximum temperatures exceed would miss many instances of days with temperature 35 °C in only parts of a country. To avoid this, we count how often temperature crosses various absolute thresholds (e.g., below 0 °C, above 35 °C and 40 °C) over the 365 days of a year and over each of a country's grid cells.

Figure 1: Illustrating the role of high spatial resolution when using absolute thresholds



Notes: This figure illustrates the importance of high spatial resolution when accounting for daily maximum temperatures exceeding 35 °C (TX35). As seen in the top row, at the beginning of summer 2019, only a small share of the US (8%) experienced temperatures higher than 35 °C. These temperatures would average out if we were to use country means. Similarly for Brazil in December 2019, the bottom row shows that only 12% of the country crosses the 35 °C threshold. In both cases, country averages would fail to capture these extreme temperatures.

Finally, to capture potential non-linear effects of temperature on macro-economic variables, we define 3 °C-wide intervals from -9 °C and below to 30 °C and above and we count how often temperatures fall in these intervals over space and time (see for example Schlenker and Roberts, 2009). This approach allows us to capture the impact of temperature on macro-fiscal variables at different temperature levels imposing minimal restrictions on the temperature response functional form.

Precipitation variables. We use the term *precipitation* throughout this paper because our data measures both rain and snow precipitations (converted into rain equivalents). We sometimes focus on "wet days", that are days with 1 mm precipitation or more, or on "dry days" with precipitation below 1 mm. Our variable set includes the country-year averages and the variance of daily precipitation, which we construct twice, on all calendar days and on wet days. We also measure precipitation on very wet and extremely wet days, where these days are defined using relative thresholds.

We build several variables to capture extended wet and dry periods. We count the largest number of consecutive dry days, wet days, very wet days, and extremely wet days. We measure precipitation in the longest period of wet, very wet and extremely wet days respectively.

Floods are among the most destructive climate disasters. To capture short but intense precipitation that may cause floods, we use the maximum amount in a year of rainfall in 1-day or 5-day intervals. To capture extreme precipitation at the local level, we also examine total monthly precipitation in each grid cell. We use these to calculate the country average of maximum and minimum monthly precipitation.

As for temperature, we make use of our data high spatial resolution to define precipitation extremes using absolute thresholds. We calculate the number of consecutive days in which a minimum percentage of the country area is experiencing a dry day using different percentage thresholds. Similarly to what we do with temperature, we define four precipitation intervals (divided by 1, 10, and 20 mm thresholds), and measure how often precipitation is in any of these intervals. We define the maximum extent of heavy and very heavy precipitation as the maximum surface of a country where precipitation exceeds 10 mm and 20 mm respectively. We also construct an indicator that measures deviations from a balanced level of precipitation. This indicator measures the absolute deviation from having precipitation between 1 and 10 mm half the time over space and time.

Wetness and drought variables. We use the Palmer Drought Severity Index (PDSI) (Palmer, 1965) to introduce a measure of dry and wet periods that combines temperature and precipitation data to estimate cumulative deviations in soil moisture from normal conditions (Dai et al., 2004; Abatzoglou et al., 2018; Lai et al., 2020).[16] The PDSI ranges from -10 to +10, but values below -4 and above +4 are very rare. To capture extreme conditions during a year we build variables measuring the share of total grid-months subject to droughts and harsh droughts (with PDSI respectively below -3 and -4), and to periods with high and very high moisture (with PDSI respectively above 3 and 4). As for precipitation, we also seek to capture the maximum geographical extent of droughts and wet conditions. For each of the four categories, we compute the share of affected grid-cells in the month where the share is at its maximum.

[16] Data downloaded from Google Earth Engine. See `http://www.climatologylab.org/terraclimate.html` and `https://developers.google.com/earth-engine/datasets/catalog/IDAHO_EPSCOR_TERRACLIMATE` for a detailed description of the datasets.

In sum, in our empirical analysis, we consider 45 different temperature variables, 29 precipitation variables, and 8 wetness-drought variables, for a total of 82 unique climate variables. For the empirical estimation, we remove perfectly collinear variables. We add the first and second lag of these variables as well as their population-weighted counterparts and we obtain a set of 480 climate variables.

Macro-fiscal variables. We use GDP per capita from the World Bank's World Development Indicators (WDI).[17] For fiscal outcomes, we collect variables from the IMF World Economic Outlook (WEO) because it has a wider coverage than the WDI. We use government revenue and expenditure expressed in percentage of GDP, also from the WEO database.[18] To examine gross debt, we draw from the Global Debt Database which improves on other databases by constructing long series with a consistent coverage over time (Mbaye et al., 2018).[19] For some countries (all countries in the case of debt), the fiscal variables only cover the central government, implying that our analysis will miss local governments' response.

3.3. Summary statistics

We start our analysis by considering all countries for which we have at least 7-year long time series for GDP per capita and climate variables. We exclude Libya, Iraq, Equatorial Guinea and Bahrain because of outliers. This leads to selecting 199 countries for a total of 6,550 country-year observations. Data on fiscal aggregates have smaller coverage. We remove Kuwait and São Tomé and Príncipe because of outlier observations, and all observations with any missing fiscal value. As a result, the sample for analyzing fiscal outcomes has 159 countries for a total of 3,859 country-year observations.

Our empirical and identification approach relies on inter-annual variation within country. Therefore, we use a standard approach to decompose the variance of variables into *between* and *within* components.[20] The *between* standard deviation measures variation of average country weather around the global mean. The *within* standard deviation measures the average deviation from country averages.

GDP per capita grew by 1.6 percent per year on average in our largest sample used for GDP analysis and by 2.0 percent per year on average in the smaller sample used for fiscal policy analysis (Table A.3 in appendix). The within standard deviation of GDP per capita growth is large, ranging from 4.7 (larger sample) to 3.7 (smaller sample) percentage points. The ratios of government revenue and expenditure to GDP grew at the same average rate of 0.1 percentage points per year. The inter-annual variation of

[17] Specifically, we use the variable "GDP per Capita constant 2015 US$" (NY.GDP.PCAP.KD).

[18] Specifically, we use the variables GGR_NGDP and GGX_NGDP for the general government.

[19] We use "Central government debt, % of GDP" which has wider coverage than general government debt.

[20] For any variable x, the variance across N countries and over T years can be decomposed by introducing country averages $\bar{x}_i$. The variance is equal to $\sum_{i,t} \frac{(x_{i,t}-\bar{x})^2}{NT} = \sum_{i,t} \frac{(x_{i,t}-\bar{x}_i)^2}{NT} + 2\sum_{i,t} \frac{(x_{i,t}-\bar{x}_i)}{T} \frac{(\bar{x}_i-\bar{x})}{N} + \sum_{i,t} \frac{(\bar{x}_i-\bar{x})^2}{NT}$. It simplifies to $\sum_{i,t} \frac{(x_{i,t}-\bar{x})^2}{NT} = \sum_{i,t} \frac{(x_{i,t}-\bar{x}_i)^2}{NT} + \sum_{i} \frac{(\bar{x}_i-\bar{x})^2}{N}$ where the terms are respectively the within and between variance. We take the square roots of each component to obtain *between*- and *within*-country standard deviations.

these variables is substantial, with *within* standard deviations ranging from 3.2 to 4.0 percentage points. Government debt-to-GDP ratios were stable on average but with a large *within* standard deviation of 11.1 percentage points.

The *within* standard variation of climate variables in first differences is typically much higher than the *between* standard deviation. This indicates that the average change in climate variables over the sample period is relatively similar across countries. By comparison, the change in climate variables from one year to the next in every country varies considerably more.

Many weather variables exhibit a trend over the sample period. Table A.2 in appendix reports results from a systematic analysis of trends in all weather variables in all countries from 1979 to 2019. We find evidence of positive and statistically significant country-specific trends in a majority of countries for variables related to temperatures. Such trends are more rare for other variables.

In our model specification, we assume that trends are time-invariant. To check the validity of this assumption, we test for a structural break in trends with unknown break date for all variables in every country. For most variables in most countries, we cannot reject the null hypothesis that there are no significant structural breaks. We conclude that the assumption of time-invariant trends is acceptable. We also test all first differences of weather variables for the presence of a unit root and we reject it in all cases with p-values close to zero.

4. GDP Results

We start by illustrating the selection of the climate variables using the LASSO. We then study the effect of the selected variables on GDP growth by applying alternative restrictions to the general model illustrated in Equation (2). Our preferred specification is parsimonious and uses the first two lags of the dependent variable, country fixed effects ($k = 0$ in Equation 2) and $\mathbf{Z}_t$ has only a vector of year dummies. We test alternative models with (1) global GDP instead of year dummies, and (2) a quadratic time trend by country.

4.1. Climate variable selection

In our baseline specification, we use country and year fixed effects. The collinearity test of Belloni et al. (2013) does not suggest dropping any of the 480 weather variables. The random search process selects 30 out of these variables, with $\lambda = 0.0166$. The selected variables include the first two lags of GDP per capita growth and a mix of variables derived from both temperature and precipitation, unweighted and weighted, contemporaneous and lagged. The full list is reported in the appendix Table A.7.

The first phase of our variable selection process reduces the total number of variables by approximately 95 percent, but many of the climate variables selected by the random search are statistically insignificant, indicating that while they contribute to explaining the variation of the dependent variable, they do not help much to understand the effect of weather on GDP growth. Therefore, we further reduce the number of variables using the grid search algorithm as described in Section 2.3.[21]

Our final selection includes three climate variables and the first two lags of the dependent variable. Figure 2 panel (a) shows how much the within R-square decreases when the number of selected variables decline as we increase λ. We examine the within R-square to focus on the explanatory power of climate variables and set aside the explanatory power of fixed effects. Our preferred specification improves the within R-square by 7 percent relative to a specification with just the 2 lags of the dependent variable as independent variables. This is a sharp reduction in the within R-square from the 17 percent improvement obtained with the specification using all the 30 variables selected by the LASSO after the random search. However, this reduction corresponds to a much more parsimonious model that we can more easily interpret. If the main goal of the analysis is prediction of GDP growth, all the variables selected in the first random search step should instead be used.

Other information criteria for model selection support our preferred specification. The Bayesian information criterion (BIC) obtained for the different variable selections is minimized for selections of 4 to 6 variables (Figure 2 panel b). The Akaike information criterion (AIC) declines monotonously as the selection of variables increase to the set chosen by the random search. Therefore, our preferred selection of 5 variables appears sensible.

4.2. The effect of weather variables on GDP growth

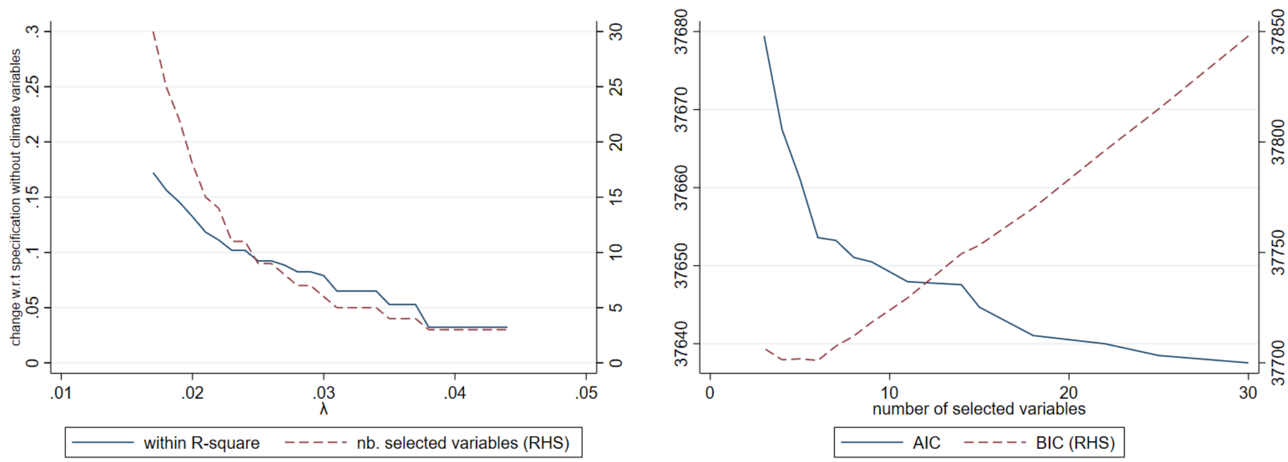
The three selected weather variables for our baseline specification are the share of grid-days with harsh drought conditions (Harsh Drought Prevalence — $PDSI_{<-4}$), the share of grid-days with maximum daily temperature above 35 °C (Max T °C above 35 — $TX35$), and the share of grid-days with mean temperature in the interval 9-12 °C (Mean T °C in [9; 12) — $TS_{9,12}$). The LASSO selects population-weighted variables except for Mean T °C in [9; 12). Summary statistics of first differences of these variables are displayed in Table A.4 and correlation coefficients between GDP growth, the fist two lags of GDP growth, and first differences of the selected climate variables are shown in Table A.5.

The correlation between the first differences and GDP growth is generally very low, ranging from 0.04 to 0.05 in absolute value. However, as a comparison, the correlation between first differences of average annual temperature (Mean Temperature — T) and GDP growth is even smaller and equal to only -0.006. Among the climate variables, the largest correlation is found between Harsh Drought Prevalence and Max T °C above 35 (0.183). Harsh Drought Prevalence is also positively correlated with Mean Temperature (0.159) because temperature plays a role in the definition of the PDSI drought indicator. Max T °C above 35 and Mean Temperature are modestly correlated (0.356) but Mean Temperature is not retained by the LASSO.

[21]We increase the hyperparameter λ by increments equal to 0.001 and we select the smallest value of λ such that the selection of variables is stable for at least three consecutive increments (+0.003).

Figure 2: Variable selection and OLS estimation outcomes as λ varies (country and year effects)

(a) Selected variables and within R-square (b) Information criteria



Note: The figures show various outcomes from implementing the LASSO for different penalty parameters. The estimated model has GDP per capita growth as the dependent variable and includes country and year effects. The within R-square, AIC, and BIC are computed based on the OLS estimation. The within R-square is reported as a percentage change relative to the within R-square obtained with a specification that only includes the first two lags of the dependent variable (within $R^2 = .0937$*).*

The selected climate variables have an intuitive effect on GDP, as shown in Table 1 where all the variables are standardized to facilitate interpretation. We find that an increase in Harsh Drought Prevalence and in Max T °C above 35 have adverse effects on contemporaneous GDP growth. By contrast, we find that an increase in Mean T °C in [9; 12) has beneficial effects on GDP. These effects are highly significant and robust across alternative model specifications.

In our baseline specification (column A) we use the unbalanced panel and year fixed effects. A positive shock equal to one standard deviation of the first difference of Harsh Drought Prevalence in a country reduces GDP growth by 0.21 percentage points. An increase in Max T °C above 35 has an equally large and significant effect on GDP growth. A positive shock equal to one standard deviation in the first difference of Max T °C above 35 reduces GDP growth by 0.20 percentage points. A positive shock equal to one standard deviation in Mean T °C in [9; 12) leads to an increase in the growth rate equal to 0.16 percentage points. In this case, the unweighted variable was chosen over the population-weighted one.

These effects are similar to those found by other studies that have included droughts using indicators for selected natural disasters (Cantelmo et al., 2019; IMF, 2020). Average annual temperature is correlated with extreme and moderate temperatures, but the correlation among first differences is generally very low. It is thus important to provide a more complete characterization of weather events than what is typically done in the literature.

The selection of significant weather shocks includes variables constructed with both absolute (Max T °C above 35, Mean T °C in [9; 12)) and relative thresholds (Harsh Drought Prevalence). For droughts, we find that drier than average conditions are harmful, no matter what is the average precipitation level. For temperature, we find that the 35 °C absolute threshold is selected over alternative definitions of high temperatures based on the deviations from local and seasonal norms.

Table 1: The effect of changes in selected climate variables on GDP per capita growth

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
First difference in							
Harsh Drought Prevalence (W)	-0.211***	-0.251***			-0.231***	-0.191***	-0.257***
	(0.0544)	(0.0527)			(0.0552)	(0.0568)	(0.0749)
Max T °C above 35 (W)	-0.201***		-0.244***		-0.175**	-0.215***	-0.254***
	(0.0745)		(0.0727)		(0.0745)	(0.0752)	(0.0929)
Mean T °C in [9; 12)	0.155***			0.174***	0.153***	0.142***	
	(0.0395)			(0.0402)	(0.0380)	(0.0400)	
Observations	6,550	6,550	6,550	6,550	6,550	6,550	4,860
Year fixed effects	Yes	Yes	Yes	Yes	No	Yes	Yes
World GDP growth	No	No	No	No	Yes	No	No
Country quadratic trends	No	No	No	No	No	Yes	No
Balanced	No	No	No	No	No	No	Yes
R-square	0.264	0.261	0.261	0.260	0.253	0.350	0.224
Within R-square	0.0998	0.0967	0.0965	0.0952	0.149	0.0375	0.0790

Note: The table presents results from the OLS estimation with country fixed effects of the effect of climate variables on the first difference of log real GDP per capita expressed in constant 2015 USD. All regressions include controls such as two lags of the dependent variables. Column E includes world growth as a control. Column G is estimated on a balanced subsample of 135 countries for 1983-2019. Coefficient estimates of additional climate variables selected in column E, F and G are reported in appendix A.4 Table A.14. Climate variables are standardized and their definitions are detailed in Appendix A.2 Table A.1. (W) indicates population-weighted variables. Standard errors are clustered by country. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We examine whether our selected climate variables have an effect on their own or whether their estimated effects result from their combination. To this end, we enter each variable separately in our specification with year and country effects as reported in columns B-D of Table 1. Coefficients estimates are very similar to those in the baseline column A, suggesting that the main effect of each variable is mostly independent and additional to the effect of the other variables.

We test the robustness of our variable selection and coefficient estimates by considering alternative specifications. For each model we repeat the LASSO exercise as for our baseline specification. In column E, we retain country fixed effects but we use world GDP per capita growth instead of year effects to control for common world-wide developments. A random search over possible penalty parameters leads to a first selection of 36 variables (see Table A.8 in appendix). The overlap of the selections resulting from the random search is remarkable. The procedure selects the same 26 variables for the baseline and the specification without year effects. Only 4 out the 30 variables selected for the baseline were not selected again. We then narrow down the number of selected variables to 8, including the two lags of the dependent variable and world growth (see Figure A.2 in appendix). The 5 selected climate variables include the same 3 used in the baseline, the duration of cold spells, and the lag of the average over space of grid-cell maximum temperatures. Column E of Table 1 shows that the coefficients of the 3 climate variables used in our baseline specification are robust to this new specification.

We additionally consider a specification with country-specific quadratic trends in addition to year effects. The random search procedure leads to the selection of 24 variables (see Table A.9 in appendix). Once again, there is a good overlap between the selection under this specification and under the baseline, with 22 common variables. After we increase the penalty parameter, we get to a stable set of 7 variables, including also in this case the same 3 climate variables selected in our baseline and the 2 lags of the dependent variable. Column F of Table 1 shows that the coefficient estimates from the OLS estimation of the climate variables that are common to the baseline and to this new specification are, once again, very similar.

Finally, we also implement our selection method on a balanced subsample with the 135 countries that have non-missing observations continuously from 1984 to 2018. The random search procedure selects 18 variables, including the 3 variables selected in our baseline. In the grid search, we lose Mean T °C in [9; 12) while the algorithm adds 2 other variables: the first lag of Cold Spell Duration (CSD) and the maximum of 1-day total precipitation in the country (1-Day PPT Maximum — $PX(1)$) (see Tables A.10 and A.14 in appendix). Results in column G in Table 1 shows that the effects of Harsh Drought Prevalence and of Max T °C above 35 remain robust.

4.3. Comparisons with the literature

Does the set of variables we select improve substantially our understanding of GDP variations? We examine this question by comparing our results with key models from the literature. We focus on two central papers in the literature, Burke et al. (2015) and Kahn et al. (2021).

We estimate the two papers' respective baseline models using our sample and confirm their robustness.[22] We follow the specification in Burke et al. (2015) and regress GDP growth on annual average temperature, precipitation, the two squares of these variables, and include two lags of GDP growth, country quadratic trends and year effects. Despite the fact that our sample is much smaller and other minor differences, we obtain very similar coefficient estimates.[23] Results in column B in Table 2 feature an inverted U-shaped

[22]Both papers examine real GDP per capita growth. We use our GDP variable to facilitate comparisons across specifications. For climate variables instead, we use the variables provided in the replication package of both papers.

[23]Our estimation sample starts in 1979 instead of 1960, and is 40 percent smaller with only 3,935 observations.

Table 2: Estimation of the effect of climate shocks on GDP growth: comparisons with the literature

	Burke et al. (2015)			Kahn et al. (2021)		
	(A) base	(B) unchanged	(C) augmented	(D) base	(E) unchanged	(F) augmented
Climate variables	none	temperature, temperature^2, precipitation, precipitation^2	temperature, temperature^2, precipitation, precipitation^2, $PDSI_{<-4}$ (W), $TX35$ (W), $TS_{9,12}$,	none	temperature, precipitation, (deviations from trend for both), both their 4 lags	temperature, precipitation, (deviations from trend for both), both their 4 lags, $PDSI_{<-4}$ (W), $TX35$ (W), $TS_{9,12}$,
Country fixed effects	yes	yes	yes	yes	yes	yes
Country quadratic trends	yes	yes	yes	no	no	no
Year effects	yes	yes	yes	no	no	no
R-squared	0.403	0.407	0.413	0.216	0.220	0.228
Within R-squared	0.0165	0.0233	0.0334	0.110	0.114	0.123
AIC	-14,731	-14,752	-14,789	-16,151	-16,154	-16,200
BIC	-14,712	-14,708	-14,726	-16,132	-16,070	-16,096

Notes: Each column corresponds to a fixed-effect regression of the first difference in log real GDP per capita on two lags of the dependent variables and on climate variables for column B, C, E, and F. Climate variables are introduced sequentially by columns. $PDSI_{<-4}$: Harsh Drought Prevalence; $TX35$: Max T °C above 35; TS_{9_12}: Mean °C in [9; 12). (W) indicates population-weighted variables. See appendix Table A.1 for further details. Coefficient estimates are reported in appendix Table A.15.

relationship between temperature and growth that is quantitatively close to that found by Burke et al. (2015), with optimal temperature estimated to be equal to 13.3 °C (instead of 13.1 °C).

We compare the performance of our approach with the model in Burke et al. (2015) by introducing climate variables sequentially. Relative to a specification without climate variables (column A in Table 2), the introduction of annual average temperature and precipitation and their squares improve the within R-square by 10 percent. If we additionally include our four selected climate variables, the within R-square increases by 102 percent (column C in Table 2). Similarly, the information criteria (AIC and BIC) unambiguously show improvement with our selected variables, while they do not clearly support the introduction of annual averages and their squares.

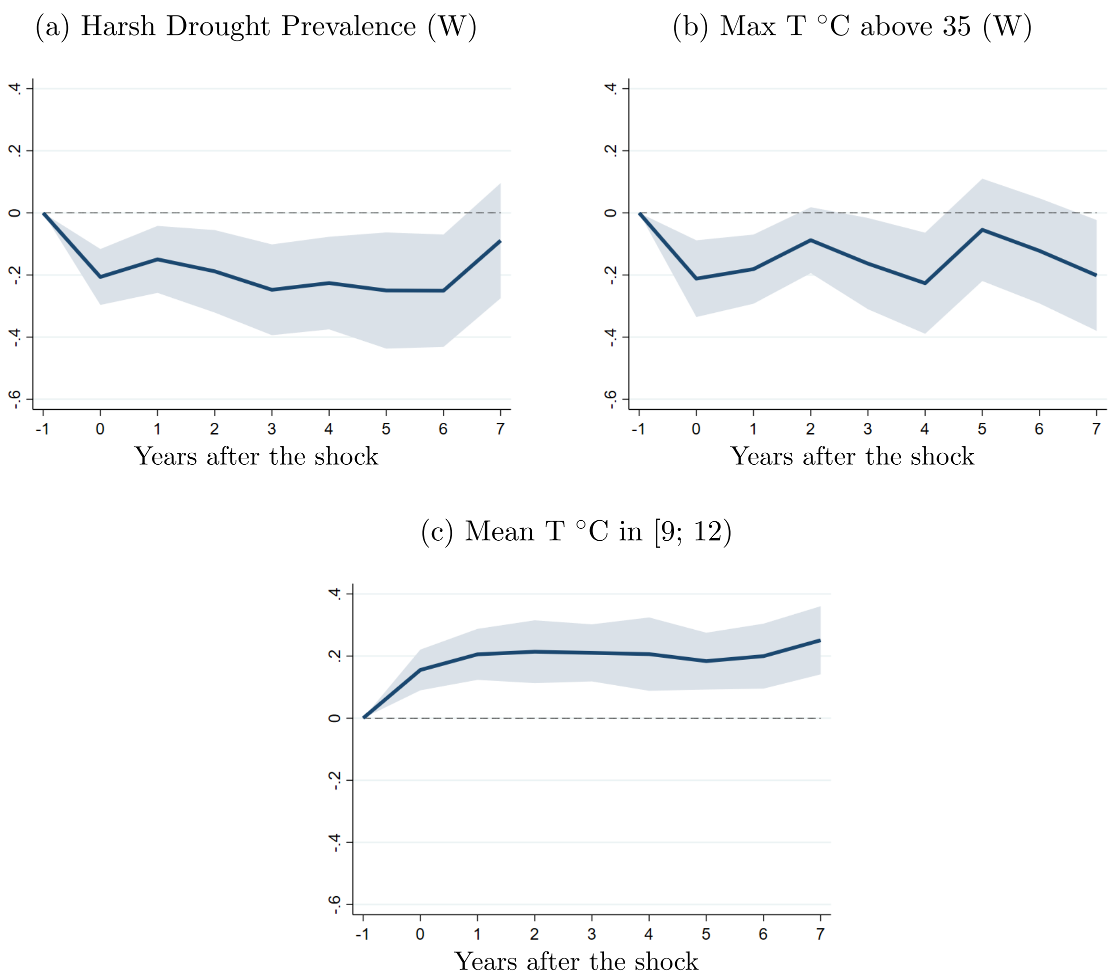
Turning our attention to Kahn et al. (2021), we adopt the same baseline specification focusing on the absolute deviations of annual average temperatures and precipitations relative to their respective 30-year moving average.[24] Column E in Table 2 reports results that are again extremely similar to those originally reported despite the smaller size of our sample.[25] In this case, the introduction of their climate variables relative to a basic case abstracting from climate improves the within R-square by 4 percent (columns D-E

[24]Their specification also includes four lags for each of these variables.

[25]Our estimation sample starts in 1979 instead of 1960, and is 25 percent smaller with only 4,917 observations.

in Table 2). By contrast, additionally including our selected variables improves the within R-square by 12 percent.[26] The superior performance of our selected variables is again confirmed by the information criteria. Therefore, a range of performance indicators suggests that our climate variables are much more relevant in explaining GDP growth variations than annual average temperature and precipitation.

Figure 3: Persistence of selected weather shocks on GDP per capita



Notes: Each panel depicts the impulse response of per capita output in levels to a one standard deviation shock of the corresponding climate variable. Horizon 0 is the year of the shock. The shaded areas show the 90 percent confidence intervals around estimates. (W) indicates population-weighted variables.

[26] Increases in the within R-squares are much smaller compared to the increases in specifications with country trends a la Burke et al. (2015) because the within R-square in the base case of no climate variable is much smaller with country trends. Country-specific quadratic trends absorb a large amount of variation, leaving little to be explained in the within R-square.

4.4. The dynamic effects of climate shocks

We examine the persistence of the GDP effects of a shock on the selected climate variables by using the local projection method. For each variable, we estimate the impulse response to a one standard deviation shock as described in the Section 2.2. The flexibility of this approach allows us to investigate if a climate shock has a temporary effect, a persistent effect on GDP levels, or a persistent effect on GDP growth.

The results in Figure 3 show that our selected climate shocks have very persistent effects on GDP levels that remain broadly significant over the 7-year horizon we consider. Specifically, a one-year increase in Mean T °C in [9; 12) has a positive effect that remains stable and significant throughout the period considered (Panel (c)). The respective adverse effects of an increase in Harsh Droughts Prevalence and in Max T °C above 35 are also stable, albeit subject to slightly more uncertainty (Panels (a) and (b)). The effects still remain significant over most of the horizons considered. The results in Figure 3 also show clearly that all effects have a persistent effect on GDP levels but no effect on GDP growth.[27]

4.5. Heterogeneity

We test if results obtained using the whole sample of countries are different from those obtained using sub-groups of homogeneous countries. This exercise provides both a robustness test and new insights on the channels thought which climate shocks affect growth of GDP per capita.

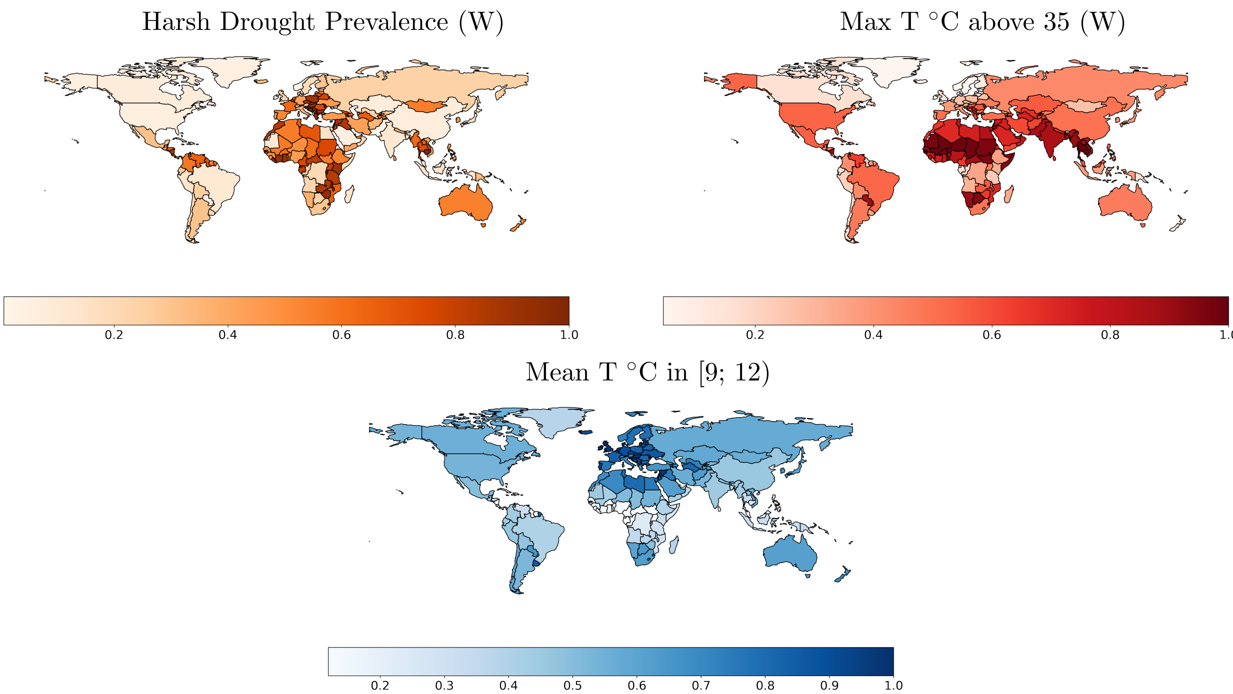
We separate countries in rich and poor, hot and cold, agricultural and non-agricultural, agricultural cold and agricultural hot, and we divide countries in six macro-regional groups. For a detailed description of each group see Notes to Figure 5. For each subgroup, we use the same variables selected by the LASSO for the baseline specification because we are primarily concerned with the robustness of estimates across groups. We leave selection of variables by group to future research.

Table A.6 in appendix features summary statistics by sub-group for GDP per capita and climate variables. Figure 4 provides a graphic representation of the standard deviation of first differences for each variable by percentile. When absolute thresholds are used to derive climate variables, their frequency changes over space as a function of local climate. It is more likely to cross the 35 °C threshold in hotter countries, keeping anything else constant. In very cold countries temperatures this high are almost never observed while in other countries they may be observed almost every year. This implies that both groups of countries will have low standard deviation of Max T °C above 35.[28] The standard deviation of Mean

[27]If any of these variables had an effect on GDP growth, the coefficient estimates would increase in absolute value with the horizon considered. The stable estimates support our chosen specification that follows the approach in Kahn et al. (2021) and introduce climate variables in first differences rather than in levels as in Burke et al. (2015). Empirical evidence that caution against regressing GDP growth on climate variables in levels is also presented in Newell et al. (2021).

[28]In the case of Canada and Scandinavian countries, for example, maximum daily temperatures above 35 °C are almost never observed, which explains why have the very low standard deviation of this variable.

Figure 4: Global distribution of standard deviations of climate shocks



Notes: Each panel shows the percentiles of the global distribution of the standard deviation of the first difference of a climate variable over the period 1979-2019. (W) indicates population-weighted variables.

T °C in [9; 12) tends to be larger at the higher latitudes, and particularly in Europe. The prevalence of harsh droughts is instead measured using the PDSI indicator, which uses relative dryness or wetness with respect to average local conditions, including the effect of both precipitation and temperature. For this reason, the spatial distribution of the standard deviation of Harsh Drought Prevalence follows a pattern that reflects regional precipitation and temperature variation.

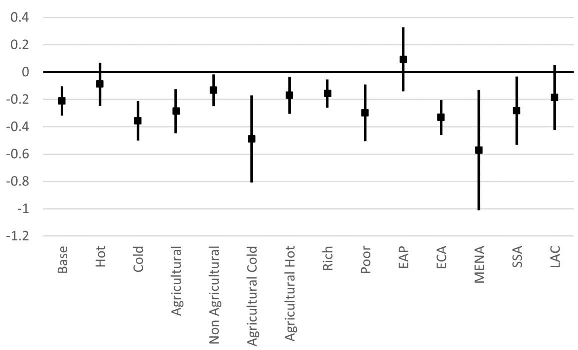
These regional differences bear important implications for our estimation strategy because the identification of impacts from extreme weather events defined using absolute thresholds rely on variation from countries that predominantly have certain climatic, geographic and also socio-economic characteristics (e.g., income per capita and average temperature are highly correlated). Instability of coefficients across groups would warrant special attention because it may be a sign of omitted variable bias.

We find that our main results are generally confirmed across groups (Figure 5). If significant, coefficients tend to remain significant. There are no significant sign switches. Coefficients are almost never significantly different between groups. However, there is suggestive evidence that aggregate results my be driven by specific vulnerabilities in sub-groups of countries.

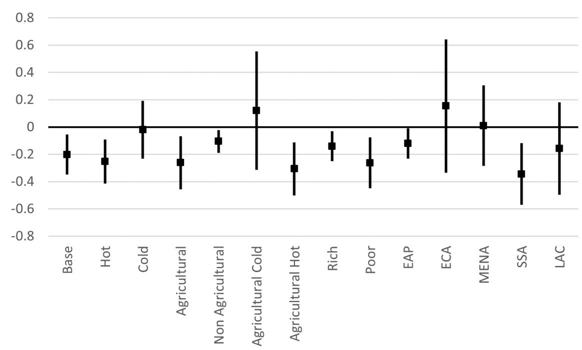
Harsh Drought Prevalence is significantly harmful in almost all groups. Severe droughts are harmful in both agricultural and non-agricultural countries, in rich and poor countries. Being hot does not neces-

Figure 5: Weather Coefficients Across Groups

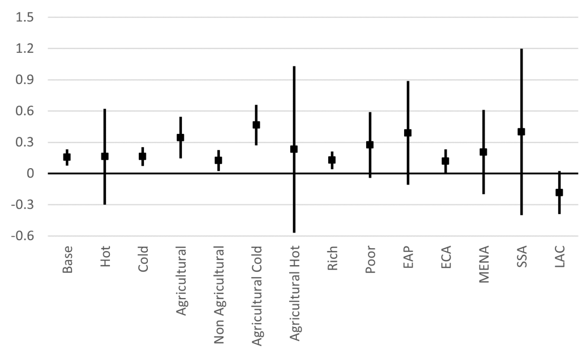
(a) Harsh Drought Prevalence (W)



(b) Max T °C above 35 (W)



(c) Mean T °C in [9; 12)



Notes: Each panel depicts the estimated coefficient for each weather variable using our baseline specification (column A in Table 1) for different sub-groups. Climate variables are standardized and their definitions are detailed in appendix Table A.1. The vertical lines show the 95 percent confidence intervals using standard errors clustered by country. (W) indicates population-weighted variables. Hot (N=3,472): 1979-2019 average temperature > 22° C. Cold (N=3,078): 1979-2019 average temperature ⩽ 22° C. Agricultural (N=3,130): share of "Agriculture, forestry, and fishing, value added (% of GDP)" in 2002 is above median across countries. Non Agricultural (N=3,062): countries that are not Agricultural. Agricultural Cold (N=1,124): agricultural and cold. Agricultural Hot (N=2,006): agricultural and hot. Rich (N=3,823): "High Income" and "Upper Middle Income" in WDI. Poor: "Low Income" and "Lower Middle Income" in WDI (N=2,727). SSA (N=1,629): Sub-Saharan Africa. MENA (N=538): Middle-East and North Africa. LAC (N=1,372): Latin America and the Caribbean. ECA (N=1,638): Eastern and Central Asia. EAP (N=1,013): Eastern Asia and Pacific. None of the coefficients is significant for North America and South Asia, due to the low number of countries in these regions.

sarily mean that droughts are significantly harmful. Across regions, droughts in Middle East and North Africa (MENA) and Sub-Saharan Africa (SSA) have large and significant negative impacts. Droughts are also significantly harmful in the Europe and Central Asia region (ECA), an area with high frequency of droughts (see Figure 4). The effect of droughts is instead not significant in Latin American and the Caribbean (LAC) and in Eastern Asia and Pacific (EAP).

The harmful effect of Max T °C above 35 is significant in most groups, with the exception of cold countries and agricultural cold countries, where maximum daily temperatures above 35 °C are rarely observed. SSA, with mostly agricultural, poor and hot countries, and EAP are the only regions with a significant harmful effect. Extreme temperatures appear to be particularly harmful in agricultural hot countries as well as in poor countries. This suggests that high vulnerability of agriculture to these high temperatures in mostly agricultural poor economies may explain the large impact on GDP growth.

The effect of Mean T °C in [9; 12) is not significant in countries that are hot, agricultural and hot, and poor. This is due to the relatively low frequency of these temperatures in these groups. The positive impact is particularly large in agricultural cold countries. This suggests that the variable is picking the beneficial effect of a longer growing season during both spring and fall in cold agricultural countries (Massetti et al., 2016). Among regional groups, the effect is positive and significant only in the EAC region, which comprises many cold agricultural countries.

5. Macro-Fiscal Outcomes

5.1. A systematic empirical approach to macro-fiscal impacts

Fiscal outcomes can be affected by weather shocks through multiple channels. In the absence of active policy, the effect of climate on GDP can affect government finances as automatic stabilizers operate. Extreme weather shocks, like floods, can also hinder daily public operations by preventing government workers to go to work or by impairing public infrastructure. Alternatively, fiscal policy may respond actively to weather shocks to provide support, foster recovery, or address fiscal sustainability issues.

We consider three main fiscal indicators: government revenue, expenditure, and debt. We start by studying the effect of climate shocks on these variable measured by their GDP ratio as is standard practice in fiscal policy analysis. We then supplement this analysis by considering implications for the fiscal balance (revenue minus expenditure), also in this case measured as a GDP ratio. Finally, we study the effect of climate shocks on the percent change of the fiscal variables expressed in constant 2011 USD.[29] Examining variations in levels allows us to separately identify the effects of climate shocks on the numerator (fiscal variable) and denominator (GDP) of the ratios, as these can be of different magnitude and opposite sign.

[29] Specifically, we examine the first difference of the logarithm of the three main fiscal variables.

The government revenue-to-GDP ratio can be affected if a weather shock disproportionately reduces activity in sectors or economic agents that are taxed above- or below-average. For example, the revenue-to-GDP ratio can increase when the impact of a drought disproportionately affects sectors that pay little or no taxes. In such a case, the reduction of taxes because of the drought would be smaller than GDP losses, thereby increasing the ratio. Governments might also actively respond to a shock with counter-cyclical policies, for example, by lowering taxes in vulnerable sectors when a shock hits. Depending on the relative magnitude of the fiscal response and the GDP impact, the revenue-to-GDP ratio can either increase, stay constant, or decrease.

We expect the expenditure-to-GDP ratio to increase in countries with counter-cyclical fiscal policy. Under this assumption, the numerator (expenditure) increases to provide support in response to an adverse shock while the denominator declines (GDP), leading to an unambiguous increase in the ratio. For example, social transfers could increase to support those affected by adverse weather shocks, through automatic or active policy responses such as unemployment insurance or ad-hoc compensation schemes. In the case of weather catastrophes, government could raise capital expenditure to address reconstruction needs and foster a post-disaster recovery. A positive shock would lead to opposite effects, leading to a reduction of the expenditure-to-GDP ratio. However, for very severe shocks, a low-capacity government may indeed suffer from disorganization leading to delayed expenditure and a public recovery lagging the private sector's. In such a case, the expenditure-to-GDP ratio may fall with an adverse shock.

When a shock leads to changes in revenue and expenditure that deteriorate the fiscal balance (i.e., when the fiscal deficit increases), this creates financing needs and we expect government debt to increase. However, timing issues could remove the correlation between fiscal variables, as a government could contract loans before actually implementing expenditure plans. Further, debt can be affected by other channels. When a government chooses to provide loans to help the private sector (or bail-outs), this form of support does not affect the fiscal balance but requires financing which is also likely to increase debt. Additionally, we cannot exclude the possibility that weather events have an effect on the exchange rate and, in turn, on the valuation of existing foreign debt. For example, this could be the case if a weather shock affects the price of export-oriented crops and thereby the terms of trade.

5.2. Estimates of the impact of climate shocks on macro-fiscal outcomes

We present empirical OLS estimates of the relationships between weather shocks and fiscal outcomes in Table 3. Our goal is to study how climate shocks affect GDP and all fiscal outcomes systematically while keeping the selection of variables compact. Therefore, we restrict the selection of climate variables: we focus on the three climate variables selected in our baseline for GDP and on the first weather variable selected by the LASSO for each of the three main fiscal ratios. The full list of the variables selected by LASSO with a random search is reported in appendix in Tables A.12-A.13. The algorithm performance as a function of the penalty parameter λ is reported in appendix in Figures A.7-A.6. We additionally report the effect of these variables on the fiscal balance and on the percentage change in the level of the other fiscal variables.

Our sample becomes smaller when we introduce fiscal variables because of their narrower coverage. To allow for a meaningful comparison across fiscal outcomes, we implement our analysis on the sample with non-missing values for all fiscal variables. The smaller sample size and the addition of other weather variables explain the difference in results obtained for GDP growth compared to the previous section (column A in Table 1 versus column A in Table 3). Weather effects tend to become smaller and the effect of Max T °C above 35 becomes slightly smaller and insignificant.

The three climate variables selected by LASSO for expenditure, revenue, and debt are new. For the revenue-to-GDP ratio, the LASSO procedure selects the contemporaneous value of the population-weighted number of days in the longest dry spell , which is defined as an uninterrupted period in which at least 80% of a country's grid cells have precipitations less than 1 mm per day (Longest Dry Spell (.80) — $LLDS_{.80}$). The first lag of Continued Heavy Precipitation ($PC95WD$) is selected as a key driver of the expenditure-to-GDP ratio. This variable is constructed as the largest number of consecutive days with precipitation above the 95^{th} percentile of a country's daily precipitation distribution. Wetness Intensity ($MPDSI_{>3}$) is selected for the debt-to-GDP ratio. To construct this variable, we first compute the share of grid cells with moisture conditions far exceeding their typical level in every month and then retain the maximum share among the 12 months of the year. Therefore, this variable measures the extent of abnormal moisture at its peak and can proxy for flood-like conditions. Table 3 shows that these newly selected variables have negative impacts on GDP growth. This was expected because they represent adverse weather conditions, but the effects are not significant.

Turning our attention to fiscal outcomes, we find that the fraction of within variation in the fiscal variables explained by the model is at least as large as for GDP growth, as shown by the within R-square. The magnitudes of the estimated effects of the new climate variables are somewhat similar to the estimated effect of weather shocks on GDP reported in the previous section.

The climate variables that we previously selected for GDP have mixed effects on fiscal variables. In some cases, the effects are small and insignificant, indicating that fiscal policy remains cyclically neutral (first three rows of climate variables in Table 3). However, there is also evidence of non-neutral fiscal responses.

First, we find evidence that Harsh Drought Prevalence increases the expenditure-to-GDP ratio. This seems to be the result of a combined increase in expenditure levels and decline in GDP (columns A, C and G). This would support the hypothesis of increased support from governments in the form of additional spending. Droughts do not seem to have an impact on the other fiscal variables.

Second, we find that revenue collection declines in response to an increase in Max T °C above 35. This results from a sharp reduction in the level of revenue (column F), which affects the revenue-to-GDP ratio (column B), even if GDP is also declining (column A). The revenue loss translates into a weakly significant negative effect on the balance-to-GDP ratio.

Third, we find that an increase in Mean T °C in [9; 12) (column F) raises revenue significantly but in roughly the same proportion as it raises GDP. This suggests that that the positive shock estimated on GDP translates into higher tax collection. As a result, the impact on the revenue-to-GDP ratio is positive but insignificant. In the absence of a significant response of expenditure (column C), the balance-to-GDP indicates an unambiguous positive effect on the fiscal balance (column D).

The new variables selected by the LASSO for the fiscal variables also have mixed effects, although they mostly point towards the counter-cyclical response of the fiscal variables.

An increase in Wetness Intensity (a proxy flood-like conditions) leads to a significant increase in public expenditure (column G) and in the expenditure-to-GDP ratio (column C). We also find that the debt and the debt-to-GDP ratio significantly increase (column E and H). The debt increase could come from a rise in expenditure, but it could additionally be due to the extension of public loans to the private sector as support. Wetness Intensity has a negative but insignificant effect on GDP, indicating a that the policy response to the shock is counter-cyclical and that the fiscal response might be effective in mitigating the effect of the shock on GDP.

An increase in Longest Dry Spell (0.80) is associated with a sizeable but insignificant increase in the fiscal deficit (column D) and a significant increase in the debt-to-GDP ratio (column E). An increase in the lag of Continued Heavy Precipitation has a similar and also insignificant negative impact on the fiscal balance. However, in the case of this shock, the response of expenditure (column G) is large and significant. These weather variables would be expected to have a negative effect on GDP but we only find very weak and insignificant negative coefficient estimates (column A). Overall and despite noisy results, we find systematic evidence of economic support from fiscal policy in response to these likely adverse weather shocks, especially in the form of increased public spending and debt.

When we consider slight variations in the definition of the weather variables selected for fiscal outcomes, we can find significant and negative effects on GDP and retain significance for the fiscal outcomes (Table A.16). For dry spells, we experiment with spells that affect 95 percent instead of 80 percent of the country (Longest Dry Spell (0.90) - $LLDS_{.95}$). Instead of Wetness Intensity, we use a variable based on a higher threshold and average annual conditions rather than on the worse month (Very Wet Conditions — $PDSI_{\geqslant 4}$). The LASSO only selects variables that are relevant for one fiscal variable at a time. Therefore, the resulting selection can miss alternative definitions with better explanatory power for other fiscal variables. By experimenting with close alternative variable definitions, we confirm that these types of weather shocks can have adverse effects on the economy.

We investigate further whether the lack of fiscal space can prevent a counter-cyclical fiscal policy response and imply more adverse GDP impacts. To this end, we interact weather shocks with a measure of fiscal space. To reflect country fiscal space, we compute the standardized deviation of the debt-to-GDP ratio from its mean by country. Our assumption is that a large deviation of debt-to-GDP above the country mean should be correlated with lower fiscal space. We experiment with non-linear functions and retain the cube of the deviation as having explanatory power. As reported in Table A.17 in appendix, we only find a significant interaction in the case of Continued Heavy Precipitation. For this weather shock, countries having more debt than they have on average experience a muted increase in debt but experience a significant reduction in GDP per capita, thereby providing support to our hypothesis.

In summary, we find that weather shocks can have rich and large effects on fiscal aggregates, although impacts are not always significant. The cyclicality and policy mix of fiscal responses depend on the nature of the weather shock. We find evidence that the response of revenue to an adverse increase in Max T °C above 35 and to a beneficial increase in Mean T °C in [9; 12) is pro-cyclical. Conversely, we find that government expenditure and debt increase in a counter-cyclical manner in response to various weather shocks related to droughts or intense precipitation.

Table 3: Estimates of macro-fiscal effects of selected climate variables

	(A) $\Delta \ln \frac{\text{GDP}}{\text{POP}}$ p.c.	(B) $\Delta \frac{\text{Revenue}}{\text{GDP}}$ p.p.	(C) $\Delta \frac{\text{Expenditure}}{\text{GDP}}$ p.p.	(D) $\Delta \frac{\text{Balance}}{\text{GDP}}$ p.p.	(E) $\Delta \frac{\text{Debt}}{\text{GDP}}$ p.p.	(F) $\Delta \ln$ Revenue p.c.	(G) $\Delta \ln$ Expenditure p.c.	(H) $\Delta \ln$ Debt p.c.
Lag(1) of Fiscal Variable	0.169***	-0.256***	-0.250***	-0.310***	0.074**	-0.199***	-0.102***	0.136***
	(0.0562)	(0.0494)	(0.0502)	(0.0315)	(0.0292)	(0.0534)	(0.0340)	(0.0318)
Lag(2) of Fiscal Variable	0.018	-0.133***	-0.062**	-0.122***	0.137**	-0.074	-0.054	0.027
	(0.0189)	(0.0175)	(0.0301)	(0.0240)	(0.0685)	(0.0467)	(0.0401)	(0.0233)
First difference in								
Harsh Drought Prevalence (W)	-0.146**	0.084	0.131**	-0.047	-0.053	0.261	0.327*	-0.143
	(0.0661)	(0.0514)	(0.0525)	(0.0516)	(0.1274)	(0.2106)	(0.1891)	(0.2384)
Max T °C above 35 (W)	-0.109	-0.150**	-0.013	-0.133*	-0.067	-1.094**	-0.301	0.063
	(0.0808)	(0.0636)	(0.0483)	(0.0745)	(0.1461)	(0.4881)	(0.3329)	(0.2433)
Mean T °C in [9; 12)	0.146***	0.047	-0.064	0.107**	0.003	0.247**	-0.003	-0.072
	(0.0455)	(0.0340)	(0.0565)	(0.0516)	(0.1117)	(0.1207)	(0.1347)	(0.2286)
Longest Dry Spell (.80) (W)	-0.008	-0.107	0.017	-0.131	0.343*	-0.356	-0.051	-0.101
	(0.0514)	(0.1026)	(0.0562)	(0.0963)	(0.1974)	(0.3077)	(0.2450)	(0.3096)
Lag(1) of Cont'd Heavy PPT	-0.019	0.056	0.132	-0.066	0.218	0.171	0.522*	0.336
	(0.0603)	(0.0673)	(0.0886)	(0.1060)	(0.1436)	(0.3100)	(0.2655)	(0.2391)
Wetness Intensity	-0.039	0.046	0.128**	-0.081	0.358*	0.022	0.387*	0.829***
	(0.0514)	(0.0563)	(0.0596)	(0.0797)	(0.1949)	(0.2276)	(0.1995)	(0.2748)
Constant	1.606***	0.143***	0.099***	0.041***	0.020	5.041***	4.456***	3.458***
	(0.1134)	(0.0057)	(0.0047)	(0.0017)	(0.0131)	(0.2936)	(0.2411)	(0.1628)
Observations	3849.000	3849.000	3849.000	3849.000	3849.000	3849.000	3849.000	3849.000
R-square	0.267	0.114	0.118	0.151	0.139	0.128	0.078	0.167
Within R-square	0.037	0.072	0.063	0.094	0.030	0.050	0.018	0.024

Note: The dependent variables are indicated in the column titles and are expressed in percentages. We use the same three climate variables used for GDP growth and the first climate variables selected by the LASSO respectively for government revenue, expenditure, and debt. All climate variables are standardized with standard deviations equal to 100 to ease interpretation. (W) indicates population-weighted variables. Controls include the first two lags of the dependent variable (reported in the first two rows), and year and country fixed effects. Standard errors are clustered by country and reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusion

In this paper, we show how to leverage large global weather datasets with high-frequency and high-resolution data to estimate the impact of weather on economic outcomes. With few minor exceptions, the literature has traditionally focused on average annual temperature and total precipitation at the country level, leaving aside many potentially relevant weather phenomena.

The main empirical challenge of using dozens of billions of weather measurements is to reduce the high dimensionality of the data to a manageable set of variables that can be related to country-year macro-fiscal aggregates. We propose a method that relies on a mix of expert judgement and machine learning techniques, including the LASSO operator. This method can identify a small set of variables that improves the ability to explain the outcome of interest without sacrificing the possibility to meaningfully interpret their effect. Applying this method leads to a substantial improvement in our ability to explain GDP growth and other macro-fiscal outcomes that had not been studied before.

We use our method to select a few variables capturing droughts and high and mild temperatures and find that they have a permanent impact on GDP per capita. We estimate that a shock of one standard deviation to any of these variables has an affect of an order of magnitude of about 0.2 percent. These impacts permanently affect the level of GDP per capita, but we do not find evidence of a permanent effect on the growth rate of GDP per capita.

Our most striking result is that country annual average temperature, the variable most frequently used in the literature, is never part of the core set of variables that is selected with our method. The weather variables we select are indeed far better in explaining GDP growth and macro-fiscal variations than average annual temperature alone, also when using data and methods of important papers in the literature.

This paper additionally contributes to the literature by identifying and estimating the effects of weather shocks on the most important fiscal aggregates. We find that high maximum daily temperatures have a pro-cyclical and negative impact on government revenue. Conversely, we find that government spending and debt increase in response to droughts and flood-like conditions, thereby mitigating the effect of these shocks on GDP. Differences in fiscal responses to different shocks could come from differences in the nature of the weather shocks or from differences in the characteristics of affected countries. A promising work avenue would be to look into these alternative explanations.

Because we find that the impact of weather shocks on the macro economy is larger than previously measured, the main policy implication is that decision-makers should pay better attention to the shocks that we identified as relevant and ensure that they have adequate capacity to address them, including by creating fiscal space. We see our work as a starting point to learn more about the macro-fiscal vulnerability of countries that are exposed to weather shocks. It should also be useful to predict the macro-fiscal effects of future weather shocks.

Our method opens avenues for future potentially policy-relevant analysis. Future extensions could examine additional climate variables such as humidity and wind, and climate phenomena that we have not studied, such as tropical cyclones. It could also be applied to study other macro-economic and sectoral outcomes, such as the impact of weather on health, agriculture, labor productivity, trade, and the impact on production inputs (human and physical capital). Future work could also examine other policy responses, like monetary policy. And by focusing on specific countries or regions, it could generate new useful insights and identify group-specific sets of relevant explanatory variables in specific contexts.

Our work highlights vulnerabilities to climate shocks but our empirical strategy cannot be easily extended to infer the long-term impacts of climate change. We rely on short-term weather fluctuations that are random, of relatively small magnitude compared to the long-term changes that we expect from climate change, and are not observed in all countries. Our method is thus inherently unable to estimate the impact of gradual but large changes in *average* conditions, and the effect of the appearance of new weather shocks in countries where they have never been observed.

However, it should be possible to project our selected variables in the near future to estimate short-term impacts from climate change. This would require constructing climate change scenarios with a spatial and temporal granularity similar to our historical data. It would also require that climate scenarios identify which weather shocks can be attributed to climate change as opposed to the high internal variability of the present climate.

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A. Appendix

A.1. Source Data

We use weather from the ERA5 dataset from 1979 to 2021.[30] The original ERA5 dataset has hourly data but we use data aggregated at daily level by Google Earth Engine (GEE).[31] This includes daily mean temperature in each day d and grid cell j, calculated using ERA5's 24 measures per day ($T_{j,d}$), the minimum of those 24 measures within a day ($TN_{j,d}$), and the maximum of those 24 measures within a day ($TX_{j,d}$). Total daily precipitation ($P_{j,d}$) is calculated by summing all the hourly precipitation measures within a day. From these daily grid-cell data points we construct all our variables.

Number of observations in the original databases. The resolution of ERA5 data is 0.25 degrees. A global map has 180 degrees along the North-South dimension and 360 degrees along the West-East dimension: the total number of cells is therefore equal to $(180/0.25) \times (360/0.25) = 1,036,800$. The percentage of Earth's surface covered land, after excluding Antarctica and Greenland, is approximately equal to 27%. This means that we use approximately 1,036,800 × 0.27 = 279,936 cells on land. For each grid and each day of the 41 years from 1979 to 2019 we have four weather data points (T, TN, TX, and P). This means that we start with approximately 279,936 × 365 × 41 × 4 = 16,756,968,960 (≈ 17 billion) temperature and precipitation data points.

The Palmer Drought Severity Index (PDSI) is from Abatzoglou et al. (2018) and is accessed using GEE.[32] PDSI data comes at monthly intervals with spatial resolution equal to 0.0416 degrees. This corresponds to (180 / .0416) × (360 / 0.0416) × 0.27 = 10,110,022 cells on land excluding Antarctica and Greenland. Summing over all months from January 1979 to December 2019 we have a total of 10,110,022 × 12 × 41 = 4,974,130,917 (≈ 5 billion) observations on PDSI from the Terra Climate data.

To sum up, we start with 21,715,195,392 (≈ 22 billion) data points on temperature, precipitation, and the PDSI.

Merging datasets and zonal statistics. We merge the ERA5 and PDSI datasets into one single geospatial dataset that uses the higher resolution of PDSI data of approximately 5 km × 5 km at the equator. This dataset is projected on a global map of countries to calculate zonal statistics at country level.[33] The whole process is managed using Google Earth Engine and delivers a total of 9,621,976 (≈ 10 million) country-matched grid cells for each one of our five core climate variables ($T_{j,d}$, $TN_{j,d}$, $TX_{j,d}$,

[30] `https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview`

[31] `https://developers.google.com/earth-engine/datasets/catalog/ECMWF_ERA5_DAILY#description`

[32] `https://developers.google.com/earth-engine/datasets/catalog/IDAHO_EPSCOR_TERRACLIMATE#bands`

[33] Zonal statistics are operations that calculate statistics of cell values of a dataset (raster) within boundaries defined by another dataset.

$P_{j,d}$, and $PDSI_{j,d}$). Each grid cell has daily data for 41 years. This means we develop our full set of climate variables using 580,705,495,552 ($\approx$ 600 billion) data points.

Weighted variables. The resolution for the population data is $\approx$ 1 km $\times$ 1 km at the equator,[34,35] and hence for the weighted data we use 1 km $\times$ 1 km grid cells during zonal statistics. By mixing population and weather data we obtain 25 additional points for each grid cell of the raw weather data. This adds 25 $\times$ 580,705,495,552 = 14,517,637,388,800 ($\approx$ 15 trillion) data points to our dataset for zonal statistics.

A.2. Definition of weather variables

This Section describes all the weather variables we construct from raw precipitation and temperature data. We start by an overview of weather variables, then give a brief presentation of mathematical notations and concepts, and finally provide the full list of the variables we construct and their mathematical definitions in table A.1.

Temperature variables. For each day in a year and country, we calculate country-wide averages of daily average, minimum, and maximum temperature (respectively T_d, TN_d, and TX_d) from daily grid level data. We aggregate average daily temperatures to get annual average temperature (T), the variance of daily temperature ($TVar$). We calculate the average diurnal temperature range (DTR) from minimum and maximum daily temperatures. Using the 10^{th} and 90^{th} percentiles of the 1979-2019 distribution of TN_d and TX_d in a 5-day window centered on each day of the year, we calculate the number of cold nights ($CN10$), cold days ($CD10$), warm nights ($WN90$) and warm days ($WD90$), to characterize cold and heat extremes using relative thresholds.

To account for impacts from extended exposure to temperature extremes, we build variables to capture heatwaves and coldwaves based on the climate literature. We follow Kim et al. (2020) and we define cold (warm) spell duration (CSD, WSD) as the number of days in which TN_d (TX_d) is below (above) the 10^{th} (90^{th}) percentile of the 1979-2019 distribution in a 5-day window centered on each day, for at least six consecutive days. We follow Perkins and Alexander (2013) to define eight additional indicators of day (night) heat waves based on exceeding the 90^{th} percentile of the 1979-2019 distribution of TX_d (TN_d) in a 15-day window centered on each day, for at least three consecutive days. We count the number of days with day (night) heat wave, the length of the longest day (night) heatwave, the number of day (night) heatwaves during a year, and the average maximum (minimum) temperature during day (night) heatwaves. Similarly, we use the 10^{th} percentile of the distribution of TX_d and TN_d to measure the characteristics of day and night cold waves.

[34] https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-adjusted-to-2015-unwpp-country-totals-rev11

[35] https://developers.google.com/earth-engine/datasets/catalog/CIESIN_GPWv411_GPW_UNWPP-Adjusted_Population_Count

We construct country averages of grid-level annual minimum of minimum daily temperature (TNn) and of grid-level maximum of maximum daily temperature (TXx), both used in the climate literature.

We also define another set of extreme temperature variables using absolute temperature thresholds based on the climate literature (e.g., IPCC, 2021a). With absolute temperature thresholds, using the highest possible level of spatial resolution is essential to avoid missing the potentially harmful events that can get averaged out over large areas. For example, if two grid cells have maximum daily temperature equal to, respectively, 33 °C and 36 °C, their average is equal to 34.5 °C, lower than the frequently used 35 °C threshold. By first averaging and then checking if the threshold is crossed, we would record zero extreme events, while temperature in 50% of the grid cells exceeds the threshold. The same does not apply to extremes measured using relative thresholds.

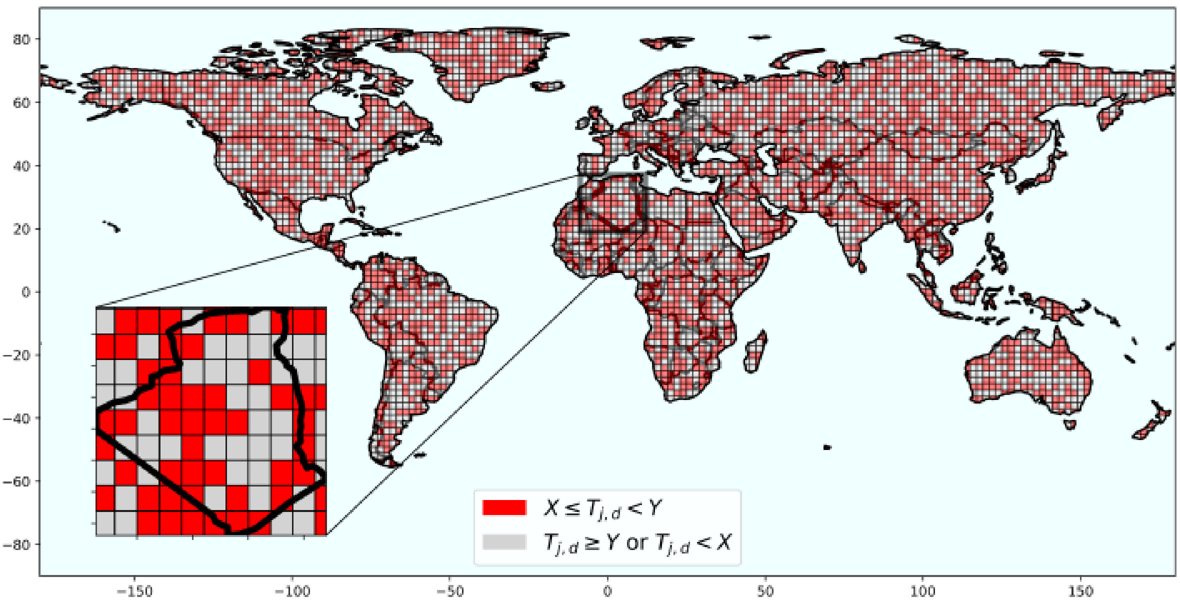
Therefore, when we use absolute thresholds, we sum the number of times a threshold is crossed in each grid cell and in each day, across all days and grid cells in a country, and then divide that number by the total number of grid-day observations ($J \times 365$). We do so to find the share of grid-days with frost (minimum daily temperature below 0°C – $TN0$), with maximum temperature above 35 °C ($TX35$) and above 40°C ($TX40$).

Finally, to capture potential non-linear effects of temperature on macro-economic variables, we divide the distribution of temperature into 3 °C-wide intervals and we measure the share of grid-day observations in each interval (e.g., Schlenker and Roberts, 2009). For example, Figure A.1 illustrates the calculation of the share of grid-days that experiences temperature levels between x_1 and x_2 degrees Celsius. By using 3 °C wide intervals we aim to balance flexibility in modeling the temperature response function and avoiding multicollinearity problems that would arise from using narrower temperature intervals (Mérel and Gammans, 2021). One of the intervals is omitted in our estimation process to avoid perfect collinearity among all interval indicators. As very low and very high average daily temperatures are rare, all the days with average temperature below -9 °C and at or above 30 °C are grouped in two terminal intervals.

Precipitation (rain or snow) variables. We start by calculating the average of total daily precipitation in each country across all grid cells (P_d). We use this variable to construct annual average precipitation (P) and the annual variance of daily precipitation ($PVar$) for every country. Following the climate literature, we focus on days that have more than 1 mm of precipitation, which are called "wet days". We calculate the number of wet days (W), average daily precipitation in wet days (PWA), and wet days precipitation variance ($PWVar$). We calculate total precipitation in very wet ($PW95T$) and extremely wet days ($PW99T$) using the 95^{th} and 99^{th} percentiles of the distribution of wet days over all days and years from 1979 to 2019.

We build several variables to capture extended wet and dry periods. We count the largest number of consecutive dry days (days with precipitation less than 1 mm — CDD), the largest number of consecutive wet days (CWD) and total precipitation during the longest wet days period ($PCWD$). To focus on

Figure A.1: Computing the share of grid-days with weather conditions in a specific interval



Notes: This figure illustrates the calculation methodology for "Share of Grid-Days with Mean Temperature in the interval $[x_1, x_2)$*" (Mean* $T\ ^\circ C$ *in* $[x_1, x_2)$ — $TS_{[x_1,x_2)}$*) for a given day d in any country j. We also zoom on Algeria. The grid cells colored in red represent the locations where* $x_1 \leqslant T_{j,d} < x_2$ *and grid cells colored in gray represent the locations where* $T_{j,d}$ *(average daily temperature in country j on day d) is outside of this range. For our study, we later obtain country-year measures by averaging daily percentages over the 365 days of a year. Note that the grid cells are pictured as much bigger than they are in the original dataset for visualization purposes. For example, there are 50 grid cells belonging to Algeria in this figure. However, there are more than 105 thousand grid cells in Algeria in the dataset.*

extreme conditions, we count the number of consecutive very ($PC95WD$) and extremely ($C99WD$) wet days in the longest periods with daily precipitation above the 95^{th} and 99^{th} percentiles of the distribution, respectively. Similarly, we calculate total precipitation in consecutive very ($PC95W$) and extremely wet days ($PC99WD$).

To capture intense precipitation that may cause floods, which are among the most destructive climate disasters, we use the maximum amount in a year of rainfall in 1-day ($PX1$) or 5-day ($PX5$) intervals. To capture extreme precipitation at the local level, we use total monthly precipitation in each grid cell and we calculate the country average of maximum ($PX(1Month)$) and minimum ($PN(1Month)$) monthly precipitation.

As for temperature, precipitation extremes can also be characterized using absolute thresholds but this requires calculations at the grid level. We calculate the length of the longest dry spell ($LLDS$) in a country as the uninterrupted series of days in which a minimum percent of the country area has daily total precipitation less than 1 mm (dry day). We use four thresholds to identify dry spells and consider spells affecting 50%, 65%, 80% and 95% of a country area. Similarly to what we do with temperature intervals, we calculate the share of total grid-days with total precipitation in four intervals: less than 1 mm, from 1 mm to 10 mm, from 10 mm to 20 mm, and above 20 mm. The maximum extent of heavy ($MaxP_{>10}$) and very heavy ($MaxP_{>20}$) precipitation is equal to the maximum daily share of the country with precipitation respectively greater than 10 mm and 20 mm. To capture deviations from conditions with balanced level of precipitation across time and space, we develop an indicator that measures the absolute deviation from having 50% of the grid-days observations of precipitation between 1 and 10 mm ($BP_{1\_10}(0.5)$).

Wetness and drought variables. Finally, we use the Palmer Drought Severity Index (PDSI) (Palmer, 1965) to introduce a measure of dry and wet periods that combines temperature and precipitation data to estimate cumulative deviations in soil moisture from normal conditions (Dai et al., 2004; Abatzoglou et al., 2018; Lai et al., 2020).[36] The PDSI ranges from -10 to +10, but values below -4 and above +4 are rare. We build variables measuring the share of total grid-months subject to extreme droughts (PDSI < -4), extreme and severe droughts (PDSI < -3), periods with extreme moisture (PDSI > 4), and periods with very high and extreme moisture (PDSI > 3). For each of these four categories and in every country, we also build variables reflecting the maximum extent of these events, that is the share of affected grid-cells in the month where the share is at its maximum.

Mathematical notations and concepts. We use d to denote calendar days, months with m, and $j = 1, \dots, J$ to denote grid cells in every country. For ease of notation, we do not index variables by country and year. In each year there are 12 months and for ease of notation we assume each year has the same number of days.

We use Iverson brackets in the definition of many variables. Iverson brackets map any statement inside brackets into a function that takes the value of the variables for which the statement is true, and take the value zero otherwise.[37] It is denoted by putting the statement inside square brackets:

$$[X] = \begin{cases} 1 & \text{if } X \text{ is true;} \\ 0 & \text{otherwise.} \end{cases}$$

Thus, to count days in which a certain condition X is met we write: $\sum_d [X]$.

Some variables capture different percentiles of the long-term distribution of daily mean temperature and daily precipitation. We use the whole time horizon of our dataset for these distributions, from 1979 to 2019. This is represents a 41-year time window that is well-suited to capture extreme realizations of

[36]Data downloaded from Google Earth Engine. See `http://www.climatologylab.org/terraclimate.html` and `https://developers.google.com/earth-engine/datasets/catalog/IDAHO_EPSCOR_TERRACLIMATE` for a detailed description of the datasets.

[37]Donald Knuth, "Two Notes on Notation", American Mathematical Monthly, Volume 99, Number 5, May 1992, pp. 403–422.

temperature and precipitation.

For daily precipitation, we use all days of the calendar year as there are no obvious seasonal patterns that apply to all countries. For temperature, there is a more marked seasonal cycle in most countries and deviations from normal conditions are more clearly dependent on the time of the year temperature is observed. For this reason, the distribution of temperature is restricted to moving windows centered on the day of interest. We use 5-day and 15-day windows following the literature Kim et al. (2020); Perkins and Alexander (2013). For example, consider August 16, 2000. To check whether precipitation is extreme, we compare daily precipitation with the distribution of precipitation over all days from 1979 to 2019. To check if temperature is extreme, we restrict the distribution of daily mean temperature to August 14, 15, 16, 17, and 18 (with a 5-day window) from 1979 to 2019.

Table A.1: Definitions of climate variables

Variable	Model	Descriptor	Spatial	Time	Definition	Ref
Temperature						
$T_{j,d}$		Mean Temperature	Grid	Day		
T_d		Mean Temperature	Country	Day	$\sum_j T_{j,d}/J$	
T	L	Mean Temperature	Country	Year	$\sum_d T_d/365$	
$TVar$	L	Temperature Variance	Country	Year	$\sum_d (T_d - T)^2 / (365 - 1)$	
$TN_{j,d}$		Daily Temperature Minimum	Grid	Day	Note: temperature minimums almost always occur at night	
$TX_{j,d}$		Daily Temperature Maximum	Grid	Day	Note: temperature maximums almost always occur in daytime	
TN_d		Daily Minimum T °C	Country	Day	$\sum_j TN_{j,d}/J$	
TX_d		Daily Maximum T °C	Country	Day	$\sum_j TX_{j,d}/J$	
DTR_d		Diurnal T °C Range	Country	Day	$TX_d - TN_d$	
DTR	L	Diurnal T °C Range	Country	Year	$\sum_d DTR_d/365$	
$TNp(k)_d$		Percentile of Daily Minimum Temperature	Country	Day	p^{th} percentile of the 1979-2019 distribution of TN_d in a k-day window centered on d	
$TXp(k)_d$		Percentile of Daily Maximum Temperature	Country	Day	p^{th} percentile of the 1979-2019 distribution of TX_d in a k-day window centered on d	
$CN10$	L	# of Cold Nights	Country	Year	$\sum_d [TN_d < TN10(5)_d]$	a
$CD10$	L	# of Cold Days	Country	Year	$\sum_d [TX_d < TX10(5)_d]$	a
$WN90$	L	# of Warm Nights	Country	Year	$\sum_d [TN_d > TN90(5)_d]$	a
$WD90$	L	# of Warm Days	Country	Year	$\sum_d [TX_d > TX90(5)_d]$	a
TNn	L	Night T °C Minimum	Country	Year	Minimum of minimum daily temperature, $\sum_j \min_d \{TN_{j,d}\} / J$	d
TXx	L, R	Day T °C Maximum	Country	Year	Maximum of maximum daily temperature, $\sum_j \max_d \{TX_{j,d}\} / J$	d

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Notes: The letter L in the second column indicates whether a variable is used in the LASSO procedure. The letter R indicates the variables used in any of the OLS regressions. In the last column, a refers to Kim et al. (2020), b refers to Perkins and Alexander (2013), c refers to Palmer (1965), and d refers to IPCC (2021c).

Table A.1 (Continued): Definitions of climate variables

Variable	Model	Descriptor	Spatial	Time	Definition	Ref
Heat Waves						
$DDHW$	L	Heat Wave Days	Country	Year	Number of days in which $TX_d > TX90(15)_d$ for at least 3 consecutive days	b
$DNHW$	L	Heat Wave Nights	Country	Year	Number of nights in which $TN_d > TN90(15)_d$ for at least 3 consecutive days	b
$LDHW$	L	Longest Day Heat Wave	Country	Year	Number of days in the longest period during which $TX_d > TX90(15)_d$ for at least 3 consecutive days	b
$LNHW$	L	Longest Night Heat Wave	Country	Year	Number of days in the longest period during which $TN_d > TN90(15)_d$ for at least 3 consecutive days	b
$NDHW$	L	# of Day Heat Waves	Country	Year	Number of intervals of at least 3 consecutive days in which $TX_d > TX90(15)_d$	b
$NNHW$	L	# of Night Heat Waves	Country	Year	Number of intervals of at least 3 consecutive days in which $TN_d > TN90(15)_d$	b
$TDHW$	L	Day Heat Wave T °C	Country	Year	Average TX_d during day heat waves (intervals of at least 3 consecutive days in which $TX_d > TX90(15)_d$)	b
$TNHW$	L	Night Heat Wave T °C	Country	Year	Average TN_d during night heat waves (intervals of at least 3 consecutive days in which $TN_d > TN90(15)_d$)	b
Cold Waves						
$DDCW$	L	Cold Wave Days	Country	Year	Number of days in which $TX_d < TX10(15)_d$ for at least 3 consecutive days	b
$DNCW$	L	Cold Wave Nights	Country	Year	Number of days in which $TN_d < TN10(15)_d$ for at least 3 consecutive days	b
$LDCW$	L	Longest Day Cold Wave	Country	Year	Number of days in the longest period during which $TX_d < TX10(15)_d$ for at least 3 consecutive days	b
$LNCW$	L	Longest Night Cold Wave	Country	Year	Number of days in the longest period during which $TN_d < TN10(15)_d$ for at least 3 consecutive days	b
$NDCW$	L	# of Day Cold Waves	Country	Year	Number of intervals of at least 3 consecutive days in which $TX_d < TX10(15)_d$	b
$NNCW$	L	# of Night Cold Waves	Country	Year	Number of intervals of at least 3 consecutive days in which $TN_d < TN10(15)_d$	b
$TDCW$	L, R	Day Cold Wave T °C	Country	Year	Average TX_d during day heat waves (intervals of at least 3 consecutive days in which $TX_d < TX10(15)_d$)	b
$TNCW$	L, R	Night Cold Wave T °C	Country	Year	Average TN_d during night heat waves (intervals of at least 3 consecutive days in which $TN_d < TN10(15)_d$)	b

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Notes: The letter L in the second column indicates whether a variable is used in the LASSO procedure. The letter R indicates the variables used in any of the OLS regressions. In the last column, a refers to Kim et al. (2020), b refers to Perkins and Alexander (2013), c refers to Palmer (1965), and d refers to IPCC (2021c).

Table A.1 (Continued): Definitions of climate variables

Variable	Model	Descriptor	Spatial	Time	Definition	Ref
Cold and Warm Spells						
CSD	L, R	Cold Spell Duration	Country	Year	Number of days in which $TN_d < TN10(5)_d$ is observed in intervals of at least 6 consecutive days	a
WSD	L	Warm Spell Duration	Country	Year	Number of days in which $TX_d > TX90(5)_d$ for at least 6 consecutive days	a
Temperature Absolute Thresholds						
$TN0$	L	Frost prevalence	Country	Year	Share of grid-days with frost, $\sum_d \sum_j \left[TN_{j,d} < 0\right]/(J \times 365)$	d
$TX35$	L, R	Max T °C above 35	Country	Year	Share of grid-days with maximum daily temperature above 35 °C, $\sum_d \sum_j \left[TX_{j,d} > 35\right]/(J \times 365)$	d
$TX40$	L	Max T °C above 40	Country	Year	Share of grid-days with maximum daily temperature above 40 °C, $\sum_d \sum_j \left[TX_{j,d} > 40\right]/(J \times 365)$	d
$TS_{<-9}$		Mean T °C below 9	Country	Year	Share of grid-days with mean temperature below -9 °C, $\sum_d \sum_j \left[T_{j,d} < -9\right]/(J \times 365)$	
$TS_{[x_1,x_2)}$	L,R	Mean T °C in $[x_1, x_2)$	Country	Year	Share of grid-days with mean temperature in the interval $[x_1, x_2)$, $\sum_d \sum_j \left[x_1 \leqslant T_{j,d} < x_2\right]/(J \times 365)$. We use increments of 3 °C from -9 °C to 30 °C for x_1, x_2.	
$TS_{\geqslant 30}$	L	Mean T °C above 30	Country	Year	Share of grid-days with mean temperature above 30 °C, $\sum_d \sum_j \left[T_{j,d} \geqslant 30\right]/(J \times 365)$	
Precipitation						
$P_{j,d}$		Precipitation (PPT)	Grid	Day		
P_d		Precipitation (PPT)	Country	Day	$\sum_j P_{j,d}/J$	
P	L	Mean Precipitation	Country	Year	$\sum_d P_d/365$	
PW_d		Wet Day Precipitation	Country	Day	$P_d\,[P_d \geqslant 1]$	
PWT		Wet Day Precipitation	Country	Year	$\sum_d P_d\,[P_d \geqslant 1]$	
W	L	# of Wet Days	Country	Year	$\sum_d [P_d \geqslant 1]$	
PWA	L	Mean Wet Day PPT	Country	Year	Average daily precipitation in wet days, PTW/W	
$PVar$	L	Precipitation Variance	Country	Year	$\sum_d (P_d - P)^2/(365-1)$	
$PWVar$	L	Wet Day PPT Variance	Country	Year	$\sum_d (P_d - PWA)^2\,[P_d \geqslant 1]/(W-1)$	
PWp_j		Percentile of Daily Precipitation in Wet Days	Grid	1979-2019	pth percentile of the 1979-2019 daily distribution of PW_d (using only wet days) in grid cell j	
PWp		Percentile of Daily Precipitation in Wet Days	Country	1979-2019	pth percentile of the 1979-2019 daily distribution of PW_d (using only wet days)	
$P95WT$	L	Very Wet Day PPT	Country	Year	$\sum_d P_d\,[P_d \geqslant 1 \text{ and } PW_d > PW95]$	a

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Notes: The letter L in the second column indicates whether a variable is used in the LASSO procedure. The letter R indicates the variables used in any of the OLS regressions. In the last column, a refers to Kim et al. (2020), b refers to Perkins and Alexander (2013), c refers to Palmer (1965), and d refers to IPCC (2021c).

Table A.1 (Continued): Definitions of climate variables

Variable	Model	Descriptor	Spatial	Time	Definition	Ref
$P99WT$	L	Extremely Wet Day PPT	Country	Year	$\sum_d P_d \left[P_d \geqslant 1 \text{ and } PW_d > PW99\right]$	a
CDD	L	Cont'd Dry Days	Country	Year	Largest number of consecutive days with $P_d < 1mm$	a
CWD	L	Cont'd Wet Days	Country	Year	Largest number of consecutive days with $P_d \geqslant 1mm$	a
$PCWD$	L	Cont'd Wet Day PPT	Country	Year	Total precipitation during the longest period of consecutive wet days with $P_d \geqslant 1$	
$C95WD$	L	Cont'd Very Wet Days	Country	Year	Largest number of consecutive wet days with $PW_d > PW95$	
$C99WD$	L	Cont'd Extra Wet Days	Country	Year	Largest number of consecutive wet days with $PW_d > PW99$	
$PC95WD$	L	Cont'd Heavy PPT	Country	Year	Total precipitation during the longest period of consecutive very wet days with $PW_d \geqslant PW95$	
$PC99WD$	L	Cont'd Extreme PPT	Country	Year	Total precipitation during the longest period of consecutive extremely wet days with $PW_d \geqslant PW99$	
$PX(5)$	L	5-Day PPT Maximum	Country	Year	Maximum 5-day precipitation, $\max_d \left\{\sum_{i=0}^{4} P_{d-i}\right\}$	a
$PX(1)$	L	1-Day PPT Maximum	Country	Year	Maximum 1-day precipitation, $\max_d \{P_d\}$	a
$P_{j,m}$		Monthly Precipitation	Grid	Month	$\sum_d P_{j,d}$	
PXM	L	PPT Maximum	Country	Year	Max 1-month precipitation, $\sum_j \max_m \{P_{j,m}\}/\mathrm{J}$	
PNM	L	PPT Minimum	Country	Year	Min 1-month precipitation, $\sum_j \min_m \{P_{j,m}\}/\mathrm{J}$	
Precipitation Absolute Thresholds						
$LLDS_{.5}$	L	Longest Dry Spell (.5)	Country	Year	Maximum number of days in a Dry Spell, defined as an uninterrupted series of days in which $\sum_j \left[P_{j,d} < 1\right]/J > 0.50$	
$LLDS_{.65}$	L	Longest Dry Spell (.65)	Country	Year	Maximum number of days in a Dry Spell, defined as an uninterrupted series of days in which $\sum_j \left[P_{j,d} < 1\right]/J > 0.65$	
$LLDS_{.80}$	L	Longest Dry Spell (.80)	Country	Year	Maximum number of days in a Dry Spell, defined as an uninterrupted series of days in which $\sum_j \left[P_{j,d} < 1\right]/J > 0.80$	
$LLDS_{.95}$	L	Longest Dry Spell (.95)	Country	Year	Maximum number of days in a Dry Spell, defined as an uninterrupted series of days in which $\sum_j \left[P_{j,d} < 1\right]/J > 0.95$	
$PS_{\leqslant 1}$	L	Less than 1 mm PPT	Country	Year	Share of grid-days with precipitation less than 1 mm, $\sum_d \sum_j \left[P_{j,d} \leqslant 1\right]/(J \times 365)$	
PS_{1_10}		1 to 10 mm PPT	Country	Year	Share of grid-days with precipitation between 1 and 10 mm, $\sum_d \sum_j \left[1 < P_{j,d} \leqslant 10\right]/(J \times 365)$	
PS_{10_20}	L	10 to 20 mm PPT	Country	Year	Share of grid-days with precipitation between 10 and 20 mm, $\sum_d \sum_j \left[10 < P_{j,d} \leqslant 20\right]/(J \times 365)$	

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Notes: The letter L in the second column indicates whether a variable is used in the LASSO procedure. The letter R indicates the variables used in any of the OLS regressions. In the last column, a refers to Kim et al. (2020), b refers to Perkins and Alexander (2013), c refers to Palmer (1965), and d refers to IPCC (2021c).

Table A.1 (Continued): Definitions of climate variables

Variable	Model	Descriptor	Spatial	Time	Definition	Ref
$PS_{>20}$	L	Above 20 mm PPT	Country	Year	Share of grid-days with precipitation above 20 mm, $\sum_d \sum_j \left[P_{j,d} > 20\right] / (J \times 365)$	
$MaxP_{>10}$	L	Heavy PPT Maximum	Country	Year	$\max_d \left\{\sum_j \left[P_{j,d} > 10\right] / J\right\}$	
$MaxP_{>20}$	L	Extreme PPT Maximum	Country	Year	$\max_d \left\{\sum_j \left[P_{j,d} > 20\right] / J\right\}$	
$BP_{1\_10}(0.5)$	L	Balanced PPT Indicator	Country	Year	$-\left\vert\sum_d \sum_j [1 < P_{j,d} \leqslant 10]/(J \times 365) - 0.5\right\vert$	
Droughts						
$PDSI_{j,m}$		Palmer Drought Severity Index	Grid	Month		c
$PDSI_{<-3}$	L	Drought Prevalence	Country	Year	$\sum_m \sum_j \left[PDSI_{j,m} < -3\right] / (J \times 12)$	c
$PDSI_{<-4}$	L, R	Harsh Drought Prevalence	Country	Year	$\sum_m \sum_j \left[PDSI_{j,m} < -4\right] / (J \times 12)$	c
$PDSI_{>3}$	L	Wet Conditions Prevalence	Country	Year	$\sum_m \sum_j \left[PDSI_{j,m} > 3\right] / (J \times 12)$	c
$PDSI_{>4}$	L	Very Wet Conditions Prevalence	Country	Year	$\sum_m \sum_j \left[PDSI_{j,m} > 4\right] / (J \times 12)$	c
$MPDSI_{<-3}$	L, R	Drought Intensity	Country	Year	$\max_m \left\{\sum_j \left[PDSI_{j,m} < -3\right] / J\right\}$	c
$MPDSI_{<-4}$	L	Harsh Drought Intensity	Country	Year	$\max_m \left\{\sum_j \left[PDSI_{j,m} < -4\right] / J\right\}$	c
$MPDSI_{>3}$	L	Wetness Intensity	Country	Year	$\max_m \left\{\sum_j \left[PDSI_{j,m} > 3\right] / J\right\}$	c
$MPDSI_{>4}$	L	High Wetness Intensity	Country	Year	$\max_m \left\{\sum_j \left[PDSI_{j,m} > 4\right] / J\right\}$	c

Notes: The letter L in the second column indicates whether a variable is in the set of climate variables used in the LASSO procedure. The letter R indicates the variables used in any of the OLS regressions. In the last column, a refers to Kim et al. (2020), b refers to Perkins and Alexander (2013), c refers to Palmer (1965), and d refers to IPCC (2021c).

A.3. Data Analysis

Trends in weather variables. Table A.2 reports tests of trends in the levels of the weather variables. For each variable and each country we estimate a linear regression of the form $w_t = \alpha + \beta t + u_t$, where w_t is the value taken by the weather variable in year t, u_t is a random component and β is the country-specific trend coefficient.

Column A reports the average β across all countries. Our results are not truly indicative of global trends, because we use country-level observations instead of area-weighted averages. For an accurate assessment of climate trends, it is important to rely on conclusions from climate science (IPCC, 2021b). However, the positive trend for average annual temperature is equal to 0.03 °C per year, a value remarkably in line with the average decadal increase of temperature equal to 0.3 °C found by the IPCC WG I.

Column B shows the percentage of countries for which the trend is significantly different from zero at the 5 percent confidence level. We use this percentage value to rank variables in decreasing order. Most of the variables built using temperature show a significant trend consistent with global warming in the majority of countries, and in some cases in virtually all countries. Variables built using precipitation do not generally show a trend that is significant for the majority of countries and in most cases trends are not significant for more than 2/3 of the countries.

Our model specification (see Equation 2) effectively removes trends in climate variables only if the trend is time invariant. To assess weather trends change over time, we conduct a test for a structural trend break with unknown break date in the time series of each climate variable, separately in each country. In column C we report the percentage of countries with both a significant trend and a significant break in the trend.[38] There is evidence of a trend with a structural break for more than 50 percent of the countries only for few variables. This suggests that our method, albeit imperfectly, helps to remove trends in weather variables.

Table A.2: Trends in weather variables

	(A) Average trend	(B) Significant trend (% of countries)	(C) Significant trend and break (% of countries)
Mean Temperature	0.0292	99%	49%
# of Warm Days	1.3430	96%	59%
# of Warm Nights	1.4725	96%	69%
# of Cold Days	-1.0482	95%	49%
# of Cold Nights	-1.1931	93%	59%
# of Day Cold Waves	-0.0855	89%	43%
Cold Wave Days	-0.5245	89%	48%
# of Night Heat Waves	0.1165	89%	62%

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[38]More precisely, we test if the null hypothesis of no structural break can be rejected at the 95 percent confidence level using a supremum Wald test which is the less restrictive of those commonly used.

Table A.2 (Continued): trends in weather variables

Heat Wave Days	0.6758	88%	55%
Heat Wave Nights	0.7412	88%	58%
# of Day Heat Waves	0.1087	88%	51%
Cold Wave Nights	-0.5890	87%	51%
# of Night Cold Waves	-0.0968	86%	48%
Longest Day Heat Wave	0.1568	81%	41%
Mean T °C in [27; 30)	0.0018	80%	46%
Longest Night Heat Wave	0.1715	78%	41%
Day T °C Maximum	0.0322	75%	32%
Max T °C above 35	0.0008	75%	35%
Warm Spell Duration	0.4277	74%	47%
Cold Spell Duration	-0.3637	72%	42%
Longest Day Cold Wave	-0.1305	72%	34%
Longest Night Cold Wave	-0.1420	72%	41%
Mean T °C in [24; 27)	-0.0008	70%	37%
Frost Prevalence	-0.0009	69%	27%
Night Heat Wave T °C	0.0788	68%	38%
Mean T °C above 30	0.0006	66%	28%
Mean T °C in [21; 24)	-0.0006	65%	30%
Day Heat Wave T °C	0.0759	59%	35%
Mean T °C in [-6; -3)	-0.0002	59%	22%
Max T °C above 40	0.0003	57%	30%
Mean T °C in [15; 18)	-0.0001	53%	25%
Diurnal T °C Range	0.0051	52%	36%
Mean T °C in [18; 21)	-0.0001	51%	21%
Mean T °C in [0; 3)	-0.0001	49%	15%
Mean T °C in [-3; 0)	-0.0002	49%	20%
Night T °C Minimum	0.0267	47%	22%
Mean T °C in [-9; -6)	-0.0002	45%	16%
Mean T °C in [12; 15)	-0.0001	40%	23%
Mean T °C in [9; 12)	-0.0001	38%	14%
Balanced PPT Indicator	0.0003	37%	22%
Mean T °C in [3; 6)	-0.0002	37%	11%
Night Cold Wave T °C	0.0042	35%	14%
Drought Intensity	0.0039	34%	29%
Less than 1 mm PPT	0.0006	34%	24%
# of Wet Days	-0.2074	34%	23%
Mean T °C in [6; 9)	-0.0001	33%	10%
Day Cold Wave T °C	0.0167	30%	13%
Harsh Drought Intensity	0.0036	30%	24%
Drought Prevalence	0.0026	29%	22%
Above 20 mm PPT	0.0001	27%	15%
Wetness Intensity	0.0007	27%	19%
Very Wet Day PPT	1.5521	27%	14%
Precipitation Variance	0.1201	26%	14%
High Wetness Intensity	0.0015	25%	18%
10 to 20 mm PPT	-0.0001	25%	17%
Harsh Drought Prevalence	0.0019	25%	19%
Wet Conditions	0.0010	25%	18%
Wet Day PPT Variance	0.1725	25%	13%
Mean Wet Day PPT	0.0048	24%	12%
PPT Maximum	0.0003	23%	12%
Mean Precipitation	0.0006	23%	14%

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Table A.2 (Continued): trends in weather variables

Very Wet Conditions	0.0011	20%	13%
Cont'd Wet Days	-0.1813	20%	8%
Longest Dry Spell (.80)	0.0535	19%	8%
Cont'd Dry Days	0.0758	19%	9%
Longest Dry Spell (.65)	0.1093	19%	8%
Extremely Wet Day PPT	0.7627	18%	11%
Cont'd Wet Day PPT	-0.6235	18%	9%
1-Day PPT Maximum	0.0968	17%	6%
PPT Minimum	0.0000	16%	6%
5-Day PPT Maximum	0.1290	16%	7%
Longest Dry Spell (.95)	0.0232	15%	9%
Extreme PPT Maximum	0.0008	15%	5%
Longest Dry Spell (.5)	0.1103	14%	6%
Cont'd Heavy PPT	0.1555	14%	7%
Cont'd Very Wet Day PPT	0.0031	12%	5%
Temperature Variance	0.0039	12%	7%
Heavy PPT Maximum	0.0000	8%	3%
Cont'd Extreme PPT	0.1723	7%	3%
Cont'd Extra Wet Day PPT	0.0043	6%	3%

Macroeconomic variables. Summary statistics for the macro-fiscal variables used in our analysis are shown in Table A.3. The Table displays separately the growth rate of GDP per capita in the larger sample used for the analysis of weather impacts on GDP growth, and the growth rate of GDP per capita in the smaller sample used for the analysis of fiscal impacts.

Table A.3: Summary statistics of macro-fiscal variables

Summary Statistics of First Differences	N	Mean	St. Dev.	St. Dev. Between	St. Dev. Within
$\Delta \ln(GDP/POP)$ in GDP Growth Sample (p.c.)	6,550	1.640%	4.99%	2.15%	4.68%
$\Delta \ln(GDP/POP)$ in Fiscal Sample (p.c.)	3,849	1.977%	4.01%	1.66%	3.69%
Δ Revenue-to-GDP (p.p.)	3,849	0.105%	3.43%	0.64%	3.41%
Δ Expenditure-to-GDP (p.p.)	3,849	0.079%	3.23%	0.87%	3.19%
Δ Balance-to-GDP (p.p.)	3,849	0.027%	4.01%	0.41%	4.01%
Δ Debt-to-GDP (p.p.)	3,849	-0.013%	11.4%	2.95%	11.1%
Δ Revenue (p.c.)	3,849	3.968%	14.5%	2.8%	14.2%
Δ Expenditure (p.c.)	3,849	3.864%	11.5%	2.7%	11.3%
Δ Debt (p.c.)	3,849	4.136%	18.6%	5.1%	18.1%

Notes: GDP per capita is measured by the difference of log GDP capita. Government revenue, Government expenditure and Government Debt growth are measured by the difference of log variables. All fiscal variables are measured as percentage of GDP and first differences are measured in percentage points.

Correlation analysis. The analysis of raw correlations between GDP growth and the explanatory variables selected by the LASSO for our main specification is displayed in Table A.5. Correlations between GDP growth and first differences of weather variables are generally small. Correlation is negative for Max T °C above 35 and Harsh Drought Prevalence, and positive for Mean T °C in [9; 12). The same

Table A.4: Summary statistics of climate variables

Summary Statistics of First Differences	Mean	St. Dev. Between	St. Dev. Within
Harsh Drought Prevalence (W)	0.005	0.010	0.173
Max T °C above 35 (W)	0.001	0.001	0.020
Mean T °C in [9; 12)	0.000	0.001	0.020
Cold Spell Duration	-0.315	0.426	14.14
Day T °C Maximum	0.044	0.050	1.282
Wetness Intensity	0.000	0.003	0.067
Longest Dry Spell (.80) (W)	-0.003	0.021	0.359
Cont'd Heavy PPT	0.029	1.013	19.52

Notes: Summary statistics of first differences of all weather variables used for either GDP analysis, including robustness tests, or for analysis of macro-fiscal outcomes. (W) indicates population-weighted variables. The sample of the baseline specification is used for all climate variables.

relationships are confirmed in our baseline regression analysis (see Table 1).

We also display the correlation of GDP growth with both average annual temperature and annual precipitation even if these two variables are not selected by the LASSO because they are the only two weather variables typically used in the literature. The correlation between GDP growth and both temperature and precipitation is very low and much lower than for our selected weather variables. This is preliminary evidence that the literature may miss a large fraction of climate induced variation in GDP growth. Interestingly, the largest correlations among climate variables are between Average Temperature and Harsh Drought Prevalence and between Mean Temperature and Max T °C above 35, but the LASSO always selects Harsh Drought Prevalence and Max T °C above 35 instead of Mean Temperature to explain GDP growth.

Table A.5: Correlation Matrix Between Baseline Variables

	GDP Growth	Lag(1) of GDP Growth	Lag(2) of GDP Growth	Harsh Drought Prevalence (W)	Max T °C above 35 (W)	Mean T °C in [9; 12)	Mean Temperature
Lag(1) of GDP Growth	0.394						
Lag(2) of GDP Growth	0.227	0.378					
Harsh Drought Prevalence (W)	-0.054	0.021	0.022				
Max T °C above 35 (W)	-0.046	0.013	0.027	0.183			
Mean T °C in [9; 12)	0.040	-0.012	0.009	-0.033	-0.032		
Mean Temperature (T)	-0.006	0.008	0.018	0.159	0.356	-0.029	
Total Precipitation (P)	0.009	-0.008	-0.011	-0.197	-0.147	0.086	-0.088

Notes: These correlations are computed using first differences using the baseline regression sample. (W) indicates population-weighted variables.

Table A.6: Summary statistics for sub-groups

	Mean	St. Dev. Between	St. Dev. Within	Mean	St. Dev. Between	St. Dev. Within
	Hot (N=3,472)			Cold (N=3,078)		
Δ GDP p.c.	130.92	243.60	451.35	201.36	163.94	485.97
Harsh Drought Prevalence (W)	0.0034	0.0073	0.1642	0.0065	0.0112	0.1827
Max T °C above 35 (W)	0.0009	0.0014	0.0252	0.0004	0.0007	0.0131
Mean T °C in [9; 12)	-0.2892	0.4472	15.810	-0.3441	0.3974	11.985
	Agricultural (N=3,130)			Non Agricultural (N=3,062)		
Δ GDP p.c.	158.44	181.68	515.55	172.07	150.45	389.75
Harsh Drought Prevalence (W)	0.0042	0.0083	0.1830	0.0052	0.0093	0.1619
Max T °C above 35 (W)	0.0009	0.0011	0.0257	0.0004	0.0007	0.0138
Mean T °C in [9; 12	-0.3530	0.4256	15.082	-0.2773	0.3263	13.308
	Agricultural and Hot (N=2,006)			Agricultural and Cold (N=1,124)		
Δ GDP p.c.	137.61	172.26	428.35	195.61	191.73	642.63
Harsh Drought Prevalence (W)	0.0030	0.0063	0.1778	0.0063	0.0104	0.1920
Max T °C above 35 (W)	0.0011	0.0012	0.0300	0.0005	0.0008	0.0154
Mean T °C in [9; 12)	-0.3485	0.4477	16.641	-0.3612	0.3914	11.803
	Rich (N=3,823)			Poor (N=2,727)		
Δ GDP p.c.	190.16	179.42	437.99	127.37	254.29	506.95
Harsh Drought Prevalence (W)	0.0054	0.0105	0.1679	0.0041	0.0078	0.1802
Max T °C above 35 (W)	0.0003	0.0007	0.0136	0.0010	0.0015	0.0273
Mean T °C in [9; 12)	-0.2597	0.3516	12.741	-0.3924	0.5115	15.900
	EAP (N=1,013)			ECA (N=1,638)		
Δ GDP p.c.	241.55	223.27	388.57	220.46	155.07	507.99
Harsh Drought Prevalence (W)	0.0017	0.0060	0.1683	0.0098	0.0113	0.1889
Max T °C above 35 (W)	0.0006	0.0014	0.0240	0.0002	0.0003	0.0089
Mean T °C in [9; 12)	-0.3662	0.4599	18.317	-0.2949	0.4069	12.416
	MENA (N=538)			SSA (N=1,629)		
Δ GDP p.c.	65.63	204.46	544.08	88.19	273.93	531.15
Harsh Drought Prevalence (W)	-0.0015	0.0060	0.1978	0.0047	0.0081	0.1899
Max T °C above 35 (W)	0.0010	0.0017	0.0234	0.0011	0.0014	0.0289
Mean T °C in [9; 12)	-0.5112	0.3819	13.750	-0.3524	0.5187	13.781
	LAC (N=1,372)			Base (N=6,550)		
Δ GDP p.c.	136.22	146.50	386.57	164.02	215.06	467.90
Harsh Drought Prevalence (W)	0.0056	0.0086	0.1388	0.0049	0.0095	0.1731
Max T °C above 35 (W)	0.0005	0.0009	0.0122	0.0006	0.0012	0.0204
Mean T °C in [9; 12)	-0.1020	0.1826	13.283	-0.3150	0.4258	14.141

Notes: Summary statistics of first difference of weather variables and GDP growth in percentage. (W) indicates population-weighted variables. Coefficients of weather variables are reported in Figure 5 and groups are described in the Notes to the Figure.

A.4. Additional Result Tables

Table A.7: Climate variables selected by LASSO after the random search and their GDP effect: baseline specification

Rank	Variable	Est.	Rank	Variable	Est.	Rank	Variable	Est.
1	Lag-1 GDP p.c. Growth	0.285***	11	Longest Night Heat Wave	-0.0887	21	Lag-2 Max T °C above 40 (W)	-0.103
		(0.0408)			(0.0643)			(0.0782)
2	Lag-2 GDP p.c. Growth	0.0407*	12	Lag-1 Cont'd Heavy PPT (W)	0.0511	22	Lag-2 Mean T °C in [21; 24)	0.129**
		(0.0218)			(0.0715)			(0.0559)
3	Harsh Drought Prevalence (W)	-0.202***	13	Lag-1 Day T °C Maximum	0.0643	23	Lag-1 Mean T °C in [18; 21)	0.0414
		(0.0529)			(0.0489)			(0.0488)
4	Max T °C above 35 (W)	-0.173**	14	Lag-2 Longest Day Cold Wave	-0.142**	24	Lag-2 Mean T °C in [6; 9) (W)	-0.0477
		(0.0730)			(0.0662)			(0.0420)
5	Mean T °C in [9; 12)	0.179***	15	Lag-1 Mean T °C in [3; 6) (W)	-0.193***	25	Lag-2 Night Cold Wave T °C	-0.116**
		(0.0424)			(0.0561)			(0.0553)
6	Lag-1 Cold Spell Duration	0.122	16	Longest Dry Spell (.95) (W)	-0.0569	26	Mean T °C in [24; 27) (W)	0.0907
		(0.0763)			(0.0613)			(0.0637)
7	Cold Spell Duration	-0.102	17	Lag-1 Longest Day Cold Wave	-0.0335	27	Lag-1 Day Cold Wave T °C	-0.0911*
		(0.0688)			(0.0670)			(0.0551)
8	Cont'd Heavy PPT (W)	-0.0445	18	Lag-2 Mean T °C in [3; 6) (W)	-0.151**	28	Lag-1 Mean T °C in [0; 3)	-0.0419
		(0.0652)			(0.0595)			(0.0441)
9	Lag-1 Harsh Drought Prevalence (W)	0.0787	19	Longest Night Heat Wave (W)	-0.0358	29	Lag-2 Temperature Variance (W)	0.0703
		(0.0527)			(0.0680)			(0.0510)
10	1-Day PPT Maximum	-0.0884	20	Lag-1 Max T °C above 35 (W)	0.0270	30	Lag-2 Longest Night Heat Wave	0.129**
		(0.0540)			(0.0603)			(0.0597)
	Observations	6,550		R-squared	0.272		Within R-squared	0.110

Notes: The table lists the climate variables selected by the LASSO for a penalty parameter λ chosen after a random search to maximize the R-square. The rank indicates the selection order, where rank number one means that the variable is the last to be dropped as λ increases to infinity. The Est. column indicate the coefficient estimates from a linear regression with country fixed effects. All climate variables are first-differenced and standardized. (W) indicates population-weighted variables. Standard errors are clustered by country and reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Climate variables selected by LASSO after the random search and their GDP effect: without year effects

Rank	Variable	Est.	Rank	Variable	Est.	Rank	Variable	Est.
1	Lag-1 GDP p.c. Growth	0.293***	13	Lag-1 Cold Spell Duration	0.100	25	Lag-1 Cont'd Heavy PPT (W)	0.0549
		(0.0394)			(0.0784)			(0.0742)
2	Lag-2 GDP p.c. Growth	0.0478**	14	Lag-1 Longest Day Heat Wave (W)	0.0871	26	Lag-1 Harsh Drought Prevalence (W)	0.0409
		(0.0216)			(0.0620)			(0.0513)
3	World GDP p.c. Growth	0.777***	15	Lag-1 Mean T °C in [3; 6) (W)	-0.198***	27	Lag-1 Day Cold Wave T °C	-0.0911*
		(0.0594)			(0.0589)			(0.0509)
4	Harsh Drought Prevalence (W)	-0.262***	16	Lag-2 Mean T °C in [3; 6) (W)	-0.170***	28	Lag-1 Mean T °C in [18; 21)	0.0455
		(0.0535)			(0.0600)			(0.0470)
5	Mean T °C in [9; 12)	0.174***	17	Longest Dry Spell (.95) (W)	-0.0351	29	Lag-2 Max T °C above 40 (W)	-0.0912
		(0.0437)			(0.0705)			(0.0812)
6	Max T °C above 35 (W)	-0.186**	18	1-Day PPT Maximum	-0.0683	30	Longest Dry Spell (.95)	-0.0505
		(0.0737)			(0.0541)			(0.0756)
7	Cold Spell Duration	-0.113	19	Longest Night Heat Wave	-0.0782	31	Mean T °C in [18; 21)	-0.0443
		(0.0691)			(0.0602)			(0.0470)
8	Lag-1 Day T °C Maximum	0.101**	20	Lag-2 Warm Spell Duration (W)	-0.0482	32	Lag-1 Cont'd Wet Day PPT (W)	-0.0920
		(0.0493)			(0.0537)			(0.0563)
9	Lag-1 Max T °C above 35 (W)	0.00179	21	Lag-2 Longest Day Cold Wave	-0.0760	33	Lag-2 Temperature Variance (W)	0.0818
		(0.0611)			(0.0924)			(0.0522)
10	Cont'd Heavy PPT (W)	-0.0286	22	Lag-2 Night Cold Wave T °C	-0.113*	34	Day Heat Wave T °C (W)	0.141**
		(0.0657)			(0.0585)			(0.0549)
11	Lag-2 Mean T °C in [6; 9) (W)	-0.0689*	23	Longest Night Heat Wave (W)	-0.0205	35	Lag-1 Mean Temperature (W)	0.0483
		(0.0402)			(0.0709)			(0.0617)
12	Lag-2 Mean T °C in [21; 24)	0.131**	24	PPT Minimums (W)	-0.133*	36	Lag-2 Cold Wave Days	-0.0817
		(0.0558)			(0.0696)			(0.0867)
	Observations	6,550		R-squared	0.261		Within R-squared	0.158

Notes: The table lists the variables selected by the LASSO after a random search for lambda to maximize the R-square. The rank indicates the selection order, where rank number one means that the variable is the last to be dropped as λ increases to infinity. The Est. column indicate the coefficient estimates from a linear regression with country fixed effects. All climate variables are first-differenced and standardized. (W) indicates population-weighted variables. Standard errors are clustered by country and reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Climate variables selected by LASSO after the random search and their GDP effect: with quadratic trends

Rank	Variable	Est.	Rank	Variable	Est.	Rank	Variable	Est.
1	Lag-1 GDP p.c. Growth	0.173***	9	1-Day PPT Maximum	-0.0996*	17	Lag-2 Mean T °C in [21; 24)	0.127**
		(0.0476)			(0.0515)			(0.0565)
2	Lag-2 GDP p.c. Growth	-0.0334	10	Lag-2 Longest Day Cold Wave	-0.118*	18	Longest Dry Spell (.95) (W)	-0.0476
		(0.0227)			(0.0624)			(0.0607)
3	Harsh Drought Prevalence (W)	-0.178***	11	Longest Night Heat Wave	-0.106**	19	Lag-1 Day T °C Maximum	0.0366
		(0.0557)			(0.0474)			(0.0435)
4	Max T °C above 35 (W)	-0.206***	12	Lag-1 Mean T °C in [3; 6) (W)	-0.184***	20	Lag-2 Max T °C above 40 (W)	-0.104
		(0.0792)			(0.0545)			(0.0720)
5	Mean T °C in [9; 12)	0.173***	13	Lag-1 Mean T °C in [0; 3)	-0.0564	21	# of Warm Days (W)	-0.000200
		(0.0446)			(0.0432)			(0.0649)
6	Lag-1 Cold Spell Duration	0.125*	14	Lag-1 Mean T °C in [18; 21)	0.0544	22	Lag-1 Cont'd Wet Days (W)	-0.0786
		(0.0752)			(0.0487)			(0.0571)
7	Cont'd Heavy PPT (W)	-0.0788	15	Lag-2 Mean T °C in [3; 6) (W)	-0.169***	23	Lag-1 Harsh Drought Prevalence (W)	0.0580
		(0.0527)			(0.0600)			(0.0531)
8	Cold Spell Duration	-0.0835	16	Lag-2 Longest Night Heat Wave	0.124**	24	Lag-1 Longest Day Cold Wave	-0.0277
		(0.0669)			(0.0623)			(0.0627)
	Observations	6,550		R-squared	0.355		Within R-squared	0.0447

Notes: The table lists the variables selected by the LASSO after a random search for lambda to maximize the R-square. The rank indicates the selection order, where rank number one means that the variable is the last to be dropped as λ increases to infinity. The Est. column indicate the coefficient estimates from a linear regression with country fixed effects. All climate variables are first-differenced and standardized. (W) indicates population-weighted variables. Standard errors are clustered by country and reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Climate variables selected by LASSO after the random search and their GDP effect: balanced sample

Rank	Variable	Est.	Rank	Variable	Est.	Rank	Variable	Est.
1	Lag-1 GDP p.c. Growth	0.243*** (0.0520)	9	Lag-1 Longest Day Cold Wave	0.0259 (0.0771)	17	Cont'd Extreme PPT	0.00580 (0.105)
2	Lag-2 GDP p.c. Growth	0.0652*** (0.0188)	10	Lag-2 Cont'd Dry Days (W)	-0.106* (0.0542)	18	Longest Night Cold Wave	-0.0679 (0.0649)
3	Harsh Drought Prevalence (W)	-0.260*** (0.0705)	11	PPT Minimums (W)	-0.231*** (0.0726)	19	Cont'd Heavy PPT (W)	-0.0165 (0.0698)
4	Lag-1 Cold Spell Duration	0.161** (0.0792)	12	Longest Night Heat Wave	-0.123* (0.0627)	20	Lag-2 Mean T °C in [21; 24)	0.119** (0.0595)
5	Max T °C above 35 (W)	-0.242** (0.0952)	13	Mean T °C in [9; 12)	0.141*** (0.0479)			
6	1-Day PPT Maximum	-0.153** (0.0651)	14	Cont'd Extreme PPT (W)	-0.0125 (0.0964)			
7	Longest Night Heat Wave (W)	0.0118 (0.0491)	15	Longest Dry Spell (.95) (W)	-0.0681 (0.0674)			
8	Lag-1 Harsh Drought Prevalence (W)	0.0884 (0.0577)	16	Lag-2 Longest Dry Spell (.5)	-0.0586 (0.0569)			
	Observations	4,860		R-squared	0.230		Within R-squared	0.0858

Notes: The table lists the variables selected by the LASSO after a random search for lambda to maximize the R-square. The rank indicates the selection order, where rank number one means that the variable is the last to be dropped as λ increases to infinity. The Est. column indicate the coefficient estimates from a linear regression with country fixed effects. All climate variables are first-differenced and standardized. (W) indicates population-weighted variables. Standard errors are clustered by country and reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Climate variables selected by LASSO for government EXPENDITURE after the random search and their estimated effect

Rank	Variable	Est.	Rank	Variable	Est.	Rank	Variable	Est.
1	Lag-1 Expenditure	-0.249***	6	Lag-1 Harsh Drought Prevalence (W)	-0.0720*	11	Lag-1 1-Day PPT Maximum	0.0688
		(0.0499)			(0.0418)			(0.0668)
2	Lag-2 Expenditure	-0.0618**	7	Harsh Drought Prevalence (W)	0.127**	12	Wet Conditions	0.180
		(0.0297)			(0.0523)			(0.135)
3	Lag-1 Cont'd Heavy PPT	0.0256	8	Mean T °C in [-6; -3)	0.0737	13	Lag-1 Extreme PPT Maximum	0.0596
		(0.102)			(0.0457)			(0.0507)
4	PPT Maximums	-0.106	9	Cont'd Heavy PPT	-0.0498			
		(0.0856)			(0.0651)			
5	Mean T °C in [-3; 0) (W)	0.114*	10	Very Wet Conditions	-0.0256			
		(0.0578)			(0.122)			
	Observations	3,849		R-squared	0.124		Within R-squared	0.0693

Notes: The table lists the climate variables selected by the LASSO for a penalty parameter λ chosen after a random search to maximize the R-square. The rank indicates the selection order, where rank number one means that the variable is the last to be dropped as λ increases to infinity. The Est. column indicate the coefficient estimates from a linear regression with year and country fixed effects. The dependent variable is the first difference of government expenditure expressed as a percentage of GDP. Lags of the dependent variable have the same construction. (W) indicates population-weighted variables. Climate variables are first-differenced and standardized. Standard errors are clustered by country and reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Climate variables selected by LASSO for government REVENUE after the random search and their estimated effect

Rank	Variable	Est.	Rank	Variable	Est.	Rank	Variable	Est.
1	Lag-1 Revenue	-0.254***	4	Cont'd Dry Days	-0.115	7	Cold Spell Duration (W)	0.0592
		(0.0491)			(0.0841)			(0.0834)
2	Lag-2 Revenue	-0.132***	5	Lag-1 Longest Dry Spell (.95) (W)	-0.126	8	Lag-1 # of Day Cold Waves	-0.108
		(0.0172)			(0.119)			(0.0761)
3	Longest Dry Spell (.80) (W)	-0.0879	6	Lag-1 # of Night Cold Waves	-0.139	9	Lag-1 Day Cold Wave T °C	0.0432
		(0.104)			(0.107)			(0.0568)
	Observations	3,849		R-squared	0.117		Within R-squared	0.0747

Notes: The table lists the climate variables selected by the LASSO for a penalty parameter λ chosen after a random search to maximize the R-square. The rank indicates the selection order, where rank number one means that the variable is the last to be dropped as λ increases to infinity. The Est. column indicate the coefficient estimates from a linear regression with year and country fixed effects. The dependent variable is the first difference of government revenue expressed as a percentage of GDP. Lags of the dependent variable have the same construction. Climate variables are first-differenced and standardized. (W) indicates population-weighted variables. Standard errors are clustered by country and reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Climate variables selected by LASSO for government DEBT after the random search and their estimated effect

Rank	Variable	Est.	Rank	Variable	Est.	Rank	Variable	Est.
1	Lag-1 Debt	0.0735**	2	Lag-2 Debt	0.136**	3	Wetness Intensity	0.370**
		(0.0293)			(0.0681)			(0.182)
	Observations	3,849		R-squared	0.138		Within R-squared	0.0285

Notes: The table lists the climate variables selected by the LASSO for a penalty parameter λ chosen after a random search to maximize the R-square. The rank indicates the selection order, where rank number one means that the variable is the last to be dropped as λ increases to infinity. The Est. column indicate the coefficient estimates from a linear regression with year and country fixed effects. The dependent variable is the first difference of government debt expressed as a percentage of GDP. Lags of the dependent variable have the same construction. Climate variables are first-differenced and standardized. (W) indicates population-weighted variables. Standard errors are clustered by country and reported in brackets. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table A.14: The effect of changes in selected climate variables on GDP per capita growth

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Lag-1 GDP p.c. Growth	0.280***	0.279***	0.279***	0.279***	0.288***	0.171***	0.239***
	(0.0407)	(0.0406)	(0.0406)	(0.0406)	(0.0393)	(0.0476)	(0.0521)
Lag-2 GDP p.c. Growth	0.0410*	0.0412*	0.0407*	0.0397*	0.0479**	-0.0342	0.0657***
	(0.0220)	(0.0219)	(0.0221)	(0.0220)	(0.0219)	(0.0229)	(0.0191)
World GDP p.c. Growth					0.782***		
					(0.0605)		
First difference in							
Harsh Drought Prevalence (W)	-0.211***	-0.251***			-0.231***	-0.191***	-0.257***
	(0.0544)	(0.0527)			(0.0552)	(0.0568)	(0.0749)
Max T °C above 35 (W)	-0.201***		-0.244***		-0.175**	-0.215***	-0.254***
	(0.0745)		(0.0727)		(0.0745)	(0.0752)	(0.0929)
Mean T °C in [9; 12)	0.155***			0.174***	0.153***	0.142***	
	(0.0395)			(0.0402)	(0.0380)	(0.0400)	
Cold Spell Duration					-0.161**		
					(0.0624)		
Lag-1 Day T °C Maximum					0.126***		
					(0.0443)		
Lag-1 Cold Spell Duration						0.172***	0.196***
						(0.0645)	(0.0722)
Cont'd Heavy PPT (W)						-0.119**	
						(0.0473)	
1-Day PPT Maximum							-0.169***
							(0.0525)
Observations	6,550	6,550	6,550	6,550	6,550	6,550	4,860
Year fixed effects	Yes	Yes	Yes	Yes	No	Yes	Yes
Country quadratic trends	No	No	No	No	No	Yes	No
Balanced	No	No	No	No	No	No	Yes
R-squared	0.264	0.261	0.261	0.260	0.253	0.350	0.224
Within R-squared	0.0998	0.0967	0.0965	0.0952	0.149	0.0375	0.0790

Notes: This is the full table corresponding to the main text summary Table 1. All regressions include country fixed effects. The dependent variable is the first difference of log real GDP per capita expressed in constant 2015 USD. Climate variables are standardized and their definitions are detailed in appendix Table A.1. (W) indicates population-weighted variables. Standard errors are clustered by country.

Table A.15: Estimation of the effect of climate on GDP growth: comparisons with the literature

	Burke et al. (2015)			Kahn et al. (2021)		
	(A) base	(B) unchanged	(C) augmented	(D) base	(E) unchanged	(F) augmented
Lag-1 GDP p.c. Growth	0.117*	0.116*	0.120*	0.300***	0.300***	0.302***
	(0.0629)	(0.0625)	(0.0624)	(0.0458)	(0.0456)	(0.0458)
Lag-2 GDP p.c. Growth	-0.0530*	-0.0531*	-0.0514*	0.0410	0.0427*	0.0432*
	(0.0298)	(0.0296)	(0.0297)	(0.0250)	(0.0252)	(0.0249)
Average Annual Temperature		0.0127***	0.0113***			
		(0.00399)	(0.00390)			
– squared		-0.000479***	-0.000364***			
		(0.000112)	(0.000114)			
Average Annual Precipitation		0.0000130	-0.00000395			
		(0.00000980)	(0.00000920)			
– squared		-4.87e-09**	-1.97e-09			
		(2.45e-09)	(2.24e-09)			
Harsh Drought Prevalence (W)			-0.327***			-0.341***
			(0.0798)			(0.0780)
Max T °C above 35 (W)			-0.229**			-0.205**
			(0.108)			(0.0954)
Mean T °C in [9; 12)			0.193***			0.236***
			(0.0543)			(0.0507)
Temperature Deviations from Trend					-0.0466	-0.00981
					(0.0376)	(0.0384)
– first lag					-0.00427	-0.00309
					(0.0344)	(0.0346)
– second lag					-0.0873**	-0.0914**
					(0.0379)	(0.0378)
– third lag					-0.128***	-0.120***
					(0.0413)	(0.0414)
– fourth lag					-0.0565*	-0.0513*
					(0.0302)	(0.0305)
Precipitation Deviations from Trend					-0.0811	-0.0445
					(0.0651)	(0.0656)
– first lag					-0.0403	-0.0126
					(0.0670)	(0.0662)
– second lag					0.0179	0.0276
					(0.0646)	(0.0643)
– third lag					-0.00152	0.00687
					(0.0632)	(0.0642)
– fourth lag					-0.0532	-0.0520
					(0.0646)	(0.0644)
$\widehat{\theta}_{\Delta\|\tilde{T}_{it}(m)\|}$					-0.491**	-0.420*
					(0.221)	(0.221)
$\widehat{\theta}_{\Delta\|\tilde{P}_{it}(m)\|}$					-0.241	-0.114
					(0.320)	(0.325)
$\widehat{\Phi}$					0.657***	0.655***
					(0.0495)	(0.0492)
Observations	4,168	4,168	4,168	4,917	4,917	4,917
R-squared	0.403	0.407	0.413	0.216	0.220	0.228
Within R-squared	0.0165	0.0233	0.0334	0.110	0.114	0.123

Notes: (W) indicates population-weighted variables. See additional notes in Table 2 in the main text.

Table A.16: Macro-fiscal effects: robustness to alternative climate variables

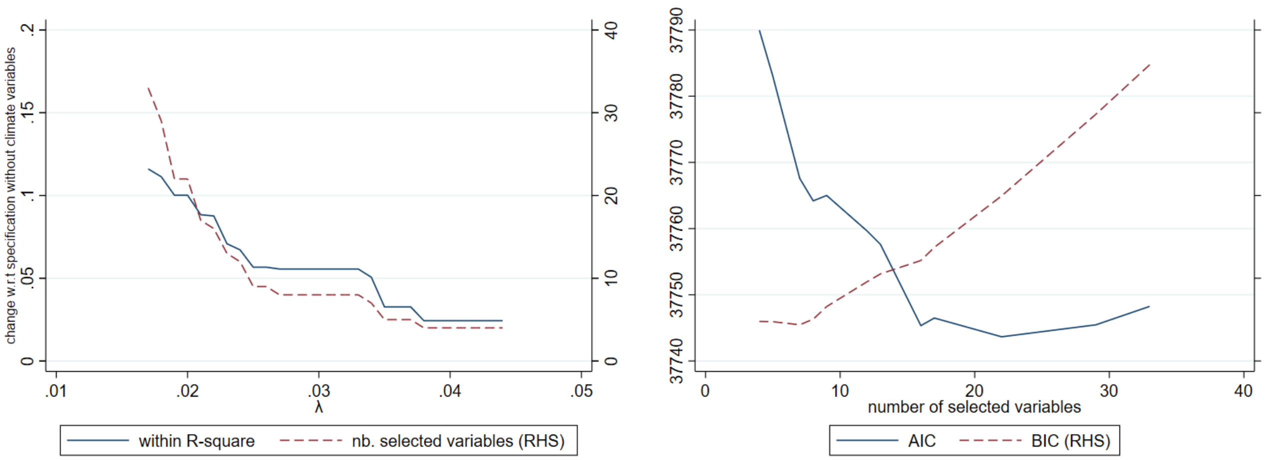
	(A) $\Delta \ln \frac{\text{GDP}}{\text{POP}}$ p.c.	(B) $\Delta \frac{\text{Revenue}}{\text{GDP}}$ p.p.	(C) $\Delta \frac{\text{Expenditure}}{\text{GDP}}$ p.p.	(D) $\Delta \frac{\text{Balance}}{\text{GDP}}$ p.p.	(E) $\Delta \frac{\text{Debt}}{\text{GDP}}$ p.p.	(F) $\Delta \ln$ Revenue p.c.	(G) $\Delta \ln$ Expenditure p.c.	(H) $\Delta \ln$ Debt p.c.
Lag(1) of Fiscal Variable	0.169***	-0.256***	-0.250***	-0.310***	0.0743**	-0.199***	-0.101***	0.136***
	(0.0561)	(0.0492)	(0.0501)	(0.0317)	(0.0287)	(0.0534)	(0.0342)	(0.0319)
Lag(2) of Fiscal Variable	0.0182	-0.134***	-0.0636**	-0.122***	0.136**	-0.0738	-0.0552	0.0272
	(0.0189)	(0.0174)	(0.0300)	(0.0240)	(0.0680)	(0.0464)	(0.0398)	(0.0234)
First difference in								
Harsh Drought Prevalence (W)	-0.149**	0.0861*	0.121**	-0.0357	-0.0821	0.266	0.301*	-0.204
	(0.0663)	(0.0509)	(0.0499)	(0.0530)	(0.114)	(0.207)	(0.179)	(0.229)
Max T °C above 35 (W)	-0.105	-0.164**	-0.0217	-0.138*	-0.0684	-1.139**	-0.334	0.0196
	(0.0815)	(0.0629)	(0.0484)	(0.0736)	(0.145)	(0.484)	(0.332)	(0.242)
Mean T °C in [9; 12)	0.145***	0.0484	-0.0651	0.109**	-0.00437	0.257**	-0.00655	-0.0918
	(0.0453)	(0.0339)	(0.0565)	(0.0519)	(0.108)	(0.122)	(0.134)	(0.225)
Longest Dry Spell (.95) (W)	-0.100*	0.0400	0.0998	-0.0668	0.404**	0.0865	0.263	0.207
	(0.0536)	(0.0422)	(0.0674)	(0.0666)	(0.190)	(0.185)	(0.251)	(0.284)
Lag-1 Cont'd Heavy PPT	-0.0214	0.0584	0.137	-0.0684	0.231	0.173	0.538**	0.368
	(0.0606)	(0.0680)	(0.0888)	(0.107)	(0.145)	(0.310)	(0.266)	(0.239)
Very Wet Conditions	-0.0788*	0.0796	0.125***	-0.0510	0.347**	0.0525	0.411***	0.858***
	(0.0424)	(0.0748)	(0.0368)	(0.0884)	(0.155)	(0.215)	(0.151)	(0.261)
Constant	1.606***	0.143***	0.1000***	0.0408***	0.0210	5.040***	4.461***	3.461***
	(0.113)	(0.00569)	(0.00459)	(0.00158)	(0.0131)	(0.293)	(0.239)	(0.164)
Observations	3849.000	3849.000	3849.000	3849.000	3849.000	3849.000	3849.000	3849.000
R-square	0.268	0.114	0.119	0.150	0.139	0.127	0.0783	0.168
Within R-square	0.0384	0.0712	0.0641	0.0934	0.0302	0.0500	0.0184	0.0244

Notes: The dependent variables are indicated in the column titles and are expressed in percentages. We use the same three climate variables used for GDP growth and the first climate variables selected by the LASSO respectively for government revenue, expenditure, and debt. All climate variables are standardized with standard deviations equal to 100 to ease interpretation. Controls include the first two lags of the dependent variable (reported in the first two rows), and year and country fixed effects. (W) indicates population-weighted variables. Standard errors are clustered by country and reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.5. Additional Figures

Figure A.2: GDP – climate variable selection and OLS estimation outcomes without year effects

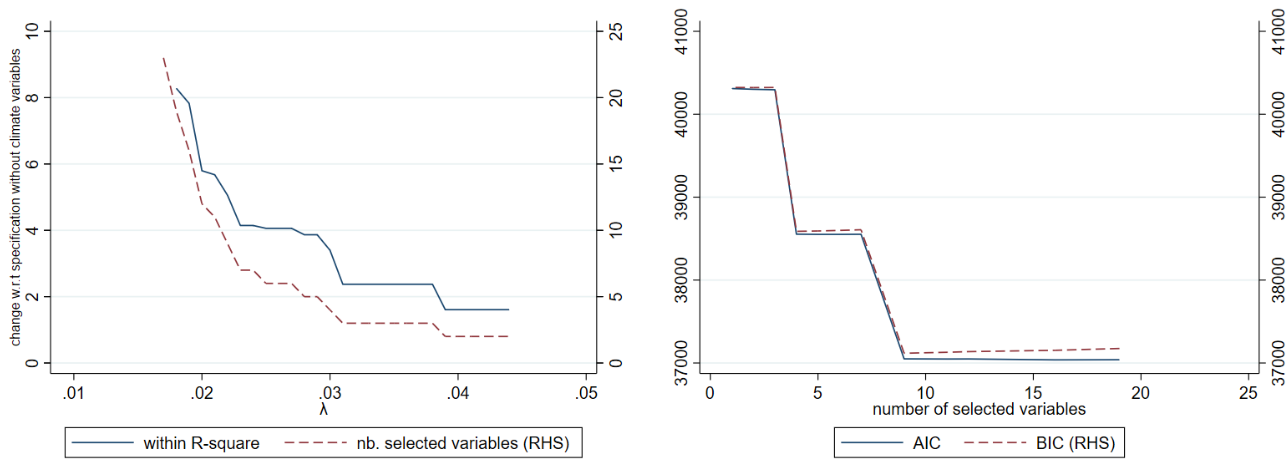
(a) Selected variables and within R-square (b) Information criteria



Notes: The figures show various outcomes from implementing the LASSO for different penalty parameters. The estimated model has GDP per capita growth as the dependent variables and includes only country effects. The within R-square, AIC, and BIC are computed based on the OLS estimation. The within R-square is reported as a percentage change relative to the within R-square obtained with a specification that only includes the first two lags of the dependent variable and world growth (within $R^2 = .141$*).*

Figure A.3: GDP – variable selection and OLS estimation outcomes with quadratic trends

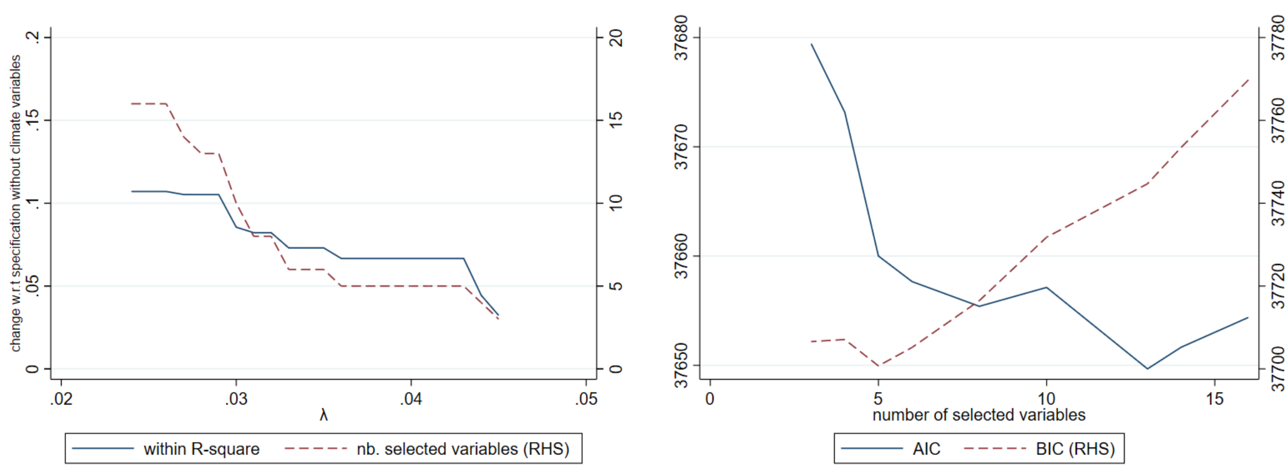
(a) Selected variables and within R-square (b) Information criteria



Notes: The figures show various outcomes from implementing the LASSO for different penalty parameters. The estimated model has GDP per capita growth as the dependent variables and includes country quadratic trends and year effects. The within R-square, AIC, and BIC are computed based on the OLS estimation. The within R-square is reported as a percentage change relative to the within R-square obtained with a specification that only includes the first two lags of the dependent variable (within $R^2 = 0.001$*).*

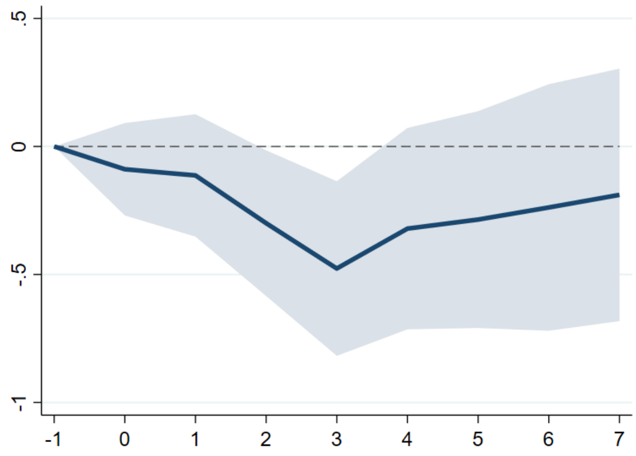
Figure A.4: GDP – variable selection and OLS estimation outcomes on the balanced sample

(a) Selected variables and within R-square (b) Information criteria



Notes: The figures show various outcomes from implementing the LASSO for different penalty parameters. The estimated model has GDP per capita growth as the dependent variables and includes country quadratic trends and year effects. The within R-square, AIC, and BIC are computed based on the OLS estimation. The within R-square is reported as a percentage change relative to the within R-square obtained with a specification that only includes the first two lags of the dependent variable (within $R^2 = 0.094$*).*

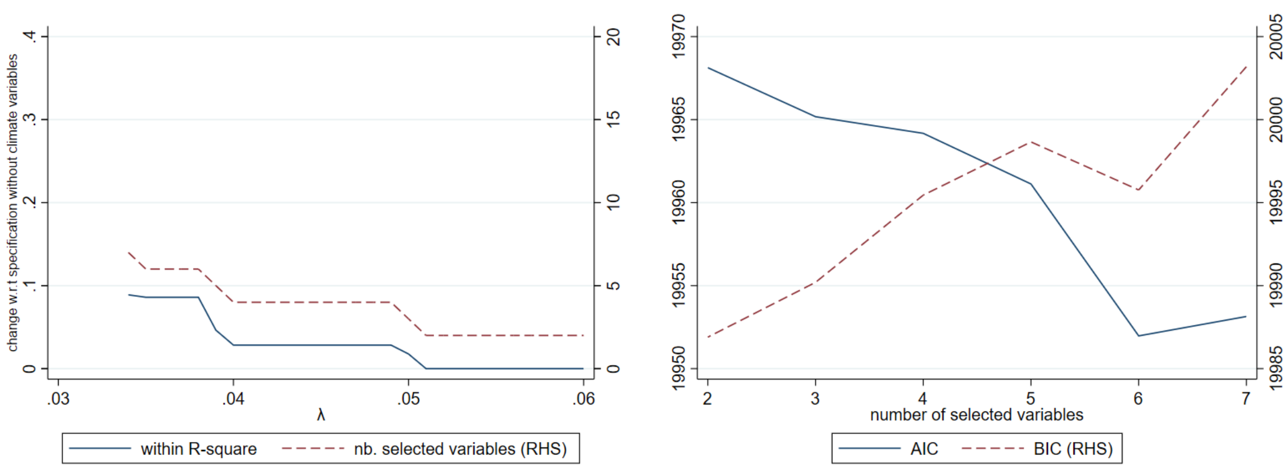
Figure A.5: Persistence of the effect of average annual temperature shocks on GDP per capita



Notes: The figure represents the impulse response of per capita output in levels to one standard deviation shock of the absolute deviation in the annual average temperature with respect to the past 30-year average. Horizon 0 is the year of the shock. The shaded area shows the 90 percent confidence intervals.

Figure A.6: Government revenue – climate variable selection and OLS estimation outcomes

(a) Selected variables and within R-square (b) Information criteria



Notes: The figures show various outcomes from implementing the LASSO for different penalty parameters. The estimated model has the ratio of government revenue to GDP as the dependent variables and includes country and year effects. The within R-square, AIC, and BIC are computed based on the OLS estimation. The within R-square is reported as a percentage change relative to the within R-square obtained with a specification that only includes the first two lags of the dependent variable (within $R^2 = 0.066$).

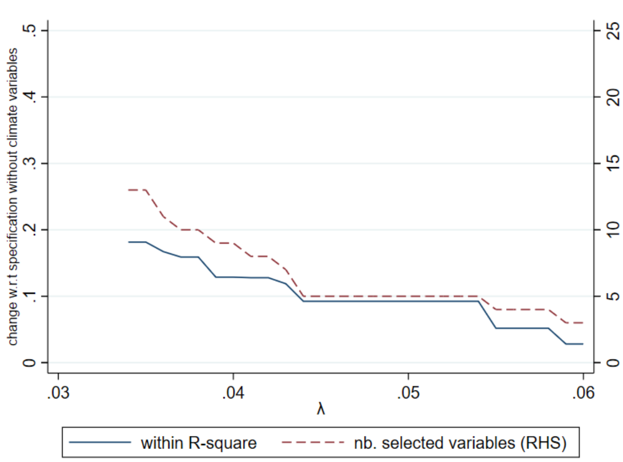
Table A.17: Macro-fiscal effects: the role of fiscal space

	(A) $\Delta \ln \frac{GDP}{POP}$ (p.c.)	(B) $\Delta \frac{Revenue}{GDP}$ (p.p.)	(C) $\Delta \frac{Expenditure}{GDP}$ (p.p.)	(E) $\Delta \frac{Debt}{GDP}$ (p.p.)
Lag(1) of Fiscal Variable	0.172***	-0.257***	-0.252***	0.139***
	(0.0576)	(0.0499)	(0.0488)	(0.0242)
Lag(2) of Fiscal Variable	0.0228	-0.133***	-0.0651**	0.177***
	(0.0191)	(0.0178)	(0.0299)	(0.0589)
Lag(1) Mean-deviation of debt (cubic)	0.0512*	0.0652***	-0.165***	-1.382***
	(0.0302)	(0.0242)	(0.0266)	(0.145)
First difference in				
Harsh Drought Prevalence (W)	-0.152**	0.0829	0.121**	-0.132
	(0.0712)	(0.0588)	(0.0550)	(0.117)
" interacted with lag(1) debt deviation	0.0246	0.0000292	0.00485	0.102
	(0.0251)	(0.0277)	(0.0298)	(0.0824)
Max T C above 35 °C (W)	-0.108	-0.150**	0.00565	0.00238
	(0.0828)	(0.0642)	(0.0501)	(0.147)
" interacted with lag(1) debt deviation	0.0346	0.00381	-0.00634	-0.258
	(0.0293)	(0.0185)	(0.0313)	(0.175)
Mean T in [9; 12) °C	0.153***	0.0546	-0.0598	-0.0326
	(0.0465)	(0.0360)	(0.0597)	(0.102)
" interacted with lag(1) debt deviation	-0.0186	-0.0109	0.00398	0.106
	(0.0175)	(0.0125)	(0.0147)	(0.0676)
Longest Dry Spell (.80) (W)	-0.00574	-0.105	0.0141	0.335*
	(0.0517)	(0.103)	(0.0518)	(0.192)
" interacted with lag(1) debt deviation	-0.0187	0.0175	0.0877	0.0815
	(0.0242)	(0.0397)	(0.0604)	(0.113)
Lag(1) of Cont'd Heavy PPT	-0.0144	0.0542	0.133	0.199
	(0.0595)	(0.0712)	(0.0868)	(0.139)
" interacted with lag(1) debt deviation	-0.0438**	0.0570*	-0.0166	-0.133*
	(0.0213)	(0.0325)	(0.0411)	(0.0783)
Wetness Intensity	-0.0295	0.0554	0.138**	0.331*
	(0.0514)	(0.0626)	(0.0606)	(0.191)
" interacted with lag(1) debt deviation	-0.000849	-0.0211	-0.0397	-0.0123
	(0.0240)	(0.0302)	(0.0336)	(0.0892)
Constant	1.568***	0.117***	0.164***	0.599***
	(0.126)	(0.0105)	(0.0119)	(0.0664)
Observations	3,849	3,849	3,849	3,849
R-square	0.269	0.118	0.135	0.219
Within R-square	0.0407	0.0752	0.0809	0.120

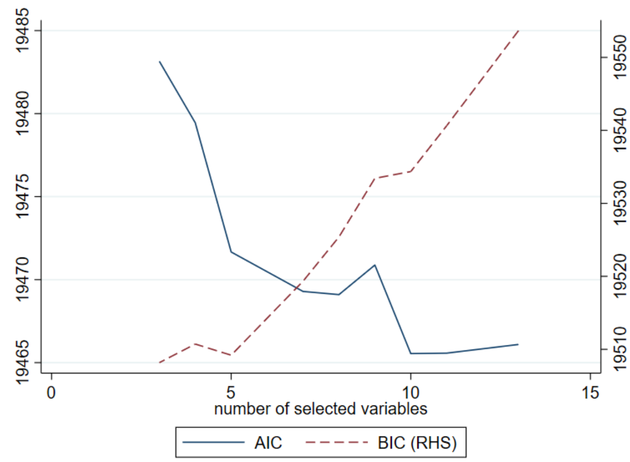
Notes: The dependent variables are indicated in the column titles and are expressed in percentages. We use the same three climate variables used for GDP growth and the first climate variables selected by the LASSO respectively for government revenue, expenditure, and debt. The "Mean-deviation of debt (cubic)" is defined as the deviations from country average debt, that is then standardized by country and raised to the cube. All climate variables are standardized with standard deviations equal to 100 to ease interpretation. Controls include the first two lags of the dependent variable (reported in the first two rows), and year and country fixed effects. (W) indicates population-weighted variables. Standard errors are clustered by country and reported in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.7: Government expenditure – climate variable selection and OLS estimation outcomes

(a) Selected variables and within R-square



(b) Information criteria



Notes: The figures show various outcomes from implementing the LASSO for different penalty parameters. The estimated model has the ratio of government expenditure to GDP as the dependent variables and includes country and year effects. The within R-square, AIC, and BIC are computed based on the OLS estimation. The within R-square is reported as a percentage change relative to the within R-square obtained with a specification that only includes the first two lags of the dependent variable (within $R^2 = .059$*).*

PUBLICATIONS

Estimating Macro-Fiscal Effects of Climate Shocks From Billions of Geospatial Weather Observations
Working Paper No. **WP/2022/156**