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Fiscal Impacts of Climate Anomalies

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public debt, climate change, panel data, structural Bayesian VAR

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1 Introduction

Climate change is actively underway and shows no signs of slowing down. Global warming is on an unprecedented trajectory, with surface temperatures reaching 1.1°C above 1850-1900 levels in the last decade, mainly due to anthropogenic greenhouse gas emissions (IPCC, 2023). The observed temperature increase is projected to continue and worsen. The 1.5°C threshold is likely to be exceeded by the end of the century, even under optimistic greenhouse gas emission scenarios, together with the frequency and intensity of climate change-related adverse events such as droughts, heat waves, floods, wildfires, cyclones and higher sea levels, which have increased fivefold in recent decades (WMO, 2021).

Combined with these natural effects, climate anomalies are clearly exerting a human influence, with tangible socio-economic consequences. Temperature shocks and variability severely affect growth, productivity, industrial and agricultural output, energy demand, inflation and inequality (see e.g. Dell et al., 2012, 2014; Kalkuhl and Wenz, 2020; De Winne and Peersman, 2021; Kahn et al., 2021; Mumtaz and Theophilopoulou, 2024). In addition, recent empirical contributions show that the macroeconomic damages from climate change are significantly higher than previously calculated (Bilal and Känzig, 2024; Nath et al., 2024).[1]

But climate change also has fiscal implications. Disruptive weather events often require significant public expenditure in the form of recovery measures, which, together with the long-term investments needed to finance adaptation measures, could pose a real risk to public finances. Given the inter-generational nature of the phenomenon, the climate-related fiscal burden will necessarily have to be spread over time, with part of these financial needs being met in the form of public debt through the adoption of lax fiscal policies (Breckenfelder et al., 2023). In addition to these direct expenditure effects, the productivity and output losses induced by climate anomalies may in turn lead to less cyclical government revenues, further jeopardising fiscal sustainability.

The main objective of this paper is to empirically investigate the impact of climate change on fiscal variables over a business cycle horizon. In particular, we analyse the effects of temperature and precipitation anomalies on the public debt and primary balance ratios of developed countries. To achieve our objective, we use a macroeconometric framework that also takes into account macroeconomic variables that may affect debt sustainability over time and that have been shown to be affected by natural weather

[1] One of the main reasons for these results, according to Bilal and Känzig (2024), is the difference between the impact of local temperature shocks on the macroeconomy, which has mainly been exploited in the empirical literature over the last decade, and global temperature shocks.

variations (i.e. real GDP, inflation and the long-term interest rate). Our focus is on the impact of physical risk of climate change on the dynamics of public finances. Policy responses aimed at mitigating and counteracting climate dynamics also entail a transition risk whose fiscal consequences, though significant, lie beyond the scope of this paper.

The analysis is based on a Bayesian Panel VAR and employs quarterly data from 14 European countries and the United States for the period 2002Q4–2022Q4. Specifically, we construct a new fiscal-climate database that combines high frequency weather observations with debt, deficit and detailed government budgetary items data, together with standard macroeconomic variables. Given the moderate temporal scale at which fiscal variables are available, the Panel VAR uses pooled estimation, controlling for static country heterogeneity by including fixed effects and assuming dynamic homogeneity. The Bayesian estimation is performed according to the prior developed by Bańbura et al. (2010), which is particularly suitable for large VARs to overcome the curse of dimensionality. The use of a Panel VAR with macro data Canova and Ciccarelli (2013) and fixed effects is a good crossroads between standard VAR models and univariate dynamic panel approaches. Indeed, we retain the main advantages of panel estimation, namely the ability to consider country-level relationships, while at the same time, thanks to the structure of the VAR, the ability to consider general equilibrium and spillover effects. Of course, pooled estimation forces us to assume that there is no cross-country correlation between the reduced-form residuals. For this reason, the VAR system is extended with exogenous global factors in the spirit of the Global VAR model (Pesaran et al., 2004) to capture spillovers between countries.

We identify temperature and precipitation shocks as exogenous, unpredictable *climate anomalies*, defined as the deviation of observed weather variables from their 30-year moving average for a given quarter. This approach is useful for isolating genuine climate effects from mere weather variations and helps us to mitigate the influence of long-term trends (in annual data) and seasonal patterns (in quarterly data), which can lead to spurious statistical results when macroeconomic variables follow a similar pattern. In addition, taking into account the time-varying nature of climate anomalies is essential for indirectly accounting for adaptation, which is by nature a dynamic process (see Kahn et al., 2021). In this approach, we first follow the standard methodology for obtaining climate anomalies, but we go further by removing a strong autocorrelated component still present in the temperature anomaly time series for the countries in our sample, which would make it an inefficient exogenous instrument. Once we have constructed temperature and precipitation shocks, the structural identification in the Panel VAR is achieved by exploiting the internal instrument approach of Plagborg-Møller and Wolf (2021), according to which a structural proxy VAR identification can be carried out by simply ordering an exogenous instrument first in a recursive VAR, also allowing for non-invertibility of the moving average representation of the VAR model. Our exogeneity assumption is that climate shocks are contemporaneously exogenous to the macroeconomic system. This is a widely used assumption in several analogous estimations with annual data, and therefore holds even more strongly with our higher frequency quarterly observations.

Structural impulse response functions for the full sample of countries show that both temperature and precipitation shocks are contractionary and significantly increase public debt and the deficit ratio over time. However, the two shocks behave differently in terms of persistence and impact on inflation. Temperature shocks have persistent fiscal and economic effects and resemble negative supply shocks, as they induce a significant increase in consumer prices. Precipitation shocks have only temporary effects on fiscal variables and real GDP and behave like negative demand shocks, significantly reducing inflation over time. These results are robust to changes in the model specification (e.g. lag order, linear trend, seasonal dummies) and in the tightness of the Bayesian prior.

In a second exercise, we exploit the cross-country nature of our dataset to investigate whether the observed results are heterogeneous according to specific country characteristics. This strategy also allows us to relax the cross-sectional homogeneity assumption required for the pooled estimation of the Panel VAR due to our moderate time span. The results of the subgroup estimations suggest that the reported negative effects of temperature shocks are remarkably stronger in warmer, more climate-vulnerable and highly indebted countries, with larger increases in debt and deficit and larger reductions in real GDP. These findings support the idea that there may be a potential non-linear effect between temperature anomalies and fiscal variables, analogous to what has already been documented for economic variables (Burke et al., 2015). In our sample, countries with a higher initial temperature level seem to be more at risk of experiencing negative fiscal outcomes. Conversely, the results for precipitation shocks do not vary across different sub-samples of countries.

Additional analyses allow us to examine the main transmission mechanisms behind the macrodynamics identified. By augmenting the Panel VAR with specific fiscal variables for government revenues and expenditures, we find that the main channels of the reported fiscal impacts are a significant reduction in tax revenues and an increase in government spending on public subsidies. In particular, we show that, in line with the supply or demand nature of the shocks, precipitation shocks mainly affect revenues from direct taxes, while temperature shocks mainly erode revenues from taxes on imports and production.

Our empirical investigation is well motivated from a policy perspective. The OECD and the World Bank have analysed the fiscal impact and consequences of large-scale adverse weather events, pointing out that the fiscal burden of climate-related disasters is often borne by governments (OECD and World Bank, 2019). The European Commission introduced climate change as a significant source of fiscal risk in the 2019 Debt Sustainability Monitor, considering potential future public spending related to more frequent disruptive natural disasters as a dangerous source of macroeconomic uncertainty (European Commission, 2020). The IMF has reformed its debt sustainability analysis to include climate change as one of the drivers of fiscal uncertainty, noting that climate shocks can significantly affect future public debt trajectories and the probability of adverse economic events (Maldonado and Gallagher, 2022).

The remainder of the paper is structured as follows. Section 2 provides a careful review of the strands of literature we draw on and describes the main transmission mechanisms motivating our empirical investigation. Section 3 describes our data, focusing on how we obtained our climate shocks from natural weather data. Section 4 presents the empirical framework, providing details on the estimation of the Bayesian Panel VAR model and the identification of structural shocks. Section 5 presents and interprets the main results. Section 6 concludes.

2 Literature and channels

Higher temperatures, increased temperature variability and frequency of extreme weather events can reduce output, productivity, agricultural production and growth (Dell et al., 2012, 2014; Burke et al., 2015; Donadelli et al., 2017; Alessandri and Mumtaz, 2022). The estimated damages are stronger in developing and hotter countries, but recent empirical evidence has also found similar impacts in global panels of regions or samples, including OECD and developed economies (Kalkuhl and Wenz, 2020; Kahn et al., 2021; Kim et al., 2024; Bilal and Känzig, 2024). The heterogeneity of these results has raised interest in the distributional effects of climate anomalies. The main results suggest that climate shocks and climate vulnerability significantly increase income inequality, affecting more low-income households, especially in hot countries and developing economies (Cevik and Jalles, 2023; Mumtaz and Theophilopoulou, 2024).

The contractionary impact of climate shocks raises the challenge of understanding their nature in order to design effective policy responses. While the initial consensus was to associate climate-related shocks with negative supply shocks, recent studies have questioned this relationship and introduced the hypothesis that climate change may also trigger demand-side shocks, leading to deflationary pressures (Ciccarelli and Marotta, 2024). Indeed, the empirical evidence on the impact of climate change on inflation is still mixed and depends significantly on the type of items included in the CPI measure, with energy prices playing a crucial role (Ciccarelli et al., 2024; Kotz et al., 2024; Lucidi et al., 2024). As we assess the fiscal impact of climate change in a macroeconometric framework that also takes into account economic activity and inflation, our analysis contributes to this debate by showing that, in our sample, temperature and precipitation shocks have different inflationary effects.

Understanding how climate change affects the dynamics of public finance is a relatively new research topic that has received little attention in the empirical economics literature and still requires considerable technical insight.[2] However, there is broad consensus that there is a notable impact of climate dynamics on public finances (Gillingham and Stock, 2018) over different time horizons, as mitigation costs tend to affect public finances in the short run, while adaptation measures affect debt in the long run. The difficulties in estimating the magnitude of these effects lie mainly in the complexity of the phenomenon, which involves several dimensions that often cannot be considered together and therefore need to be assessed at the macro level.

As highlighted in detail by the European Commission (2020), climate change can have *non-discretionary* fiscal impacts, which are exogenous and can be either direct (e.g. public spending needed to face adverse weather events, social transfers to households) and indirect (e.g. reduction in tax revenues due to reduced economic activity, impact on the country's ability to pay its debt in the medium term, increase in health care spending) and *discretionary* fiscal impacts that are endogenously driven by climate adaptation and mitigation policies (e.g, carbon taxes or emissions trading schemes revenues, public subsidies for clean energy transitions, investments in climate-resilient infrastructure). Of course, not all of these impacts have a negative impact on public finances (e.g., the imposition of carbon taxes may increase government budgets over time). However, the costs of adaptation and mitigation, which represent the largest financial effort in the long run, are mostly associated with significant public expenditure (Jones et al., 2012; Baur et al., 2021). As our analysis focuses on the physical risks of climate change, we can only assess the magnitude of the non-discretionary fiscal impact of climate anomalies. However, we are aware that discretionary fiscal effects induced by policies aimed at limiting climate damages to the economy may not be negligible (i.e. transition risk).

As argued by Zenios (2021), another important channel through which climate-related risks may affect public finances is through the effect on the pricing of sovereign bonds,

[2] For a recent review see Barrage (2024).

which consistently distorts the perceived creditworthiness of countries and could affect interest expenditure over time. This mechanism is now the best documented in the empirical economics literature. Recent academic work has focused attention on the contribution of climate change to sovereign bond pricing, attempting to identify the impact of climate vulnerability (or other proxies for climate change) on borrowing costs and sovereign risk. The general conclusion is that a higher exposure to climate-related risks or a higher degree of vulnerability to climate change leads to a significantly higher cost of debt (Kling et al., 2018; Battiston and Monasterolo, 2020; Beirne et al., 2021; Klusak et al., 2023; Boitan and Marchewka-Bartkowiak, 2022; Diarra and Jaber, 2022). The idea that climate trends will have a significant impact on countries' fiscal sustainability as perceived by the bond market is also supported by some of the major rating agencies (Standard and Poor's, 2017; Kamins, 2023). However, none of these studies has analysed the related potential macroeconomic impact of this mechanism on fiscal variables.

Our paper is one of the first empirical attempts to assess the fiscal impact of climate change by investigating how climate anomalies affect debt and deficit dynamics over a business cycle horizon in developed countries.[3] Two recent noteworthy contributions are Barrage (2023) and Akyapi et al. (2024).

Barrage (2023) explores both theoretically and empirically the potential channels of the fiscal impact of climate change in the United States. In particular, she theoretically develops an extension of the COMET (Climate Optimization Model of the Economy and Taxation) model (Barrage, 2020) for the United States that explores several transmission mechanisms of adverse climate dynamics on public finances. Our work complements her theoretical contribution, but differs from her empirical analysis for at least two reasons. First, while she focuses specifically on the impact on public health expenditures using Medicare data in the United States, we assess a broader macro effect on public debt and deficit dynamics in a panel of 15 developed countries, including the United States. In addition, we measure climate change using natural weather anomalies in temperature and precipitation, while she uses extreme temperature realisations (i.e., extreme heat and freezing days). Second, Barrage (2023) estimates a univariate panel dynamic regression framework, which by construction cannot account for bidirectional links between climate and economic variables that our Panel VAR model is able to capture. In this respect, our paper joins a recent and growing literature of empirical contributions analysing the macroeconomic impacts of climate change using structural multivariate regression models.

Akyapi et al. (2024) construct hundreds of variables from high frequency, high spatial resolution weather measurements and identify the parsimonious subset of variables that

[3] Recent contributions for developing countries focus mainly on African economies (see Kunawotor et al., 2022 and Giovanis and Ozdamar, 2022).

can best explain GDP and key macro-fiscal variables. They find that an increase in the frequency of high temperatures, severe droughts, and a decrease in the frequency of mild temperatures reduce GDP. Additional evidence suggests that fiscal policy may help in mitigating the economic damages from weather shocks.

Finally, our empirical investigations closely connect with the literature which tries to evaluate the fiscal impacts and policy response of governments to specific natural disasters (e.g., Melecky and Raddatz, 2011; Noy and Nualsri, 2011; Acevedo, 2014; Ouattara et al., 2018; Fuje et al., 2023). However, this literature does not consider long-term climate anomalies.

3 Data

For our Bayesian Panel VAR analysis, we build a new fiscal-climate database which merges weather observations with macroeconomic variables. We use quarterly data from 15 developed countries over the period 2002Q4 to 2022Q4. In the context of large panel estimations, the number of units considered (i.e. countries) is the result of a crucial trade-off between sample size, data frequency and time span, especially in our analysis, as quarterly time series for public debt ratios are often not available for a significant time span. For these reasons, we focus on 14 European countries[4] and the United States. Our macro-climate dataset combines two weather variables (air temperature and precipitation), which are used to identify exogenous instruments for climate change, with a set of macro-economic variables, including fiscal variables. The weather variables are also available at monthly or weekly frequency, but the quarterly dimension is the smallest that allows us to match climate observations with debt and primary balance data.

3.1 Weather variables

To measure climate change, we rely on the most commonly used proxies for weather conditions, namely temperature and precipitation. These two variables serve as distinct proxies for climate change and are included one at a time in the vector of endogenous variables of the Panel VAR. This decision stems from the bidirectional and complex relationship between temperature and precipitation, where both variables influence each other in different climatic contexts (Vrac et al., 2022). For example, rising temperatures can increase evaporation, leading to increased precipitation, especially during extreme weather events. Conversely, precipitation events can affect local temperatures through

[4] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Ireland, Luxembourg, the Netherlands, Spain, Portugal and Sweden.

mechanisms such as evaporation and cloud formation, further complicating their interaction. Therefore, including both variables as endogenous in a structural VAR model with shocks identified by recursive methods requires an assumption of contemporaneous exogeneity of one variable relative to the other, a condition that does not reflect the reality of their interdependence.[5] This underlines the importance of treating these variables independently in order to capture their unique contributions to the dynamics of climate change. Without imposing unrealistic restrictions on their relationship, we treat the two measures as alternatives to assess the potential difference in their impact on fiscal and economic dynamics.

The data are from the Climatic Research Unit gridded Time Series (CRU TS) dataset, produced by the UK's National Centre for Atmospheric Science at the University of East Anglia. The CRU TS dataset is a widely used climate database covering the global land surface (excluding Antarctica) on a grid of 0.5° latitude by 0.5° longitude. It is produced by interpolating monthly climate anomalies using information from extensive networks of weather station observations. Data are available down to daily frequency. We use the latest version of the dataset (CRU TS v4), where the interpolation method has been updated and angular distance weighting (ADW) is used (Harris et al., 2010). For temperatures, we take the monthly average of the 2-m air temperature level, measured in Celsius degrees. For precipitation, we use the precipitation rate, measured in mm per month. In order to obtain weather variables suitable for our macroeconometric analysis, we directly collected the average homogenised observations per month and per country provided by the CRU TS over the period 1908-2022, which are the area-weighted measures of weather conditions. We aggregate the monthly observations into quarters by averaging the monthly temperatures and summing the precipitation over the three months of each quarter. Detailed descriptive statistics for temperature and precipitation for each country in our sample are given in table A.1 in the appendix.

3.2 Climate shocks

Climate change is a gradual phenomenon that differs significantly from observable weather variations. Specifically, while weather reflects short-term variations in atmospheric conditions, including temperature and precipitation, climate refers to the long-term averages and variability of these weather patterns. Climate change therefore involves changes in the state of the climate that are statistically detectable through structural changes in the

[5] Studies including both temperature and precipitation in a structural VAR framework do not use recursive identification strategies to avoid this crucial assumption. See for example Mumtaz and Theophilopoulou (2024), who identify the climate shocks as those that explain most of the variance in the long run of both climate variables considered.

mean or variability of its properties, and which are highly persistent over time (IPCC, 2014). Similarly, in terms of extremes, while short-term weather conditions are strongly influenced by the magnitude of adverse events, climate change affects the variability and frequency of such natural disasters. For these reasons, it is unlikely that simply using the levels of weather variables effectively captures any climate change effects on the macroeconomic outcomes of interest. Moreover, from a statistical perspective, estimating econometric models using levels of weather variables may lead to spurious correlations when analysed alongside macroeconomic variables that show similar patterns.

Figure 1 shows that annual temperatures are typically characterised by a strong trend behaviour (top left subplot), while quarterly temperatures show both a trend and a seasonal pattern (top right and bottom left subplot).[6] Since both temperature levels and real GDP share an upward trend across all countries in our sample, a simple econometric analysis might suggest that increases in temperature are associated with higher real GDP. However, this is only a co-movement of the two variables whose main long-term transmission mechanism is represented by greenhouse gas emissions (e.g. higher economic activity increases the volume of greenhouse gas emissions, which gradually raise global temperature). These purely statistical features are less pronounced in the precipitation time series of Figure 2. However, as argued above, the use of precipitation levels would still be inappropriate for interpreting climate change effects in the data.

As a consequence, instead of considering temperature and precipitation levels, we use natural weather realisations to build specific exogenous instruments that we will call *temperature shocks* and *precipitation shocks*. The shocks are constructed using a two-step procedure. First, we obtain the quarterly climate *anomalies* for both temperature and precipitation in each country in the sample. Anomalies are typical measures widely used in climatology to convey long-term weather variability. They are given by the deviations of the observed weather variables in a given period with respect to a fixed historical norm. The conventional approach exploited by the World Meteorological Organization (WMO) is to use the historical norm of the last 30 years to account for the average climate dynamics.The choice of a 30-year period is primarily driven by its ability to balance key considerations. It is long enough to smooth out short-term variability, such as interannual fluctuations caused by phenomena like El Niño or volcanic eruptions, while remaining short enough to avoid obscuring recent trends, including the accelerating impacts of climate change. In addition, recent studies have suggested that climate anomalies should be calculated with respect to a time-varying rather than a fixed historical norm (i.e., a 30-year moving average) in order to account for adaptation (Kahn et al., 2021). Intu-

[6]The data shown in Figure 1 and Figure 2 are observations for the *average economy* of our sample. However, trend and seasonality are readily apparent in all the country-specific time series.

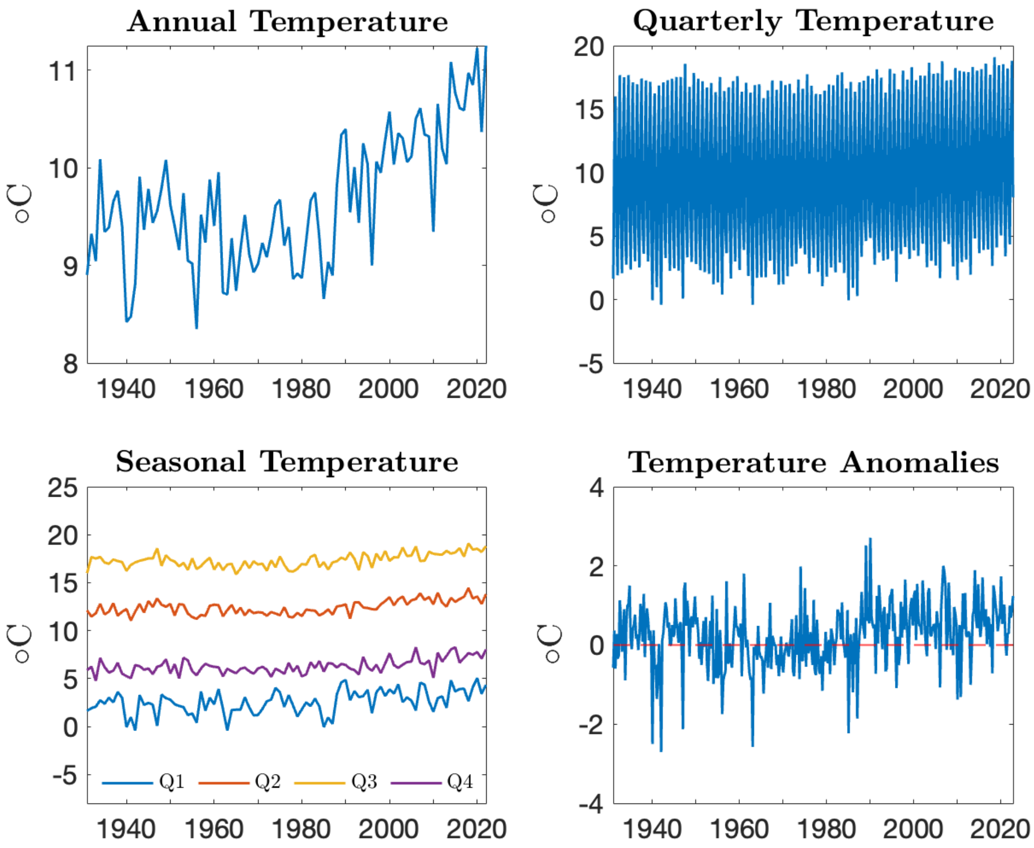

Figure 1: Temperature data in the average economy of our panel of 15 countries in the period 1931-2022.

itively, adaptation to climate change is an inherently dynamic process, which makes very old anomalies perceived as standard dependent on acquired knowledge of past weather realisations.

Formally, we calculate temperature and precipitation anomalies for country i in quarter t as follows:

$$TA_{i,t} = T_{i,t} - \bar{T}^{30}_{i,t} \tag{1}$$

$$PA_{i,t} = P_{i,t} - \bar{P}^{30}_{i,t} \tag{2}$$

where $\bar{T}^{30}_{i,t} = \frac{1}{30}\sum_{j=1}^{30} T_{i,t-j}$ and $\bar{P}^{30}_{i,t} = \frac{1}{30}\sum_{j=1}^{30} P_{i,t-j}$ are the time-varying historical norms for temperature and precipitation, namely the 30-years moving average for a fixed quarter. The temperature and precipitation anomalies obtained using equations (1) and (2) are shown for the average economy in our sample in the lower right subplots of Figure 1 and Figure 2, respectively. A closer look at the plots shows that these time series no longer show any trend or seasonal pattern. Moreover, the way in which they have been

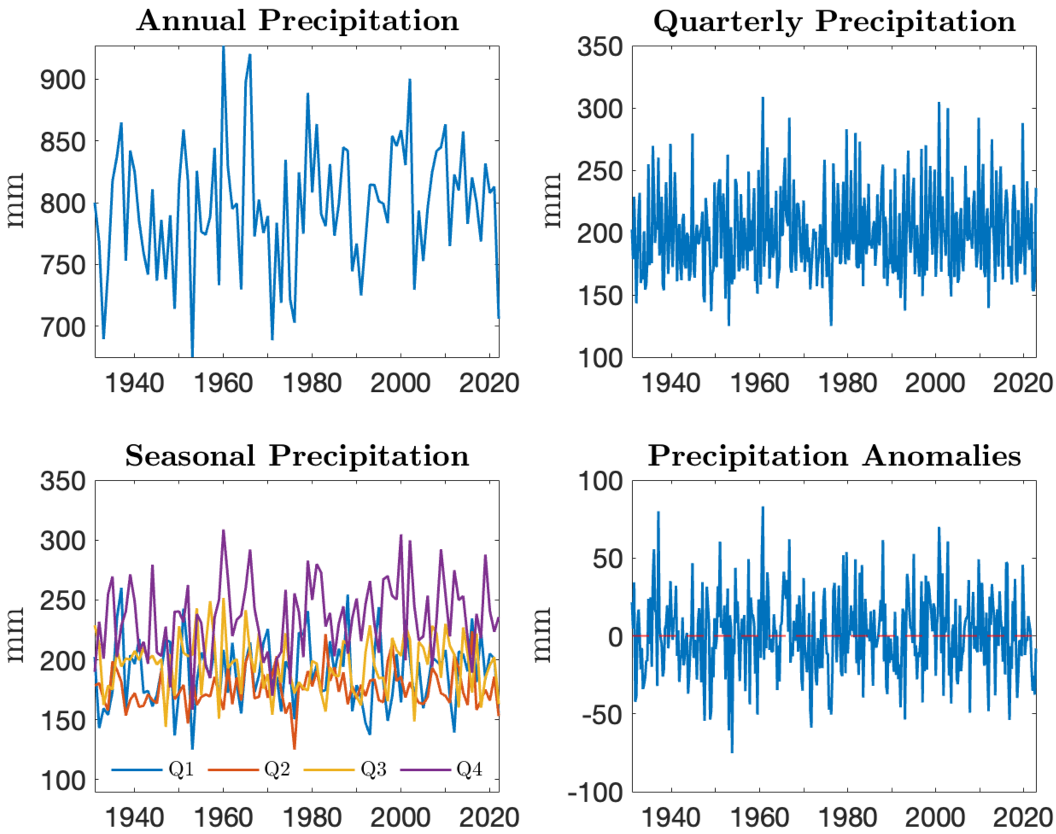

Figure 2: Precipitation data in the average economy of our panel of 15 countries in the period 1931-2022.

retrieved gives them a strong climatic significance. Descriptive statistics for the climate anomalies in each country are reported in detail in Appendix A.1.[7]

Once we have the climate anomalies, the second step in the retrieval of exogenous climate instruments is to investigate whether positive and negative anomalies are randomly distributed over time or show some time-dependent behaviour. To do this, we plot the absolute values of positive (red bars) and negative (blue bars) anomalies for both temperature and precipitation in the average economy over the period 1938–2022 in Figure 3. While the anomalies for temperature appear to be randomly distributed until the 1990s, the histogram for more recent decades shows a clear prevalence of positive deviations from the historical norm compared to negative ones. Autocorrelation tests on temperature anomalies show that the autocorrelogram for most countries in the sample shows significant autocorrelation in the first lags, which is also confirmed by the Ljung Box test. These results do not hold for the time series of precipitation anomalies, which

[7]Temperatures vary from a maximum of 4° to a minimum of -3.96°, both observed in Finland, the country with the highest standard deviation. Quarterly precipitation anomalies range from 362 mm/quarter to -196 mm/quarter, both recorded in Portugal.

are not significantly autocorrelated.[8]

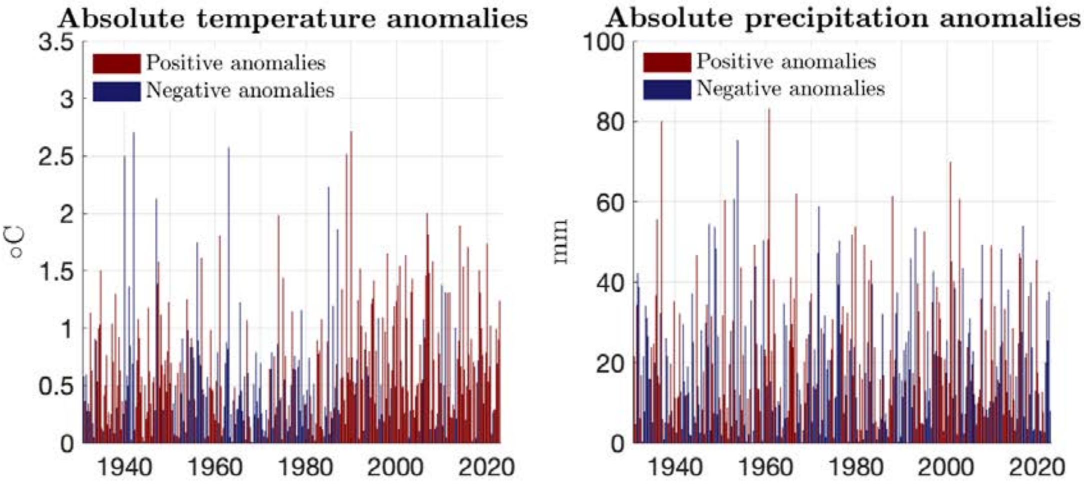

Figure 3: Absolute values of the climate anomalies for the average economy in the sample. Red (blue) bars are the quarters characterized by an higher (lower) temperature and precipitation values with respect to the observed 30 years moving historical norm.

Time-dependency is a potential threat to our measurement of climate shocks. Any shock in a Proxy-VAR framework, and therefore equivalently in recursive identification with an internal instrument (see Plagborg-Møller and Wolf, 2021), must involve an *unanticipated movement* in an exogenous variable (Ramey, 2016). The serial correlation found in temperature anomalies violates this assumption, making the instruments partially predictable by their own lags.[9] We address this issue, as previously suggested by Miranda-Agrippino and Ricco (2021) and Kilian (2024), by regressing the autocorrelated shocks on their own lags. Formally, our temperature and precipitation[10] shocks for all countries i and each quarter t are the innovations estimated by the following regressions:

$$TA_t = \beta^T + \sum_{j=1}^{4} TA_{t-j} + \varepsilon_t^T \tag{3}$$

$$PA_t = \beta^P + \sum_{j=1}^{4} PA_{t-j} + \varepsilon_t^P. \tag{4}$$

[8]Results for the autocorrelogram and the Ljung-Box test for all countries in the sample are reported in Appendices A.2 and A.3.

[9]A possible cause of this behaviour is the temporal aggregation of shocks required to merge climate anomalies with the endogenous macroeconomic variables (see Miranda-Agrippino and Ricco, 2021 and Kilian, 2024 for further discussion).

[10]For the sake of consistency we also apply the second step of our procedure to precipitation anomalies. Since this series is not serially correlated, the two series of precipitation anomalies and precipitation shocks are more or less identical in each country of the sample.

The estimated residuals $\hat{\varepsilon}_t^T$ and $\hat{\varepsilon}_t^P$ of equations (3) and (4) in each country are the exogenous shocks that we use in our panel VAR analysis to identify climate change. The two shocks are zero mean and serially uncorrelated for each country in the sample; Figure 4 shows the shocks for the average economy; country-specific shocks are reported in detail in Appendix A.4.

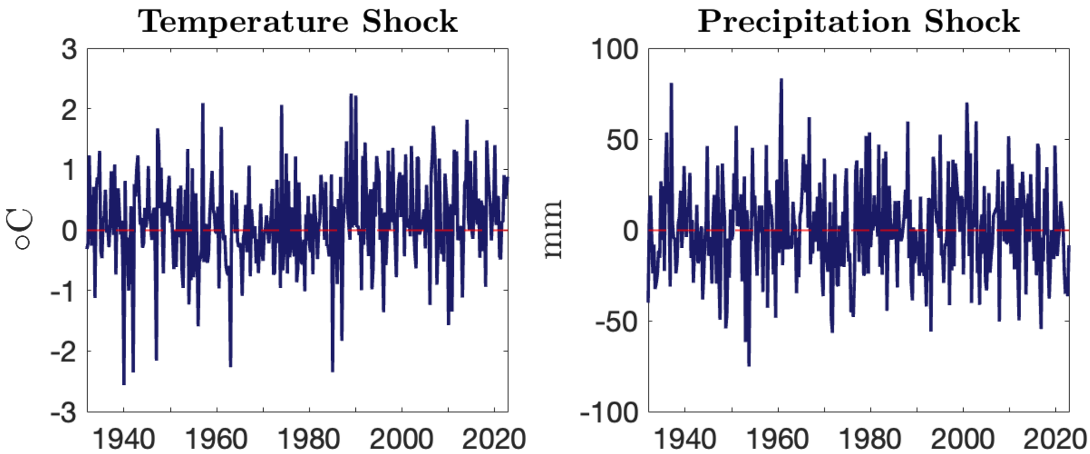

Figure 4: Climate shocks in the countries in the sample and for the average economy in the period 1932Q1–2022Q4. Shocks have been identified as the innovation of climate anomalies when regressed on its on first four lags.

We use the entire available time series (1908–2022) to construct the climate shocks, thus exploiting the full available historical information set. We adjust their time frame to align with the macroeconomic variables, enabling us to estimate the Panel VAR.

3.3 Macroeconomic variables

The quarterly data for the macroeconomic variables have been obtained, with a few exceptions, from the ECB's data warehouse, the OECD and the World Bank's publicly available datasets.[11] Specifically, we include in the vector of endogenous variables: the primary balance-to-GDP ratio (PB_t), constructed so that a positive value stands for primary surpluses and a negative value for primary deficits; the real public debt (D_t); real GDP (Y_t); the long-term nominal interest rate (LT_t), in percentages; and the all-items consumer price index (CPI_t). In order to gain a clearer understanding of the fiscal impact of climate change, we use the gross real value of debt instead of the debt ratio in our Panel VAR model. This choice is motivated by the need to disentangle the specific impact of climate on public finances from a possible denominator effect caused by the contractionary nature of climate shocks. However, we retain the primary balance

[11]The primary balance measure for the United States has been calculated according to Bianchi and Melosi (2017) from the Federal Government Current Receipts Receipts and Expenditures Tables.

as a ratio, which is a standard flow measure for capturing fiscal sustainability over time. Descriptive statistics and time series graphs for the macroeconomic variables are provided in Appendix A.5.

4 Econometric Framework: Bayesian Panel VAR

4.1 Model description

We empirically analyse the fiscal impact of climate change in a Bayesian structural panel VAR. The panel is balanced over the period 2002Q2–2022Q4 and quite homogeneous, as all countries in the sample are industrialised democracies with stable political systems and well-developed social welfare schemes. For country i in quarter t, the reduced form model is as follows

$$\boldsymbol{Z}_{i,t} = \boldsymbol{\alpha}_i + \boldsymbol{\beta}_i t + \sum_{l=1}^{L} \boldsymbol{A}_{i,l} \boldsymbol{Z}_{i,t-l} + \boldsymbol{\epsilon}_{i,t} \quad (5)$$

where $\boldsymbol{A}_{i,l}$ are the matrices of coefficients for country i at each lag l, $\boldsymbol{\alpha}_i$ is a matrix of country fixed effects dummies, $\boldsymbol{\beta}_i t$ is a matrix of country-specific deterministic trends, $\boldsymbol{\epsilon_{i,t}}$ is a vector of normally distributed zero mean reduced form shocks with variance-covariance matrix $\boldsymbol{\Sigma_i}$, and $\boldsymbol{Z}_{i,t}$ is the vector of endogenous variables, including our set of macroeconomic variables and, one at a time, the two instruments we constructed for exogenous climate change shocks. The baseline model includes three lags of the endogenous variables, as suggested by the Akaike criterion. However, we test the robustness of our results by varying the number of lags included in the estimation. Other robustness checks exclude deterministic trends and include seasonal dummies to capture any quarter-dependent co-movement.[12]

As argued in section 3, we do not include both climate shocks together in the same model specification. We estimate the panel VAR twice, changing the instrument. This increases the vector of endogenous variables. For the macroeconomic variables, we take the log multiplied by 100 of real debt, real GDP and CPI, so that the results of the impulse responses can be easily interpreted as percentage changes. However, we leave the other variables at their levels. Therefore, the VAR predicts the percentage point change for the long-term interest rate and the percentage point change over GDP for the primary balance. We define the two vectors of endogenous variables as follows:

$$\boldsymbol{Z}^{w}_{i,t} = [\hat{\varepsilon}^{w}_{i,t},\, \log(Y_{i,t}),\, LT_{i,t},\, \log(CPI)_{i,t},\, PB_{i,t},\, \log(D)_{i,t}]', \quad (6)$$

[12] All robustness checks for the full sample results are reported in Appendix A.7. The results are not significantly different from the baseline specification.

with $w = T, P$. The objective of estimating the model with two different proxies of climate change is to assess the potential heterogeneity in the results conditional to the climate variable used. Some studies have shown that precipitation generally has milder economic effects than temperature (e.g., Dell et al., 2012; Kalkuhl and Wenz, 2020; Kahn et al., 2021), but there is no evidence so far about the difference in terms of fiscal impacts.

The Panel VAR allows us to investigate the dynamic response of the average economy to a specific exogenous climate shock. However, after the baseline estimations subgroup exercises as shown in section 5.2 will help us in analysing whether cross-country differences are significant in these mechanisms and lead to different results.

4.2 Model estimation

The econometric estimation of the Panel VAR can follow different approaches that require specific assumptions on the reduced form equation. Given the limited time span available for each country's data, we rely on a pooled estimation with country fixed effects to capture potential idiosyncratic (and constant) heterogeneity across countries and variables. According to Canova and Ciccarelli (2013), this is the classic and most efficient way to estimate panel VAR parameters under two key assumptions: (i) the data generation process is characterised by dynamic homogeneity; hence, the parameter matrices and the variance-covariance matrix of the reduced-form disturbances are assumed to be country-independent, i.e, are the same across units (i.e., $\boldsymbol{A}_{i,l} = \boldsymbol{A}$ and $\boldsymbol{\Sigma}_i = \boldsymbol{\Sigma}\ \forall\ i$); (ii) the reduced-form shocks $\boldsymbol{\epsilon_{i,t}}$ are serially and cross-sectionally uncorrelated. However, both assumptions are questionable in a macroeconomic context such as ours and may imply significant problems in the estimation.

Dynamic homogeneity across countries with inherently different economic dynamics can lead to a biased and inconsistent fixed-effects estimator, even when both the cross-sectional dimension and the time span are large (Pesaran and Smith, 1995). In our sample, the homogeneity assumption is mainly driven by the limited data availability. The short time span precludes the use of a group mean estimator, which would ideally account for dynamic heterogeneity. To address this limitation, we partially relax the homogeneity assumption by performing subgroup estimations based on specific characteristics of each country. By estimating the model separately for different groups of countries, we avoid imposing a single overarching macroeconomic dynamic on the entire sample and allow the parameter matrix to vary across groups. A similar empirical strategy to overcome the drawback of cross-sectional homogeneity is followed by Cipollini and Parla (2023) and Ciccarelli and Marotta (2024). We find that although the results may differ significantly across subgroups, the macroeconomic dynamics remain broadly consistent across subgroups. This suggests that in our sample the assumption of dynamic homogeneity may be reasonable when controlling for country fixed effects.

While the assumption of no serial correlation is common practice in structural VAR estimations, the assumption of no cross-sectional correlation in reduced-form residuals may pose a challenge. In the analysis of macroeconomic dynamics in a homogeneous panel of countries, such as the euro area countries and the United States, the existence of non-negligible international spillovers is widely recognised and empirically confirmed (e.g., Caporale and Girardi, 2013). Therefore, in order to reliably assume that the reduced form innovations of equation (5) are not correlated across countries, we need to filter out the international spillover components from these residuals. In the spirit of the Global VAR (Pesaran et al., 2004), we do this by adding two global variables to the vector of endogenous variables: the World Industrial Production Index from Baumeister and Hamilton (2019)[13] and the S&P Global Commodity Price Index.[14] This strategy allows us to avoid potential spurious results due to omitted variable bias. In particular, it is possible that our temperature and precipitation shocks are coincidentally correlated with the global financial crisis or the sovereign debt crisis, and that we incorrectly attribute these effects to climate shocks.

The Panel VAR model is estimated using Bayesian techniques, which impose prior beliefs on the parameters to overcome the curse of dimensionality. We employ the modified version of the Minnesota prior proposed by Bańbura et al. (2010) to deal with large-scale VARs, which assumes a Normal-Inverse Wishart prior distribution for the VAR parameters and fixed prior hyper-parameters to imply a loose prior belief.[15] In the Bayesian prior of Bańbura et al. (2010), all variables are treated symmetrically, regardless of their association with specific units or whether they represent the same measurement across different units. During estimation, the prior itself does not take into account the panel dimension of the data, which is instead addressed in the specification of the reduced-form model. The details of the Bayesian prior distributions from Bańbura et al. (2010) are reported in Appendix A.6.

We approximate the posterior distribution using a Gibbs sampling algorithm with 25,000 replications, using the last 10,000 for inference. Finally, we impose the value of the prior's hyperparameter $\lambda = 2.5$. In our robustness analyses, we will vary the value of λ to assess the sensitivity of the results to the weight given to the distribution of prior beliefs with respect to the information in the data, see Appendix A.7.

[13]Monthly data are aggregated to quarters here.
[14]The two global variables are also included with three lags, as are the other endogenous variables.
[15]A nice application of Bańbura et al. (2010) priors to fixed effects panel VAR estimation is provided by Beetsma et al. (2021), who assess the impact of fiscal consolidation announcements on economic activity in thirteen European countries.

4.3 Identification of structural shocks: exogeneity assumption

For the identification of structural shocks we rely on the *internal instrument* approach proposed by Plagborg-Møller and Wolf (2021). They show that a valid structural estimation with a well-identified (and exogenous) instrument can be easily realised with a recursive VAR in which the instrument is ordered first, equivalent to what can be done using the shock series as an external instrument (cf. Mertens and Ravn, 2013). Moreover, the impulse responses generated by this approach are valid even under the non-invertibility of the shock, which is not the case in a standard external instrument framework.

Formally, we recover the structural shocks $\boldsymbol{\mu_{i,t}}$ through a Cholesky decomposition of the reduced-form variance-covariance matrix $\boldsymbol{\Sigma}$ of the Panel VAR. In particular, given the reduced-form disturbances $\boldsymbol{\epsilon_{i,t}}$, the contemporaneous impact matrix is the lower triangular $\boldsymbol{A_0}$ such that $\boldsymbol{\Sigma} = \boldsymbol{A_0 A_0'}$ and the structural shocks of the VAR model:

$$\boldsymbol{\mu_{i,t}} = \boldsymbol{A_0 \epsilon_{i,t}} \tag{7}$$

The exogeneity of our instruments is guaranteed because the climate system is assumed to be exogenous, on impact, to macroeconomic dynamics.Treating the climate dimension as an exogenous driver of the economy is common practice in the recent empirical literature assessing the economic impact of weather conditions (e.g., Kahn et al., 2021; Mumtaz and Theophilopoulou, 2024; Kim et al., 2024; Ciccarelli and Marotta, 2024; Bilal and Känzig, 2024). Of course, we are aware that there may be a significant reverse causality between the economy and the climate, which is already included in the first Dynamic Integrated Climate-Economy (DICE) model (Nordhaus, 1992). This feedback is primarily manifested through the effect of increasing economic activity on greenhouse gas emissions, which in turn may structurally influence the behaviour of weather variables in the long term. However, since this mechanism is likely to operate over a longer time horizon than a quarter, the exogeneity assumption is valid in our context.

By ordering our instruments first in the recursive VAR identification scheme, we only assume that the climate shocks are orthogonal to the macroeconomic shocks. Therefore, our temperature and precipitation shocks cannot be contemporaneously predicted by the dynamics of the macroeconomic variables. However, quarterly lagged bi-directional effects are possible, making our framework more reliable than others that use a stronger form of exogeneity for the climate variables.

5 Results

In this section we report the main results of the structural impulse response functions (IRFs) to temperature and precipitation shocks. The Panel VAR specification allows us to observe the response in the endogenous variables for the *average economy* in the sample or in specific subgroups of countries. The black solid lines are the median IRFs, while the darker (lighter) shaded areas are the 68 (95) per cent Bayesian credible intervals. In the rest of the paper, we refer to significant results when the 68 percent interval does not include zero. The size of the climate shocks is set to about two standard deviations on average across countries, which corresponds to 1°C for temperature and 50mm for precipitation. However, forecasts of the dynamics of climate change are potentially worse. According to different scenarios for future greenhouse gas emissions and mitigation, the global average temperature could deviate from the historical norm by more than 3°C in the coming decades (IPCC, 2023). Similarly, the magnitude of precipitation shocks is limited compared to projections of precipitation to 2060. For these reasons, the main focus of our results is on the macroeconomic dynamics we detect with our identification, while the size should be interpreted as an optimistic lower bound of the impact.

5.1 Full-sample results

Figures 5 and 6 show the dynamic response of the endogenous variables in the Panel VAR to a recursively identified temperature and precipitation shock, respectively. The structural IRFs are plotted over a time horizon of five years (20 quarters). Both temperature and precipitation shocks have a negative impact on the dynamics of public finances, with a significant increase in real debt and in the primary deficit ratio. Moreover, both climate shocks are contractionary, significantly reducing real GDP. The deterioration in the primary balance suggests that governments respond to the negative economic impact of climate shocks by implementing fiscal stimulus measures—either through increased expenditure or reduced revenues—which in turn increase the stock of public debt.[16] However, the two shocks have quite different effects in terms of timing, persistence and inflationary impact. In particular, temperature shocks tend to have adverse fiscal effects in the medium term that persist over time, with a reduction in the primary balance of around 0.05% of GDP which increases the real debt by about 0.3% at the peak after 20 quarters. A precipitation shock leads to an immediate negative impact on public

[16]When interpreting the results for the primary balance ratio, it should always be borne in mind that the actual impact on the government balance is higher. The primary balance ratio shows a significant reduction, although the numerator effect in a recessionary environment exerts the opposite pressure (i.e. a lower GDP increases, ceteris paribus, the primary balance ratio).

finances, with a peak increase in the deficit of around 0.1% of GDP after three quarters and a corresponding increase in real debt of almost 0.5% after less than a year. However, these effects are temporary, as both fiscal variables show a significant recovery within a business cycle horizon.

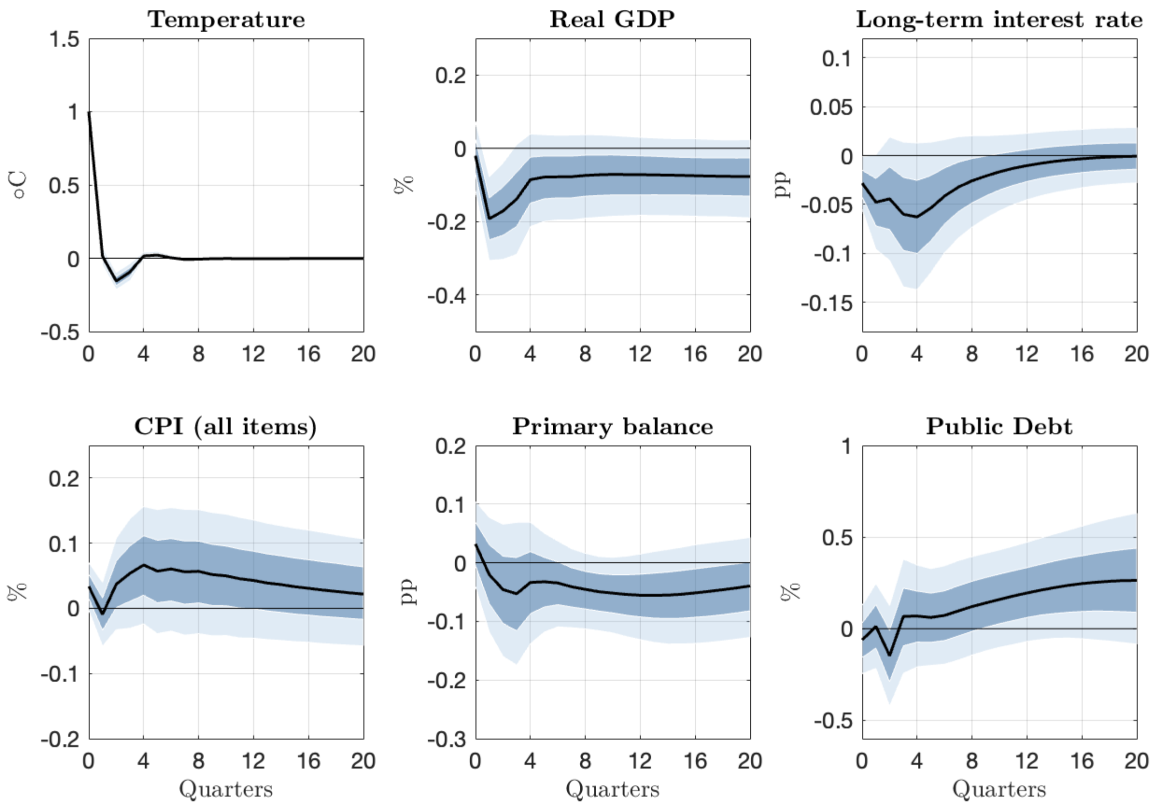

Figure 5: Structural IRF from a 1°C temperature shock: results from the full sample of 15 countries. Both 68% (dark shaded area) and 95% (light shaded area) Bayesian credible intervals are reported. The black solid lines are the median IRFs.

The difference in the persistence of the effects is confirmed by the negative economic responses. Although real GDP falls significantly after two quarters in both scenarios, temperature shocks cause a permanent slowdown in economic activity, with only a partial recovery after the initial shock. In contrast, precipitation shocks have only short-term recessionary effects lasting up to three years, with real GDP rising steadily and recovering fully in the following quarters.

The dynamic responses of the long-term interest rate to climate shocks also show some notable differences. For the temperature shock, there is a significant decline in the long-term interest rate, consistent with a flight-to-safety scenario induced by the recession (i.e. uncertainty about the future prospects of the economy increases and investors seek safer, lower-risk assets). For the precipitation shock, this decline is preceded by a moderate

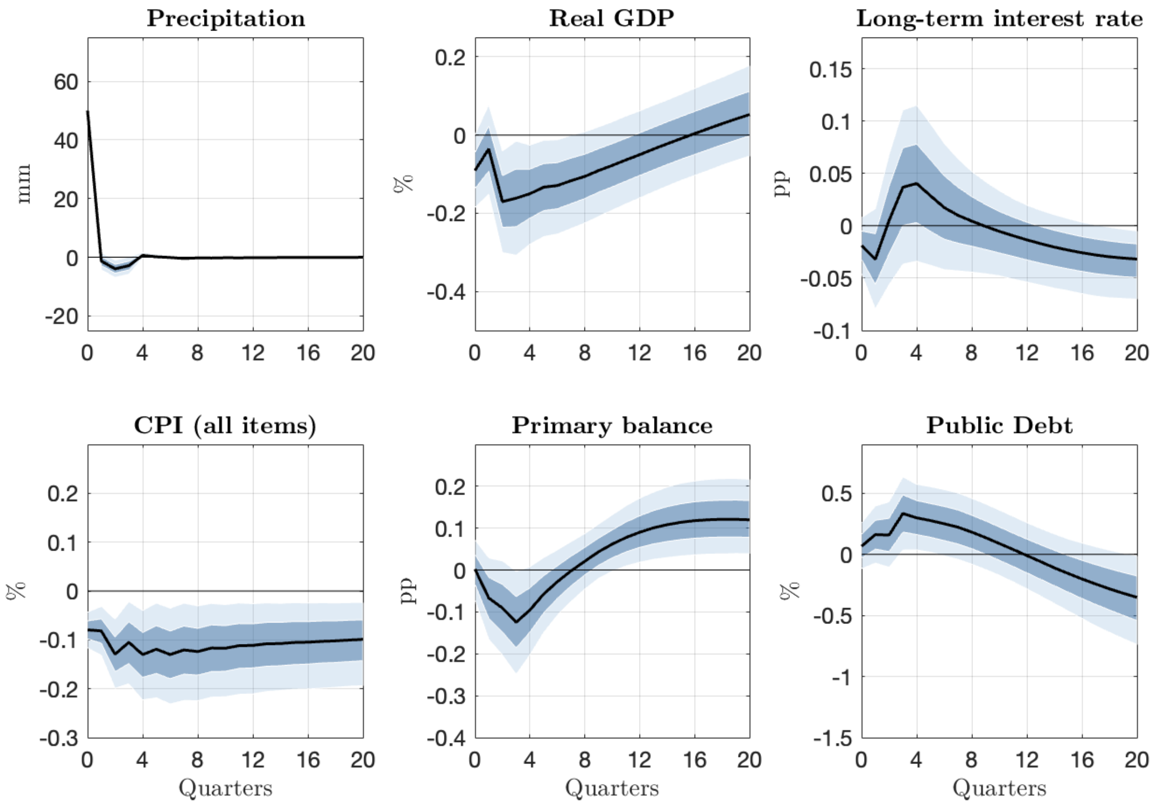

Figure 6: Structural IRF from a 50 mm precipitation shock: results from the full sample of 15 countries. Both 68% (dark shaded area) and 95% (light shaded area) Bayesian credible intervals are reported. The black solid lines are the median IRFs.

increase in the value of the interest rate in the short run, which is likely to represent a decline in market-perceived creditworthiness in response to the shock.

These results confirm the notion that physical climate risk has a significant impact on real GDP and public finances, inducing debt-financed fiscal stimulus to counteract the negative consequences of weather anomalies. However, the heterogeneity of the results when using temperature or precipitation to construct the climate shocks requires further economic discussions and valid interpretations as follows.

Inflationary effects play a prominent role in explaining the impulse responses of the two climate shocks. In our sample, temperature shocks behave like negative supply shocks and, together with a recessionary effect, induce a significant increase in consumer prices of 0.1% at the peak after one year, which persists for almost 12 periods. In contrast, precipitation shocks behave like negative demand shocks, causing significant deflation over time that persists after five years. These results contribute to the ongoing debate questioning the real nature of negative climate-related shocks. In particular, our evidence supports the idea that physical risk can be associated with both demand and supply shocks, depending on the weather observations used to proxy for climate change.[17] Moreover, we find that when climate change affects the supply side of the economy, the macroeconomic effects are more persistent and difficult to counteract, requiring long-lasting fiscal stimulus. Demand-side shocks, on the other hand, have short-term negative effects that can be reliably dampened over a business cycle horizon. This is in line with evidence showing that, from a monetary policy perspective, supply shocks (e.g., energy price shocks) are more difficult to deal with, as tightening policy to fight inflation may end up exacerbating the scarring effects on the demand side of the economy. Therefore, a policy mix including an expansionary fiscal policy in the medium term may be required (see Fornaro and Wolf, 2023).

Another interpretation of the impulse responses from our model is that precipitation shocks are more similar to the short-term effects of adverse weather events, with immediate and temporary effects on the demand side of the economy. Temperature shocks, on the other hand, may have more significant implications for gradual global warming, with long-lasting effects on the production side. Natural disasters with negative demand effects require rapid but temporary fiscal stimulus in the form of mitigation expenditure (e.g. public subsidies, environmental protection, reconstruction), whereas global warming is an unavoidable process that is more likely to require adaptation measures with long-term effects on public finances (e.g. coastal infrastructure). This view is supported by the frequency of adverse weather events, for which we obtained data from the EM-DAT (International Disaster) database. In our sample, only 17% of natural disasters are directly related to extreme temperatures (i.e. heat wave or cold wave) in the period 2002Q4–2022Q4, while more than 60% of them are likely to involve anomalous amounts of precipitation (e.g. storms, floods).[18] The frequency series of adverse events for the countries in our sample are, on average and for most countries, more correlated with precipitation shocks than with temperature shocks. Both categories of adverse events in our dataset and the correlation with climate shocks are reported in the Appendix A.8.

5.2 Country heterogeneity

So far, our analysis provides empirical support for the idea that climate shocks to physical risks pose a threat to public finances and the economy, increasing debt and deficits and exerting downward pressure on real GDP over a business cycle horizon. The moderate size of the estimated responses for the full sample and the width of the Bayesian credibility

[17] See Ciccarelli and Marotta (2024) for a detailed discussion. Their evidence supports the idea that physical risks are mainly associated with negative demand shocks, while transition and policy risks affect the supply side of the economy.

[18] Events not related to climate change were excluded from the dataset (e.g. earthquakes).

intervals suggest that our results may be characterised by a high degree of cross-country heterogeneity. Here, we estimate the Panel VAR for homogeneous subgroups of countries according to specific climate and economic characteristics. In particular, once a qualitative criterion is identified, the group is divided into two main subgroups, one above and one below a quantitative threshold. The size of the temperature and precipitation shocks is set at 1°C and 50mm respectively, as above, in order to make the magnitude of the results comparable between the sub-samples. From an econometric point of view, these exercises allow us to relax the assumption of dynamic homogeneity. The matrices of the parameters $\boldsymbol{A}_l$ and the variance-covariance matrix of the reduced-form shocks $\boldsymbol{\Sigma}$ vary for different subgroups of countries. It is worth noting that, despite differences in the timing, magnitude and significance of fiscal effects across sub-samples, the macroeconomic dynamics characterising the system remain broadly consistent even when estimating the Panel VAR for different groups of units. In particular, inflationary effects are similarly induced across sub-samples: contractionary temperature shocks resemble negative supply shocks, while precipitation shocks mainly affect the demand side, leading to deflationary pressures. This result supports the notion that the assumption of dynamic homogeneity can be considered quite reliable in our framework.

Specifically, we assess whether the fiscal and economic impacts of our identified climate shocks differ significantly according to: (i) observed historical weather conditions (i.e. temperature and precipitation); (ii) the degree of climate vulnerability; and (iii) fiscal discipline (e.g. debt levels). The full lists of countries in the different subgroups can be found in Appendix A.9.

5.2.1 Weather conditions

The idea that temperature shocks can have non-linear effects on economies is widely recognised (e.g. Dell et al., 2012, Burke et al., 2015, Kotz et al., 2021, Mumtaz and Theophilopoulou, 2024). The initial climate conditions play a crucial role in determining the severity of these impacts. Countries with warmer baseline temperatures are more vulnerable to economic disruption from even small increases in temperature. For example, regions with hot climates often experience sharp declines in productivity in sectors such as agriculture and labour-intensive industries as temperatures rise. Similarly, unexpected increases in precipitation can expose countries that are already very wet to a higher probability of extreme events. This suggests that identical temperature (and precipitation) shocks may pose higher economic risks for countries with hotter (more rainy) climates, highlighting the importance of considering baseline weather conditions when assessing climate-related economic vulnerability.

We examine this channel for our climate shocks by dividing our full sample of countries into two subgroups according to their median historical temperature and precipitation. Countries with a median historical temperature above (below) the mean are classified as *hot (cold)* countries; countries with a median historical precipitation below (above) the average are classified as *drier (wetter)* countries. In line with the idea of detecting evidence of potential non-linear effects, we only evaluate the effects of temperature shocks for hot and cold countries and the effects of precipitation shocks for more and less rainy countries.

The response of the endogenous variables of the model to a temperature and precipitation shock in hot and cold countries is shown in the first column of Figures 7 and 8 respectively. The structural IRFs for the two subgroups show that both the fiscal and the economic impact of temperature shocks vary significantly according to the baseline temperature level. Hot countries experience a higher peak increase in real debt (around 0.55%), which is more persistent than the result observed for the full sample, Figure 5. Similarly, the decline in the primary balance in response to a temperature shock is remarkably larger in hot countries, peaking at almost -0.2% of GDP. These fiscal effects also differ in timing with respect to the average economy effects of the previous section, as both negative effects manifest themselves in warmer economies in the short term after the shock. Similarly, the contractionary effects of temperature shocks are higher and more persistent in hot countries, with a larger fall in real GDP. Both fiscal and economic effects disappear for cold countries, which in our sample appear to be significantly less exposed to physical climate risk. For the precipitation shock, we find no significant difference in the response of fiscal variables and real GDP in more and less rainy countries.

Estimating the Panel VAR model separately for hot and cold countries helps us to enrich our results in two directions: (i) the fiscal impact of climate change involves some form of non-linearities: hot countries are significantly more exposed to temperature shocks than cold countries; (ii) similarly to what the literature has already pointed out, the economic impact of temperature shocks also depends on the baseline level of temperature (Dell et al., 2014; Burke et al., 2015; Kotz et al., 2021; Mumtaz and Theophilopoulou, 2024).

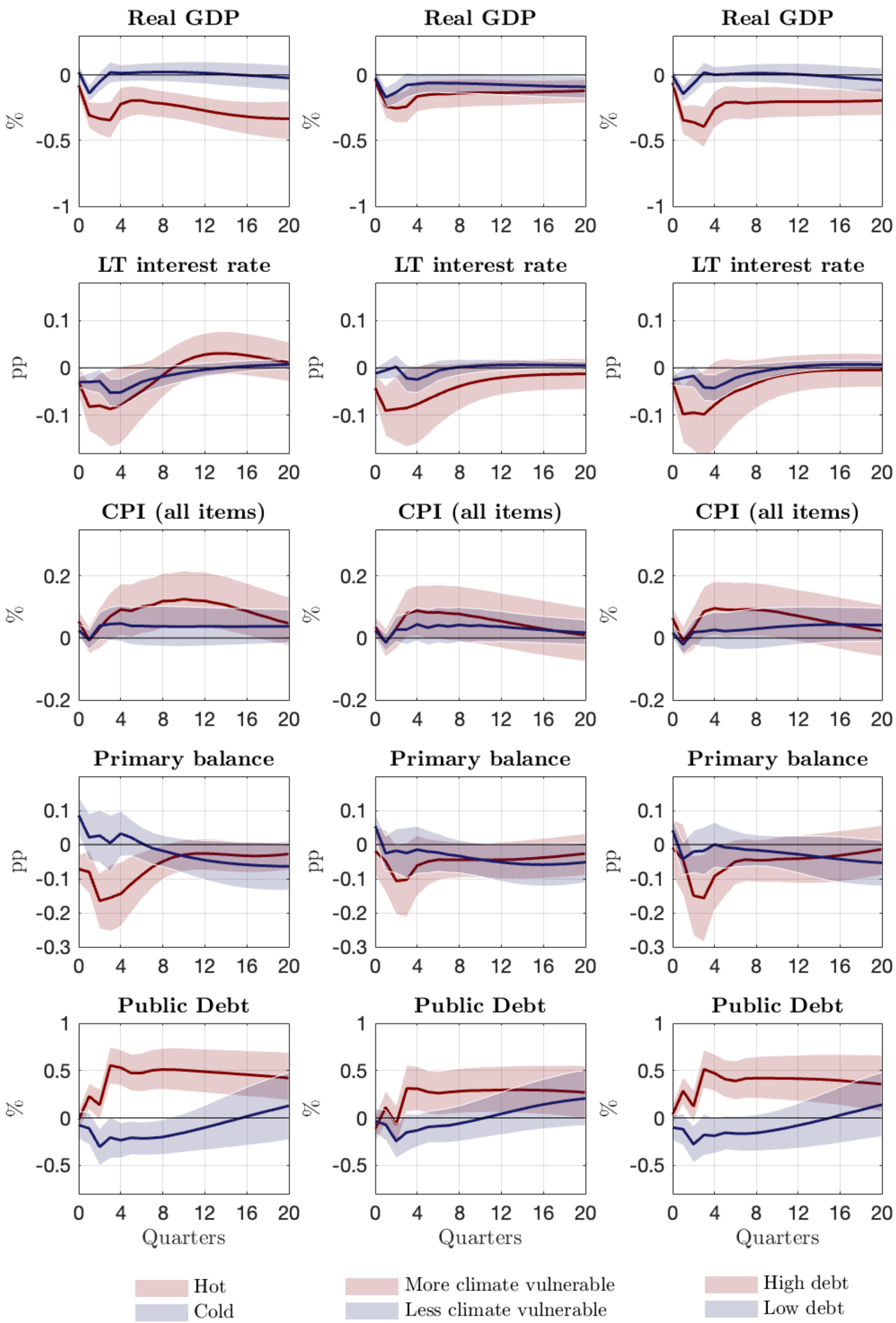

Figure 7: Structural IRF from a 1°C temperature shock: Results from the subgroups estimations. The shaded area report the 68% Bayesian credible intervals. The black solid lines are the median IRFs.

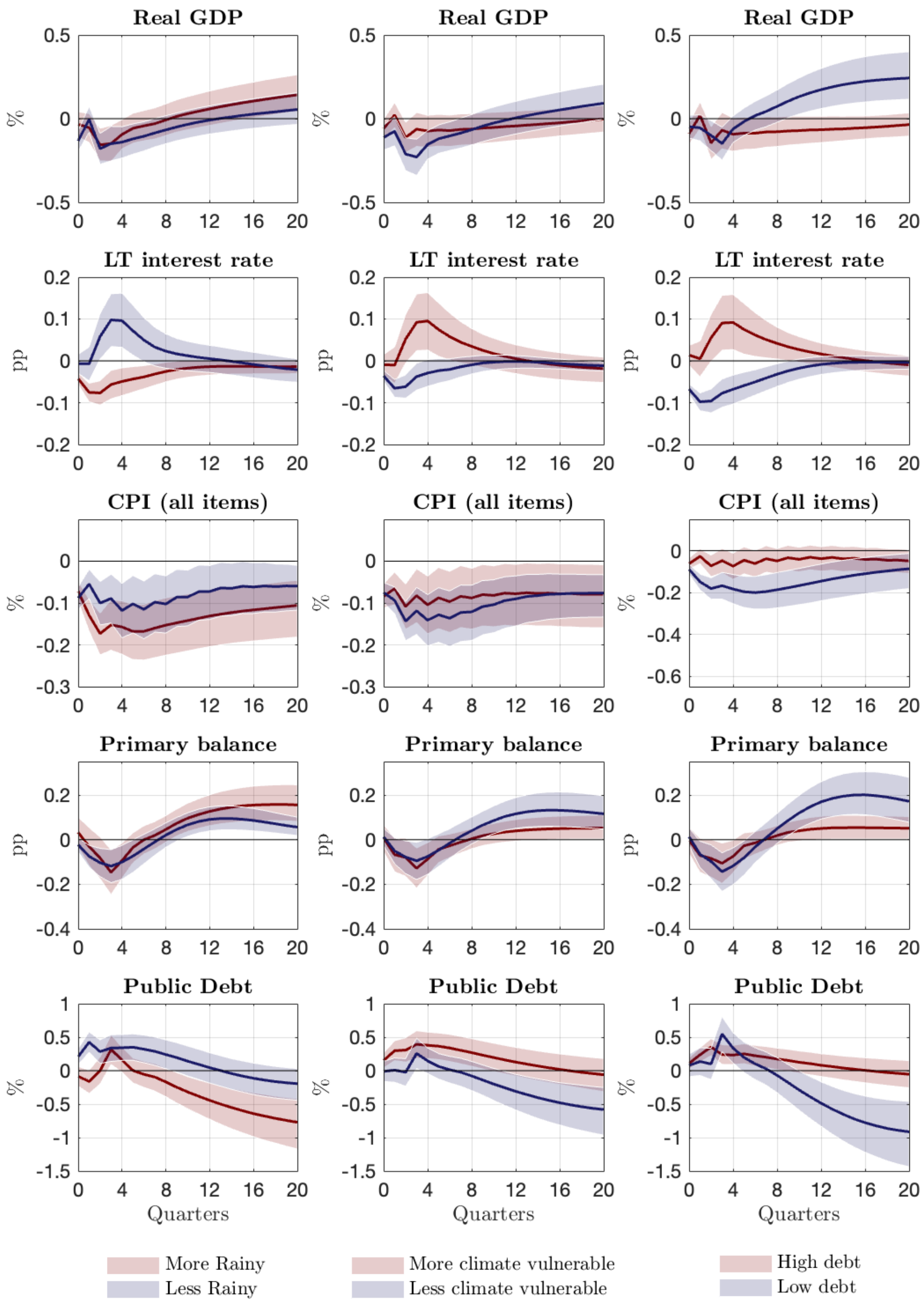

Figure 8: Structural IRF from a 50 mm precipitation shock: Results from the subgroups estimations. The shaded area report the 68% Bayesian credible intervals. The black solid lines are the median IRFs.

5.2.2 Climate vulnerability

The level of climate vulnerability can also be a key factor influencing the intensity of the fiscal impact of physical risks. The resilience of an economy to unexpected climate shocks plays a crucial role in determining both the need and the capacity to mitigate the damage from extreme events and to adapt to long-term changes in weather patterns. Consequently, higher levels of climate vulnerability can potentially increase the risk to a country's fiscal sustainability. To measure climate vulnerability, we rely on the ND-GAIN (Notre Dame Global Adaptation Initiative) country index calculated by University of Notre Dame (2023). Specifically, the ND-GAIN Country Index aims to help governments, businesses and communities strategically prioritize investments to enhance their ability to address the pressing global challenges that lie ahead. It provides a score for every country in the world, representing the difference between a country's level of readiness (i.e. ability to leverage adaptation investments) and vulnerability.[19] Here we only collect data for our countries for the vulnerability factor and divide the sample according to the relative ranking into *more vulnerable* and *less vulnerable* countries.

The response of the model's endogenous variables to a temperature and precipitation shock in more and less climate vulnerable countries is shown in the second column of Figures 7 and 8 respectively. Similar to the results for hot and cold countries, the structural IRFs suggest that temperature shocks lead to higher negative fiscal impacts for more climate-vulnerable economies, with barely significant effects in less vulnerable economies. In particular, a 1°C shock leads to a significant short-term increase in real debt of around 0.4% after three quarters, together with a fall in the primary balance that is twice as large as that observed in the full-sample estimation. However, the recessionary nature of the shocks does not seem to vary significantly with the degree of climate vulnerability; the fall in real GDP in the two subgroups is similar and comparable in magnitude and timing to the full sample results. For precipitation shocks, we find no significant difference in the response of fiscal variables and real GDP according to the degree of climate vulnerability.

Splitting the sample of countries into more and less climate-vulnerable economies enriches our results in two ways: (i) economies that are less resilient to adverse climate dynamics experience significantly higher negative fiscal impacts when exposed to a temperature shock; (ii) the difference is clearly focused on public finances, with homogeneous results in terms of real GDP, suggesting that a country's degree of climate vulnerability,

[19]Specifically, the vulnerability factor of the ND-GAIN index is constructed according to the "degree to which a system is exposed to significant climate change from a biophysical perspective independent of the socio-economic context; the extent to which a country is dependent on a sector negatively affected by climate hazards; the availability of social resources for sector-specific adaptation." (University of Notre Dame, 2023).

as calculated by the ND-GAIN index, can be considered as a specific proxy for countries' exposure to climate-related fiscal risks. This is consistent with the criteria used to calculate the index, which take into account a country's degree of exposure to climate change dynamics and its ability to leverage investments for sector-specific adaptation, irrespective of the socio-economic context.

5.2.3 Fiscal discipline

Finally, we examine whether the initial level of public debt influences the magnitude of the fiscal impact of climate change. Less fiscally disciplined countries may face greater fiscal strains in responding to climate-related disruptions due to limited fiscal space, which could amplify the adverse effects of temperature and precipitation shocks on fiscal outcomes and GDP growth. In contrast, low debt countries generally have more flexibility to use fiscal policy to absorb and mitigate the economic impact of these shocks, which could lead to milder long-term economic consequences. Testing this channel is well motivated by the literature highlighting the existence of a potential debt threshold that may alter the transmission of economic shocks (Reinhart and Rogoff, 2010; Cecchetti et al., 2011; Checherita-Westphal and Rother, 2012). This approach allows us to capture possible non-linearities in the relationship between debt and climate shocks, and to assess how fiscal discipline may mitigate the fiscal impact of physical climate risk. To assess this potential heterogeneity, we split our sample according to the historical median debt-to-GDP ratio, classifying countries with ratios above the median as *high debt* and those below the median as *low debt*.

The responses of the endogenous variables of the model to a temperature and precipitation shock in high and low debt countries are shown in the third column of Figures 7 and 8 respectively. Highly indebted countries experience significantly more severe fiscal consequences of temperature shocks compared to fiscally disciplined economies. In particular, a temperature shock worsens public finances in highly indebted countries, leading to a permanent increase in real debt that peaks at around 0.5% within the first year. This impact is largely due to a decline in primary balances to mitigate the economic impact, with real GDP falling by almost 0.5%. These effects are both larger and more persistent than those observed in the full sample analysis, while fiscally disciplined economies experience milder downturns and avoid adverse fiscal dynamics.

For precipitation shocks, there is a notable difference for low debt countries, which seem to cope better with the short-term economic and fiscal damage of climate change. The dynamics in the two subgroups are similar to our baseline, with precipitation shocks resembling temporary negative demand shocks, but countries with a lower initial public debt ratio experience a significantly better recovery, with higher increases in real GDP and primary balance and lower real debt in the medium term.

5.3 Transmission mechanisms

We found that climate shocks resulting from temperature and precipitation anomalies can have adverse fiscal effects, increasing real debt and the deficit ratio, particularly in hot, highly indebted and climate-vulnerable countries. Are these negative fiscal dynamics primarily the result of lower government revenues or higher government expenditures? Which categories of government revenues and expenditures are most affected by physical climate risks? Do temperature and precipitation shocks have different fiscal impacts? To answer these questions, we analyse the impact of the identified climate shocks on a number of fiscal variables. The structural IRFs are computed by sequentially augmenting the vector of endogenous variables in the Panel VAR model, adding one fiscal variable at a time, avoiding the need for shrinkage and keeping the estimation process simple, as in Känzig (2021). The augmented Panel VARs are always estimated for the same panel of 15 countries in the reference period 2002Q4–2022Q4, ensuring a high degree of compatibility across all estimations.

Our analysis consists of two steps. First, we examine whether the adverse fiscal impact of our baseline estimates is driven more by revenue losses than by expenditure increases. We then go deeper to capture the importance of specific revenue and expenditure categories in the propagation of the shock. On the revenue side, we focus on the dynamic response of government revenues from: (i) direct taxes; (ii) taxes on imports and production; (iii) social contributions from both employers and households. On the expenditure side, we distinguish government expenditure on: (i) public subsidies; (ii) government consumption; (iii) social benefits. Data for all specific government budget items have been obtained from the ECB data warehouse and from the U.S. Bureau of Economic Analysis dataset.[20] Detailed descriptive statistics for these additional fiscal variables are provided in Appendix A.10.

The structural IRFs to a temperature and precipitation shock in each extended Panel VAR are shown in Figure 9 and Figure 10 respectively. The additional fiscal variables

[20] European countries and the U.S. government budget items on the revenue side do not always match perfectly. Therefore, the merging of the two data sources for some variables requires additional calculations or reliable approximations: (i) direct tax receipts are provided directly in the ECB database, while for the U.S. they have been calculated as the sum of *personal current tax receipts* and taxes on *corporate income* receipts; (ii) receipts from taxes on imports and production for the U.S. have been merged with ECB data on *indirect taxes* receipts; (iii) receipts from social contributions are provided directly for the U.S., while for the European countries they have been calculated as the sum of receipts from *employers* and *households* social contributions.

are included as log levels so that their dynamic responses can be easily interpreted as percentages. Due to space limitations, we show only the structural IRFs to a 1°C temperature shock and a 50 mm precipitation shock for the additional fiscal variable regressors used to uncover the transmission mechanisms.[21] Below, we provide a comprehensive interpretation of both results and the underlying analogies and differences between the two climate shocks.

Including aggregate fiscal variables shows that for both temperature and precipitation shocks, the primary driver of the increase in public debt is a significant reduction in government revenues, with a negative peak occurring three quarters after the shock. Government expenditure shows no significant response to temperature shocks at the aggregate level. However, they show a clear counter-cyclical response to precipitation shocks, with a slight increase after the shock and a marked decrease in the following quarters. This suggests that public spending is mainly associated with the fiscal stimulus needed to boost the recovery. This is consistent with the temporary nature of the negative macroeconomic effects of precipitation shocks in our baseline estimates, which reduce real GDP and the primary balance only in the short run. This behaviour is not observed for temperature shocks, which, according to our baseline results, have a more permanent impact on the macroeconomy.

A closer look at the specific revenue categories most affected by physical climate risks reveals important differences between the two types of shocks. In particular, the decrease in government revenues following a temperature shock is mainly due to a decrease in revenues from taxes on imports and production (i.e. indirect taxes), while other revenue categories experience only mild or negligible effects. On the other hand, precipitation shocks affect government revenues mainly through a significant reduction in direct taxes, with no significant differences in the results for the other budget items. These results are strongly consistent with our basic findings on the macroeconomic impacts of climate change, which suggest that temperature shocks behave like negative and persistent supply shocks, thus affecting the production side of the economy and eroding the associated tax revenues. Meanwhile, precipitation anomalies mainly affect the demand side of the economy in the short run, reducing direct tax revenues.

On the expenditure side, while we do not observe substantial changes in total government expenditure, public subsidies show a notable increase in response to both types of climate shocks, rising by 2% to 4% in the first two years after the shocks in the different

[21] Plots of the structural IRFs for the other variables are available on request. However, adding the additional fiscal regressors one by one in the panel VAR does not significantly change the dynamic responses of the endogenous variables with respect to the baseline results reported in Figure 5 and Figure 6.

sub-samples. However, the dynamics of this increase differ between the two shocks. Temperature shocks lead to a sustained and permanent increase in public subsidy expenditure, reflecting their critical role in cushioning supply-side damage and supporting affected sectors in the long run. In contrast, precipitation shocks produce only a short-lived peak in public subsidies, which disappears within two years, in line with their more transitory demand-side effects. The main reason why these substantial increases in public subsidies are not detectable at the aggregate level in the dynamic response of total government revenue is that these categories of expenditure account for only a small fraction of total expenditure (around 5% on average across countries).

Consistent with our subgroup results in section 5.2, all the significant results we find for the different categories of budgetary items are stronger for hotter, highly indebted and more climate-vulnerable countries in response to a temperature shock. In contrast, the structural IRFs to a precipitation shock are quite homogeneous across subgroups for all budgetary items.

In short, by extending our Panel VAR model to a wide range of fiscal variables in order to identify the main transmission mechanism behind the negative debt dynamics induced by climate shocks, we find that: (i) most of the negative fiscal impact caused by physical climate risk comes from a decrease in government revenues, more than from a decrease in expenditures; (ii) the categories of government revenues that are more affected depend on the nature of the climate shocks, with temperature shocks (permanent supply) affecting more revenues from taxes on imports and production, and precipitation shocks (temporary demand) eroding direct tax revenues; (iii) although not detectable at the aggregate level, both types of shocks induce a significant and substantial increase in government expenditure on public subsidies, providing strong evidence for the implementation of mitigation policies in the short term to counter the disruptive effects of climate change.

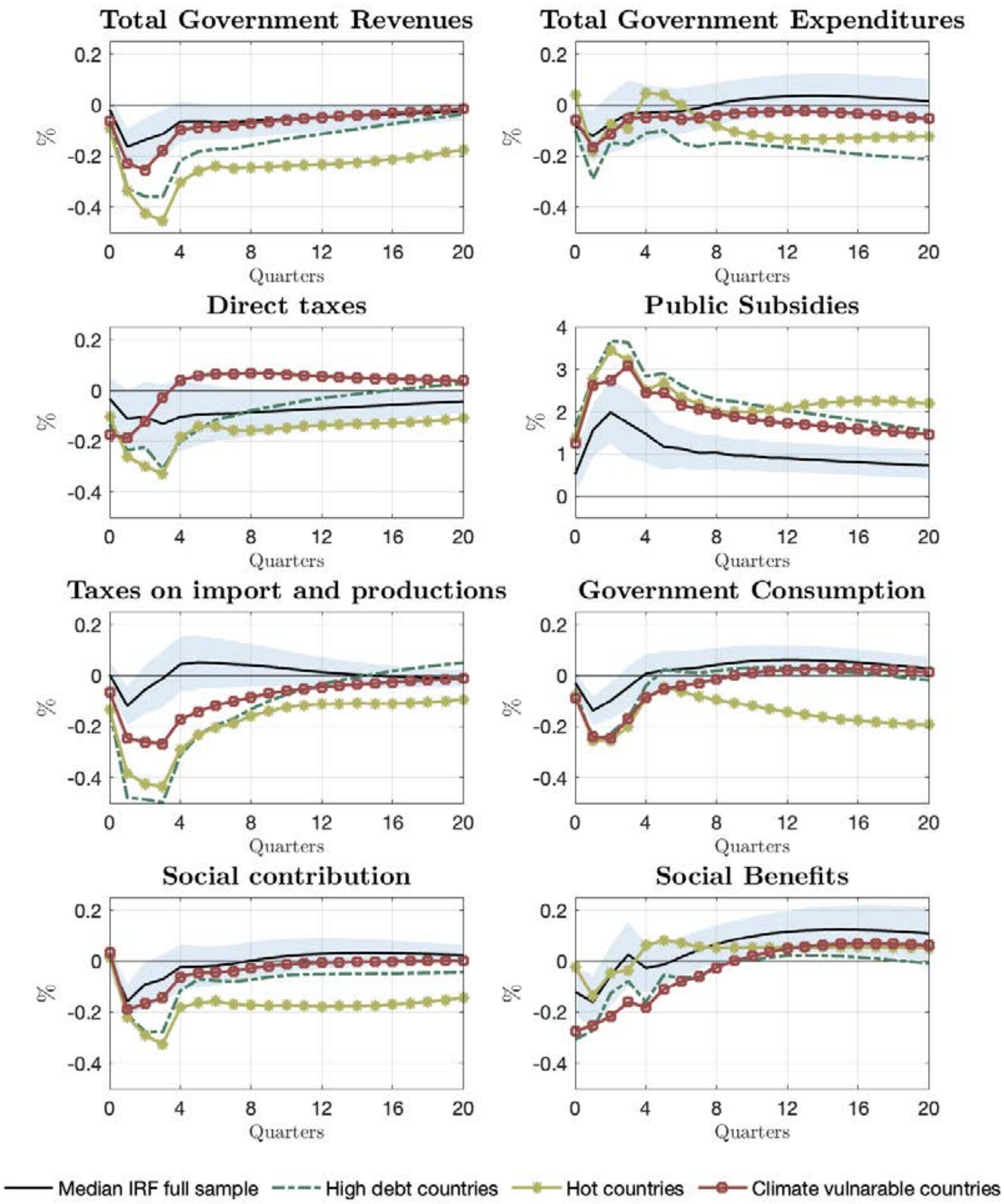

Figure 9: Structural IRFs to a 1°C temperature shock: transmissions mechanisms. Variables are included as extra regressor one at time in the vector endogenous variable and the Panel VAR is re-estimated. Median IRFs and 68% Bayesian credible intervals are reported for the full sample estimations. Median IRfs are reported for the sub-sample of countries.

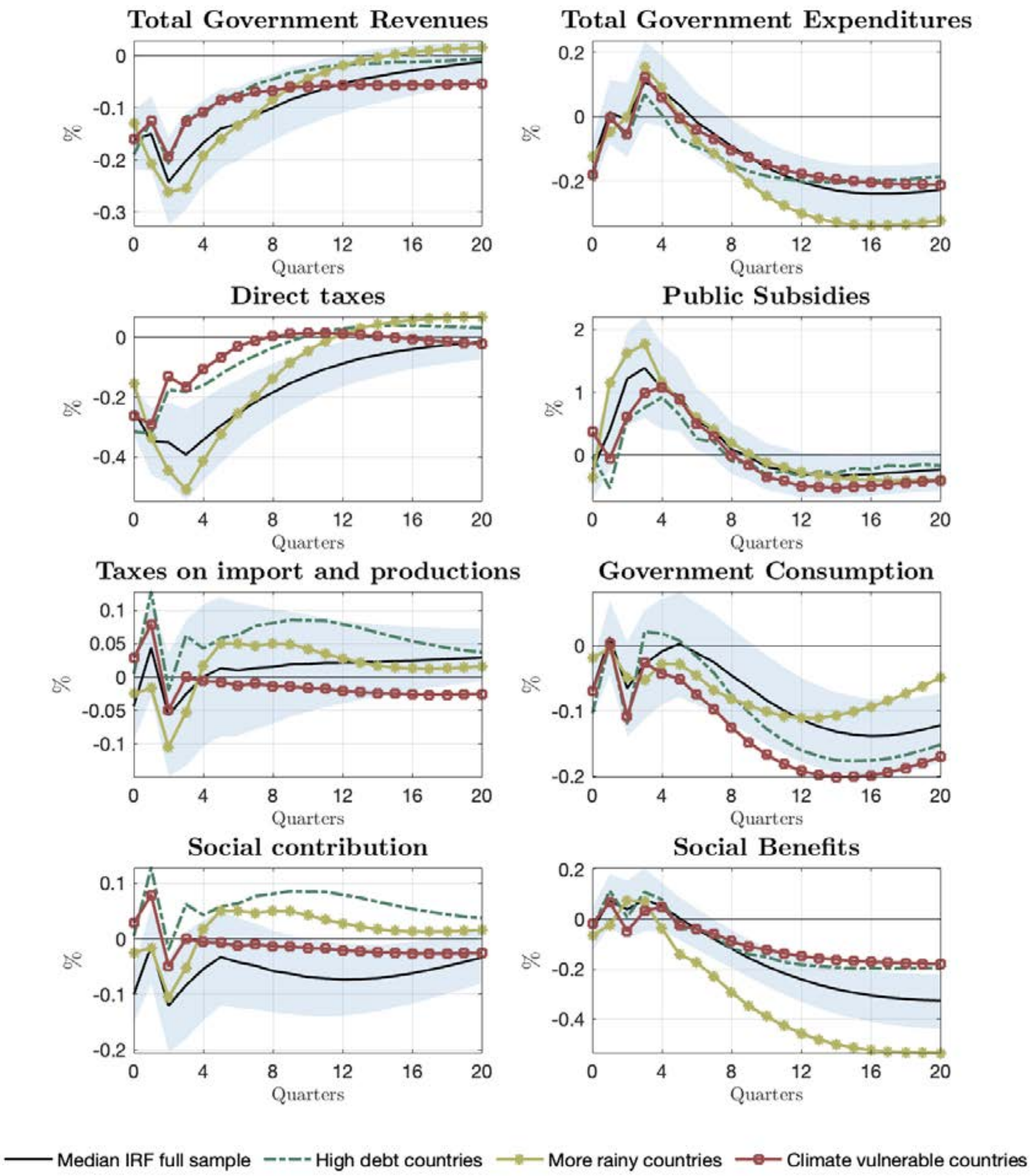

Figure 10: Structural IRFs to a 50mm precipitation shock: transmissions mechanisms. Variables are included as extra regressor one at time in the vector endogenous variable and the Panel VAR is re-estimated. Median IRFs and 68% Bayesian credible intervals are reported for the full sample estimations. Median IRfs are reported for the sub-sample of countries.

6 Conclusion

The empirical measurement of the impact of climate change on public finances in developed countries has received little attention in the macroeconomic literature. This paper attempts to fill this gap by analysing the impact of climate anomalies on fiscal variables in a standard macroeconometric framework that also takes into account economic activity. Focusing on the impact of physical climate risks on public finances, we construct exogenous temperature and precipitation shocks from natural variations in weather time series in a panel of 14 European countries and the United States. Using the shocks as internal instruments in a recursive VAR identification scheme, IRFs from a structural Bayesian Panel VAR show that adverse climate shocks are contractionary and significantly increase public debt and deficits over a business cycle horizon. In particular, in our sample, temperature shocks have a persistent and medium-term impact on public finances and are similar to negative supply shocks, leading to a significant decline in real GDP and an increase in consumer prices. In contrast, precipitation shocks have negative fiscal and economic effects only in the short term and are more likely to affect the demand side of the economy, leading to persistent deflationary pressures.

Inflationary effects play a prominent role in explaining the impulse responses of the two climate shocks. In our sample, temperature shocks behave like negative supply shocks and, together with a recessionary effect, induce a significant increase in consumer prices. In contrast, precipitation shocks behave like negative demand shocks, causing significant deflation over time. These results contribute to the ongoing debate about the real nature of negative climate-related shocks. Our evidence supports the idea that physical risk can be associated with both demand and supply shocks, depending on the weather observations used to proxy for climate change. We find that when climate change affects the supply side of the economy, the macroeconomic effects are more persistent and difficult to counteract, requiring long-lasting fiscal stimulus. Demand-side shocks, on the other hand, have short-term negative effects that can be reliably mitigated over a business cycle horizon.

Subgroup estimates of the panel VAR allow us to identify a significant degree of country heterogeneity in our results. The negative fiscal and economic consequences of temperature anomalies are remarkably stronger for warmer, more climate-vulnerable and highly indebted countries, suggesting that the same non-linearities in the temperature-debt relationship may hold. The subgroup results for precipitation shocks show no tendency to vary significantly across different subgroups of countries.

We have augmented our empirical model with a number of detailed government budgetary items in order to more specifically identify the channels behind the baseline macroeconomic results. These further analyses enrich our investigation and suggest that the main transmission mechanisms of the reported fiscal impacts are significantly lower tax revenues combined with an increase in government spending on public subsidies, likely related to climate change mitigation spending. In particular, the reduction in tax revenues is consistent with the economic nature of the shocks. Temperature shocks mainly reduce government revenues from taxes on imports and production, in line with their negative supply-side behavior, while precipitation shocks erode government revenues from direct taxes, likely affecting the demand side of the economy.

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A Appendix

A.1 Descriptive Statistics of the climate variables

Country	**Temperature**				**Temp. Anomalies**				**Precipitation**				**Precip. Anomalies**			
	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Austria	7.63	1.05	5.15	10.72	0.64	1.02	-2.17	3.15	88.70	16.44	52.43	127.43	8.25	50.05	-81.17	129.09
Belgium	10.84	1.07	7.99	13.35	0.61	1.05	-2.26	3.01	70.86	15.63	40.55	124.03	-5.72	50.54	-86.78	130.09
Germany	9.62	1.15	6.59	12.72	0.70	1.20	-2.15	3.98	57.34	9.90	39.10	80.55	-5.73	34.84	-83.79	83.26
Denmark	8.78	1.24	4.85	11.47	0.58	1.20	-2.89	3.58	59.05	11.97	32.30	93.03	1.97	39.35	-70.74	116.28
Spain	14.29	0.67	12.66	16.41	0.49	0.67	-1.27	2.10	49.15	12.58	17.07	82.97	-0.95	47.16	-97.20	148.47
Finland	2.50	1.57	-3.72	6.41	0.69	1.51	-3.96	4.01	48.80	8.84	25.43	70.26	3.89	29.06	-89.53	91.67
France	11.84	0.91	9.59	13.79	0.59	0.90	-1.38	2.11	67.47	14.80	32.68	99.04	-8.06	48.63	-107.78	133.48
Greece	15.90	0.74	13.97	17.50	0.62	0.72	-1.28	2.16	48.58	13.68	23.60	89.51	11.16	46.68	-103.62	132.31
Ireland	9.89	0.69	7.66	11.47	0.19	0.71	-2.02	1.61	99.16	19.95	54.43	162.97	5.68	69.85	-172.41	198.59
Italy	14.72	0.67	13.44	16.44	0.58	0.67	-1.23	1.96	59.60	11.12	35.20	87.99	-6.03	40.39	-114.39	101.52
Luxembourg	9.73	1.08	6.96	12.36	0.64	1.06	-2.08	2.94	76.14	16.76	48.23	137.02	-11.07	55.99	-111.10	150.83
Netherlands	10.53	1.09	7.49	13.12	0.61	1.07	-2.30	3.16	64.34	13.39	35.59	93.52	-4.21	45.69	-91.37	94.34
Portugal	16.19	0.61	14.69	18.04	0.40	0.64	-1.16	1.90	56.86	22.05	12.49	129.38	-2.80	94.23	-196.63	362.34
Sweden	3.28	1.30	-1.22	6.42	0.55	1.24	-3.31	3.06	51.25	7.08	34.31	74.83	-1.38	22.22	-44.33	72.18
United States	9.18	0.63	8.13	11.33	0.46	0.58	-0.62	2.30	65.18	5.69	53.13	87.29	3.65	18.10	-23.85	63.09

Table A.1: Descriptive statistics of the climatic variables in our dataset by countries in the period 2002Q4-2022Q4.

A.2 Autocorrelograms for climate anomalies

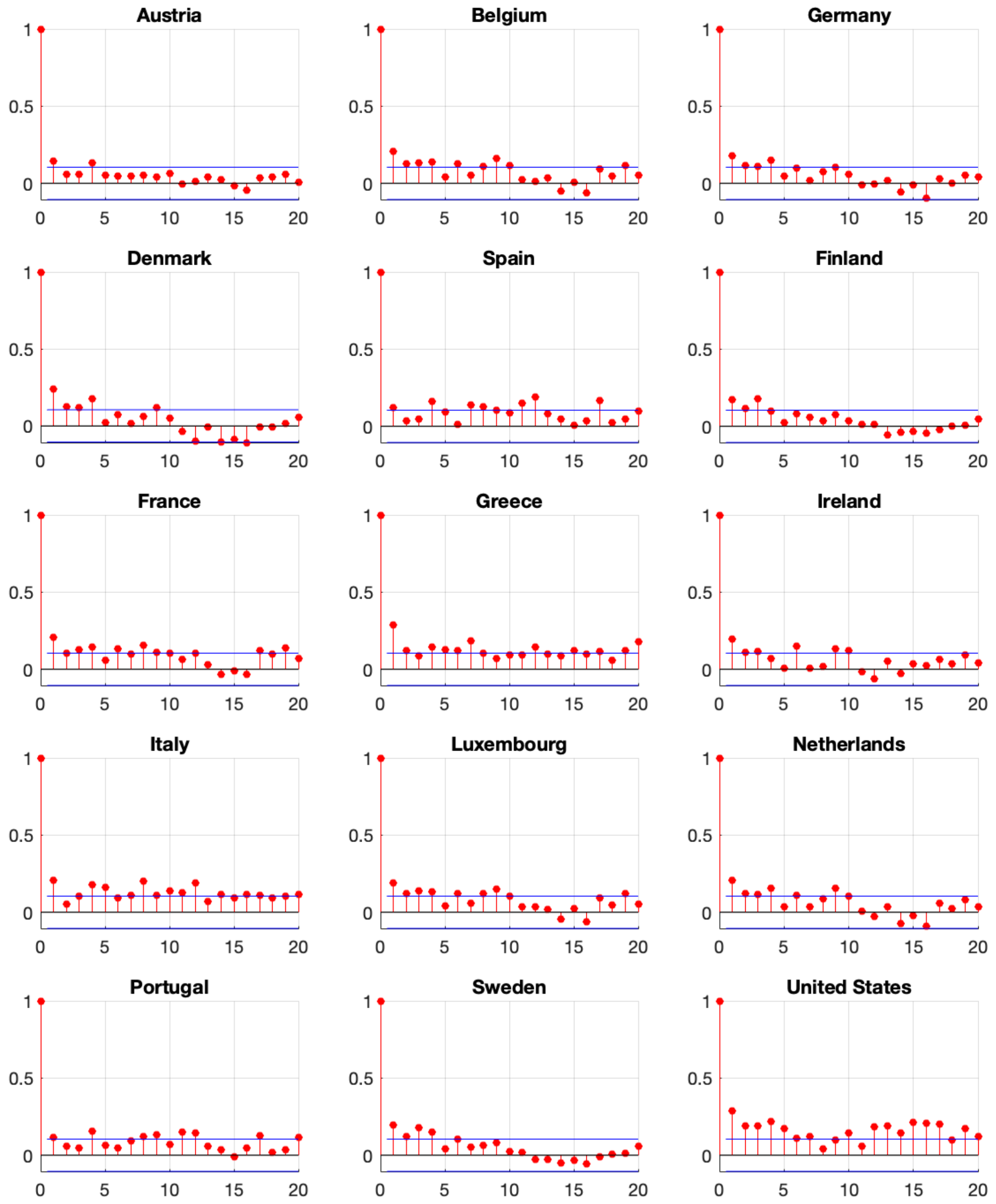

Figure A.1: Country-specific autocorrelograms for the time-series of temperature anomalies.

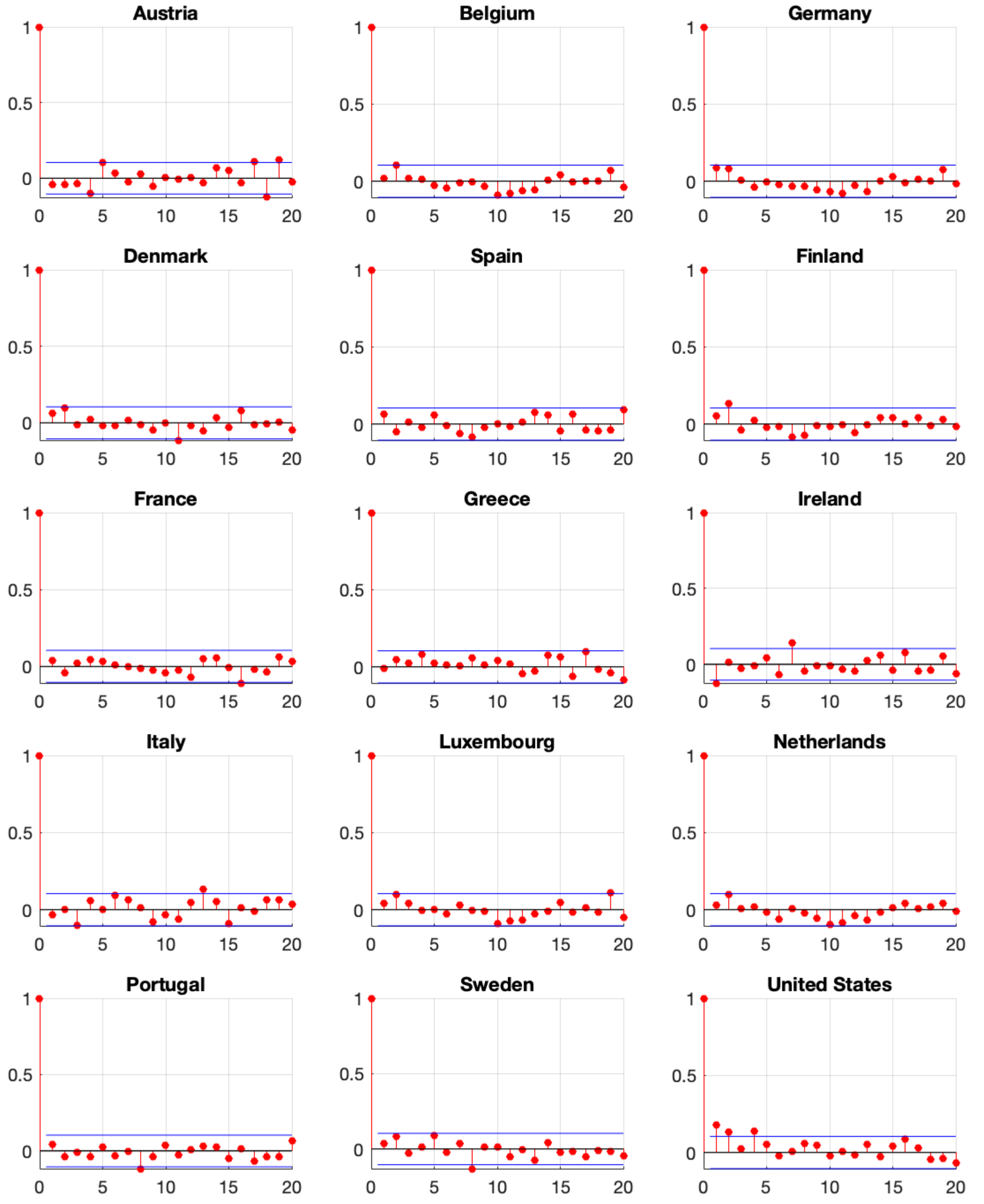

Figure A.2: Country-specific autocorrelograms for the time-series of precipitation anomalies.

A.3 Ljung-Box test results for climate anomalies

Country	Test Statistics	P-value
Austria	17.280	0.001
Belgium	35.513	0.000
Germany	29.980	0.000
Denmark	43.446	0.000
Spain	16.535	0.002
Finland	31.231	0.000
France	34.051	0.000
Greece	47.190	0.000
Ireland	25.101	0.000
Italy	32.512	0.000
Luxembourg	32.736	0.000
Netherlands	35.712	0.000
Portugal	16.455	0.002
Sweden	40.398	0.000
United States	76.120	0.000

Table A.2: Country specific Ljung-Box Test results for the Temperature Anomalies time series. Both Test statistic and P-Value are reported.

Country	Test Statistics	P-value
Austria	5.724	0.220
Belgium	4.570	0.334
Germany	6.095	0.192
Denmark	5.342	0.253
Spain	2.602	0.626
Finland	8.253	0.082
France	2.095	0.718
Greece	3.396	0.493
Ireland	5.879	0.208
Italy	5.483	0.241
Luxembourg	5.164	0.270
Netherlands	4.191	0.380
Portugal	1.812	0.770
Sweden	3.304	0.508
United States	25.792	0.000

Table A.3: Country specific Ljung-Box Test results for the Precipitation Anomalies time series. Both Test statistic and P-Value are reported.

A.4 Final climate shocks in all countries

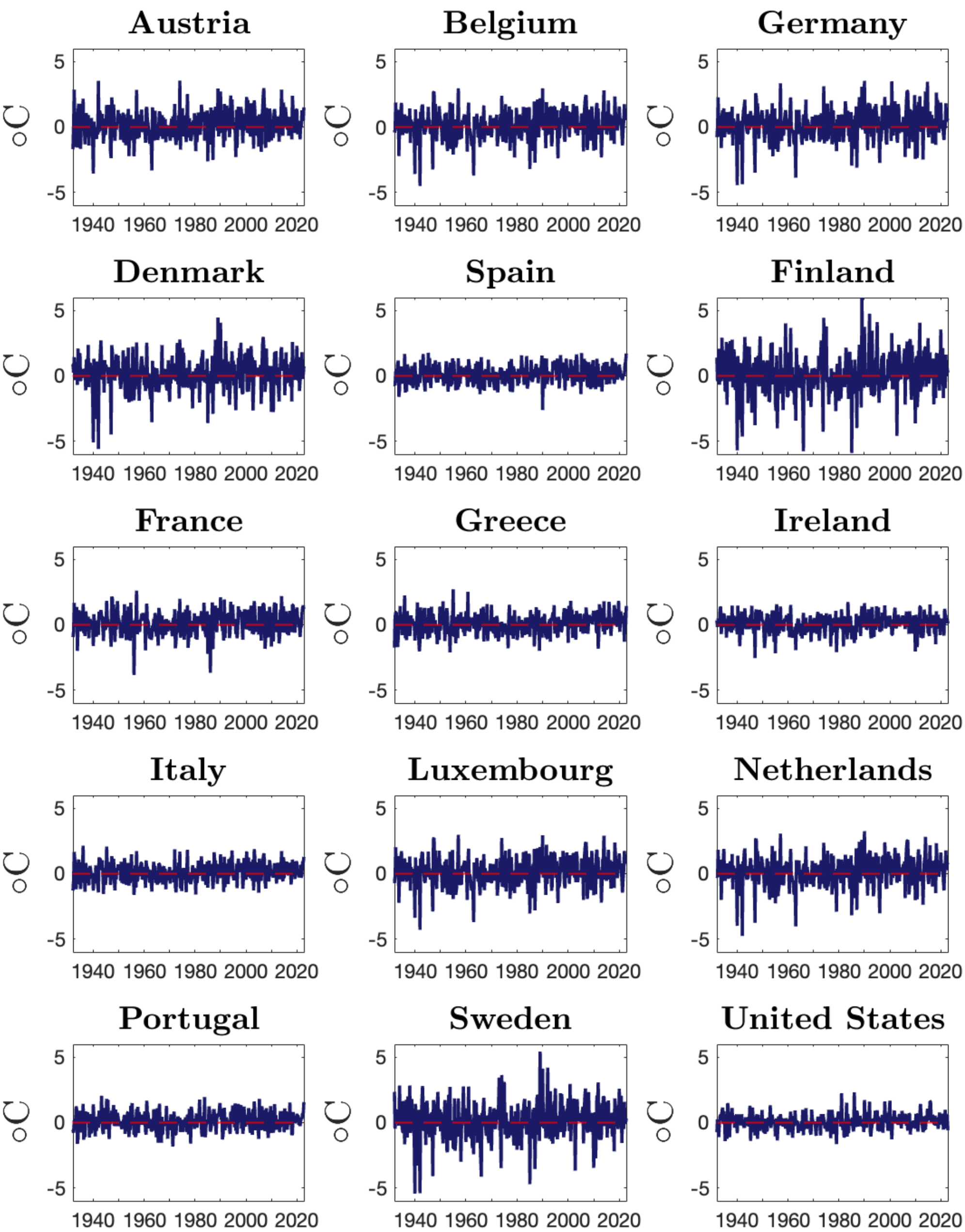

Figure A.3: Final temperature shocks retrieved for all 15 countries in our sample. Shocks are built according to our two step procedure: 1) Temperature anomalies are computed as deviations from the time-varying 30-year historical norm; 2) Temperature anomalies are regressed on its own lags and the innovations of these regression are the final shocks.

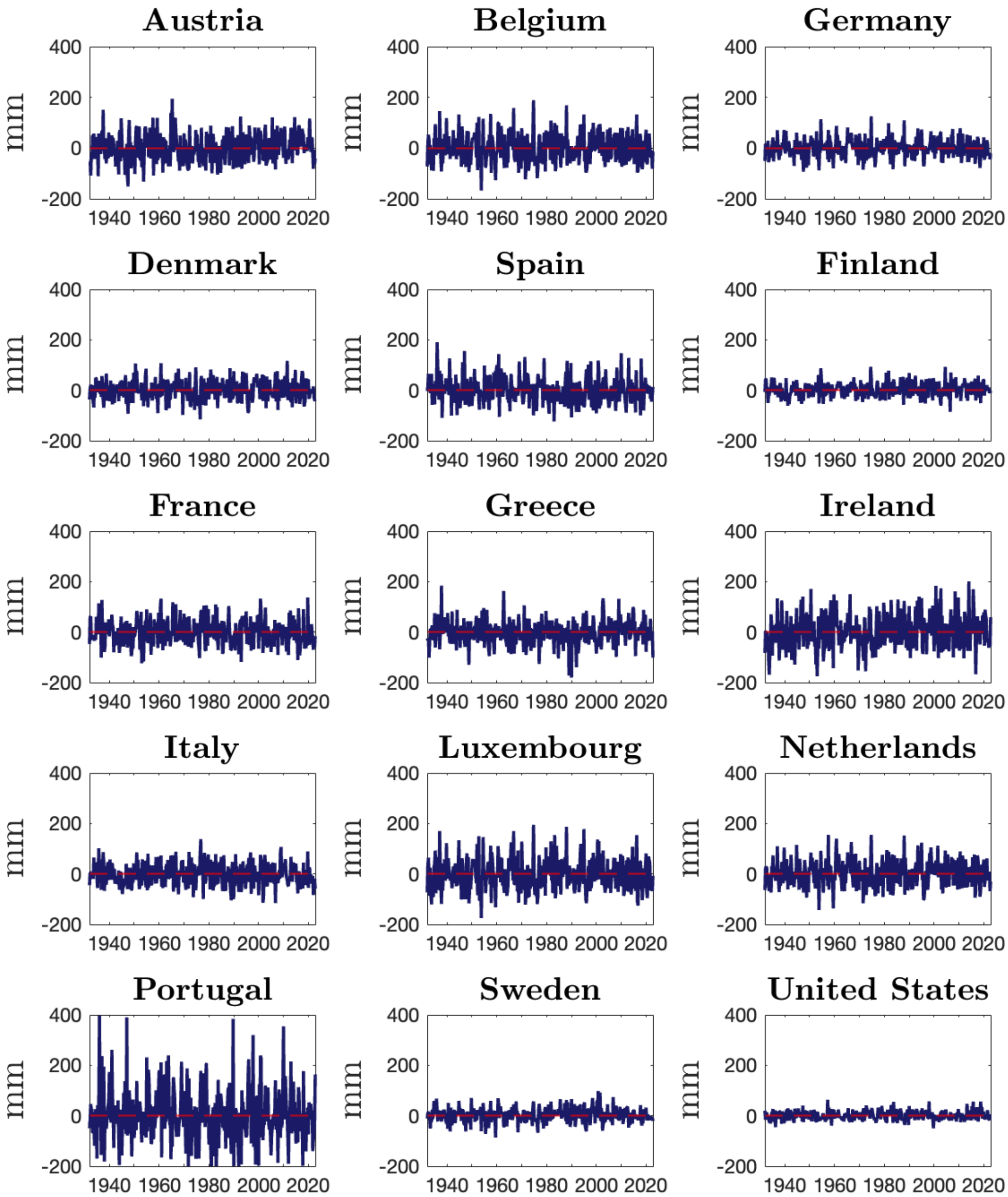

Figure A.4: Final precipitation shocks retrieved for all 15 countries in our sample. Shocks are built according to our two step procedure: 1) Precipitation anomalies are computed as deviations from the time-varying 30-year historical norm; 2) Precipitation anomalies are regressed on its own lags and the innovations of these regression are the final shocks.

A.5 Details of the macroeconomic variables of the Panel VAR

Variables	Mean	Min	Max	Standard Deviation	Unit of Measurement
Public Debt (Gross Real Debt)	2206119.67	4531.50	35025770.00	5500730.23	Millions of dollars
Primary Balance-to-GDP ratio	-0.39	-29.28	7.33	3.64	% of GDP
Long-term Interest Rate	2.82	-0.61	25.40	2.45	Percentages
Inflation (CPI All Items)	96.60	76.43	126.80	9.15	Base year 2015 = 100
Real GDP - expenditure approach	2113.12	43.59	21399.75	4296694.22	Billions of U.S. dollars, fixed PPPs

Table A.4: Descriptive statistics of the macroeconomic variables in our dataset. Statistics are computed for the time series of the variables across all countries in the sample, therefore values are referred to the average economy.

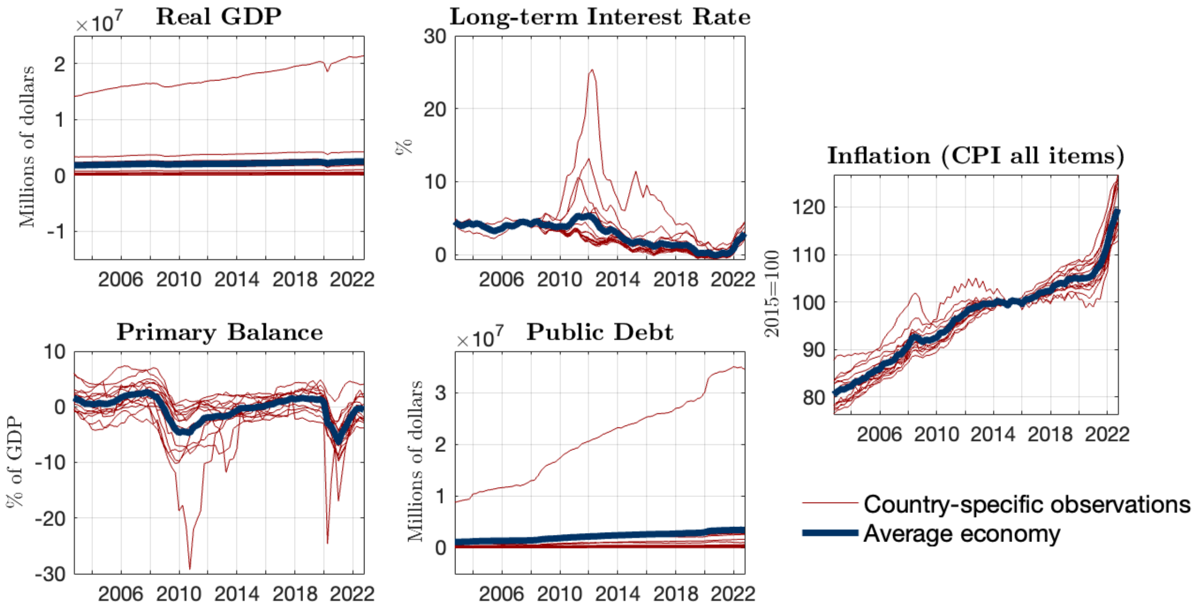

Figure A.5: Time series of the macroeconomic variables exploited as endogenous variables in the Panel VAR model. Both the average economy and the country-specific observations are displayed.

A.6 Bayesian Prior (Banbura et al., 2010)

Bańbura et al. (2010) propose a modified version of the Minnesota Prior for large-scale VARs to overcome the curse of dimensionality. The prior is specifically designed for macroeconomic variables. The standard Minnesota prior assumes that all the VAR equations are averaged around the random walk with drift, therefore in the matrix of parameters the diagonal elements tend to one while the remaining coefficients approach zero. Moreover, the beliefs are built according to the idea that more recent lags are more informative than lags farther away and that, for each variable, own lags explain most of the observed variation with respect to lagged interdependencies. Formally, given the following moments for the prior beliefs distribution on the matrix of parameters $\boldsymbol{A}_k$, with k large:

$$E[(\boldsymbol{A}_k)_{i,j}] = \begin{cases} \delta_i & j = i, k = 1 \\ 0 & \text{otherwise} \end{cases} \qquad V[(\boldsymbol{A}_k)_{i,j}] = \begin{cases} \frac{\lambda^2}{k^2} & j = i \\ \theta \frac{\lambda^2}{k^2} \frac{\sigma_i^2}{\sigma_j^2} & \text{otherwise} \end{cases} \tag{8}$$

with $\boldsymbol{A}_1, ..., \boldsymbol{A}_L$ independent and normally distributed and the residuals variance-covariance matrix $\boldsymbol{\Sigma}$ is assumed to be diagonal and fixed with elements $(\sigma_1^2, ..., \sigma_n^2)$. The Minnesota prior originally introduced by Litterman (1986) assumes $\delta_i = 1 \; \forall \, i$ (high persistence) and a low value of $\theta \in (0, 1)$, which conveys the relative importance of past lags with respect to more recent ones. λ is an hyper-parameter that controls the weight of prior beliefs with respect to the data-driven information within the estimation process. For values of $\lambda \to 0$ the posterior tends to the prior and data are always less informative, while for $\lambda \to \infty$ the posterior expectations are equivalent to the OLS estimate.

Bańbura et al. (2010) propose two modifications to the Minnesota's moments: 1) Given that the random walk hypothesis implies a high level of persistence in all the time series of the VAR but macroeconomic variables are generally characterized by a mean-reversion behaviour, they assume $\delta_i = 0$ (white-noise prior beliefs); 2) Since the assumption of fixed and diagonal variance-covariance matrix is too strict for structural analyses which requires to consider potential correlation between the residuals of different variables, they impose a normal inverted Wishart (iW) prior assuming $\theta = 1$, as follows:

$$\text{vec}(A)|\Sigma \sim N(\text{vec}(A_0), \Sigma \otimes \Omega_0) \;\; \text{and} \;\; \Sigma \sim iW(S_0, \alpha_0) \tag{9}$$

where the parameters A_0, Σ_0, S_0 and α_0 are such that the moments of $\boldsymbol{A}$ are equal to the ones presented in Equation (8).

The prior is implemented via dummy variables and rigorously follows the implementation of Bańbura et al. (2010).

A.7 Robustness checks for the full-sample

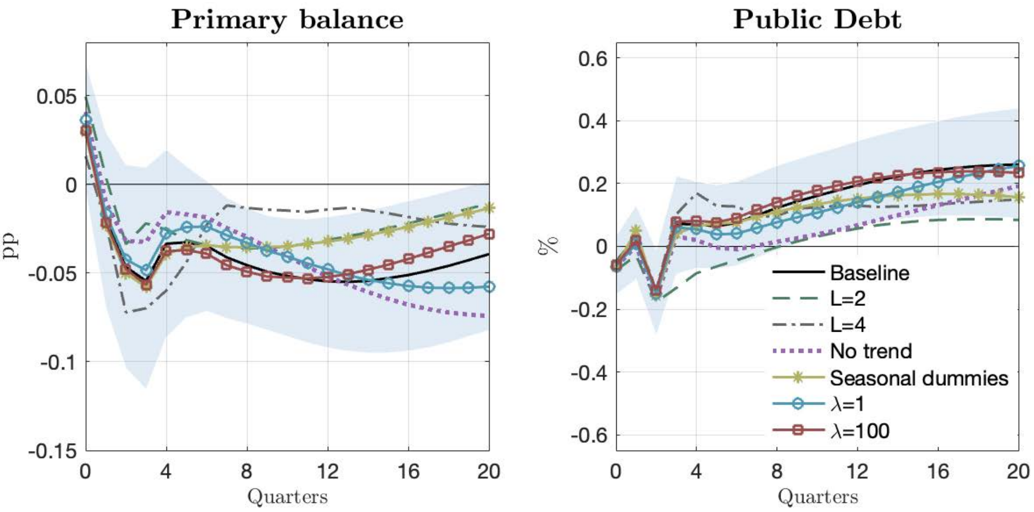

Figure A.6: Structural IRFs of primary balance ratio and real debt to a 1°C temperature shocks in the full sample of countries. Robustness checks: (i) reduce the lags of the endogenous variables to 2; (ii) increase the lag of the endogenous variables to 4; (iii) excluding the deterministic trend from the model specification; (iv) include seasonal dummies in the model specification; (v) increase the weight attached to the Bayesian prior distribution; (vi) increase the weight attached to the data information.

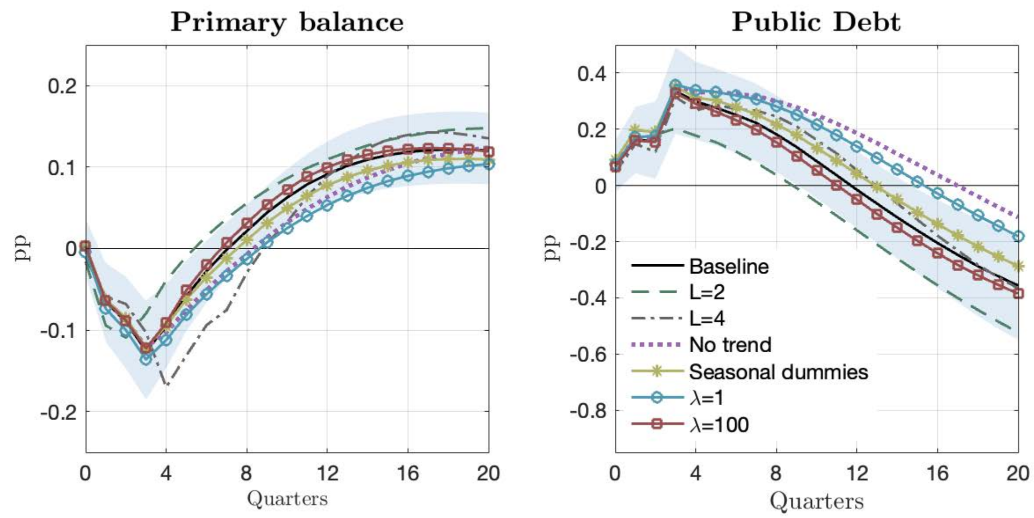

Figure A.7: Structural IRFs of primary balance ratio and real debt to a 50mm precipitation shocks in the full sample of countries.

A.8 Frequency of adverse weather events (EM-DAT data)

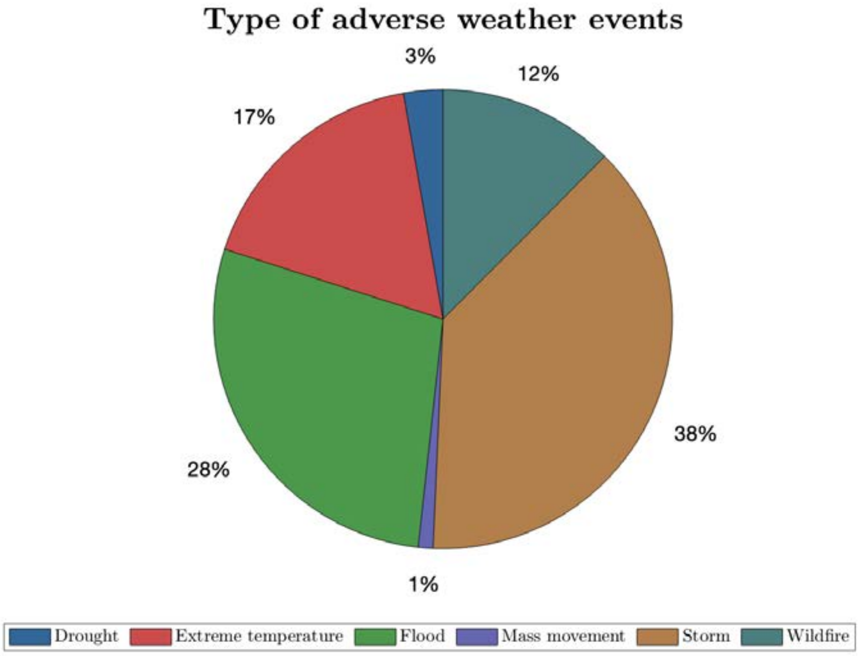

Figure A.8: Percentage of different types of climate change-related natural disasters for the 15 countries in our sample in the periods 2002Q4–2022Q4.

Country	**Correlations with . . .**	
	temperature shock	**precipitation shock**
Austria	-0.0347	0.2548
Belgium	-0.0238	0.0142
Germany	-0.0105	0.2722
Denmark	0.0053	0.0219
Spain	-0.0630	0.0116
Finland	-0.0338	0.0200
France	0.1267	0.2047
Greece	-0.2108	0.3103
Ireland	0.0597	0.2367
Italy	0.0840	0.0617
Luxembourg	-0.0689	-0.0930
Netherlands	0.1308	-0.0346
Portugal	0.2188	0.1758
Sweden	0.0511	-0.0950
United States	-0.0001	-0.0861
Average economy	**0.0155**	**0.0850**

Table A.5: Country specific correlations at the quarterly frequency of adverse weather events with our temperature and precipitation shocks in the period 2002Q4–2022Q4.

A.9 List of countries for subgroup estimations

Sub-samples	**List of included countries**
Hot countries	Belgium, Spain, France, Greece Italy, Netherlands, Portugal
Cold countries	Austria, Germany, Denmark, Finland, Ireland, Luxembourg, Sweden, United States
More climate vulnerable countries	Belgium, Denmark, Greece, Italy, Netherlands, Portugal, United States
Less climate vulnerable countries	Austria, Germany, Spain, Finland, France, Ireland, Luxembourg, Sweden
More rainy countries	Austria, Belgium, France, Ireland, Luxembourg, Netherlands, United States
Less rainy countries	Germany, Denmark, Spain, Finland, Greece, Italy, Portugal, Sweden
High debt countries	Belgium, Spain, France, Greece, Italy, Portugal, United States
Low debt countries	Austria, Germany, Denmark, Finland, Ireland, Luxembourg, Netherlands, Sweden

Table A.6: List of countries according to the specific features exploited for the subgroup estimations.

A.10 Descriptive statistics of fiscal variables

Variables	Mean	Min	Max	Standard Deviation	Unit of Measurement
Total government revenues	757882.06	19068.05	8095004	1244602.96	Billions of dollars
Total government expenditures	869576.56	18227.82	11186668	1559540.00	Billions of dollars
Direct taxes revenues	258045.90	5956.59	3872081	525358.57	Billions of dollars
Revenues from taxes on imports and productions	206315.52	5353.23	1868471	310885.18	Billions of dollars
Revenues from social contributions	200522.17	1994.54	1751768	308320.82	Billions of dollars
Expenditures for public subsidies	34716.92	157.63	1163936	67734.95	Billions of dollars
Expenditures for social benefits	323544.19	6433.42	6049283	661755.55	Billions of dollars
Expenditures for government consumption	368445.98	6971.61	3641910	635857.25	Billions of dollars

Table A.7: Descriptive statistics of the fiscal variables in our dataset exploited for the transmission mechanism analyses. Results refer to the appended data, therefore the statistics are computed for the time series of the variables across all countries in the sample. The ECB data only provides the seasonally adjusted variables as GDP ratio. To focus only on the fiscal impacts, we multiply the variables for the real GDP to obtain the real value of the budgetary items.