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Summary

The identification of the effects of climate shocks on economic growth is central to design effective policies aiming at managing the future global climate change challenge. In this study, we investigate the effects of temperature and precipitation shocks on economic growth across different countries by means of a new methodology, namely a Bayesian Structural Global VARX model. This setup accommodates economic interpretation of the shocks and accounts for cross-sectional spillovers among countries, as well as endogeneity of the climate variables with respect to the economy. Results show a high degree of heterogeneity, with some economies positively and some others negatively affected by climate shocks. In contrast with a consistent strand of the literature, according to which hot and poor countries bear the heaviest burden, we show that climate shocks may have severe effects for the economic growth of rich and cold countries as well. Furthermore, accounting for trade interdependence across countries, we document that, in response to unexpected temperature and precipitation shocks, some economies benefit from interconnections, while some others are damaged, depending on some key structural characteristics as the import-export mix, the relevant trade partners network and the level of economic development.

Keywords: Climate econometrics, Bayesian Structural VARs, Identification theory, Global VARs

JEL Classification: C11, C32, O44, Q51, Q54

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Modelling the effects of climate change on economic growth: a Bayesian Structural Global Vector Autoregressive approach

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Abstract

The identification of the effects of climate shocks on economic growth is central to design effective policies aiming at managing the future global climate change challenge. In this study, we investigate the effects of temperature and precipitation shocks on economic growth across different countries by means of a new methodology, namely a Bayesian Structural Global VARX model. This setup accommodates economic interpretation of the shocks and accounts for cross-sectional spillovers among countries, as well as endogeneity of the climate variables with respect to the economy. Results show a high degree of heterogeneity, with some economies positively and some others negatively affected by climate shocks. In contrast with a consistent strand of the literature, according to which hot and poor countries bear the heaviest burden, we show that climate shocks may have severe effects for the economic growth of rich and cold countries as well. Furthermore, accounting for trade interdependence across countries, we document that, in response to unexpected temperature and precipitation shocks, some economies benefit from interconnections, while some others are damaged, depending on some key structural characteristics as the import-export mix, the relevant trade partners network and the level of economic development.

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1 Introduction

Earth's climate is rapidly changing and its impact on the economic environment is indisputable. Nevertheless, the measurement of losses and benefits triggered by climate shocks in terms of real economic activity is not a simple endeavor. The interpretation of the link between climate conditions and economic growth is crucial for designing effective policy responses to one of the biggest challenges of the century: climate change.

In recent years, many econometric analyses have focused on the estimation of this effect, aimed at assessing the relationship between climate variables and economic output. Subsequent to the introduction of Integrated Assessment Models, empirical studies on the economics of climate change have been growing in number. However, the different setups and methodologies adopted within this literature have led to very heterogeneous results, so that it is hard to establish a clear picture of how climate variables affect economic activity in different geographical regions and at different time periods (see Dell et al., 2014; Tol, 2018; Kolstad and Moore, 2020, for recent surveys on the topic).

A large part of the literature on climate econometrics is based on regression models, where the outcome variable of interest is a proxy of economic activity, chosen in general among GDP, in levels or growth rates (Dell et al., 2012; Burke et al., 2015; Adom and Amoani, 2021; Newell et al., 2021), Total Factor Productivity (Letta and Tol, 2019) or agricultural output (Deschênes and Greenstone, 2007; Auffhammer and Schlenker, 2014; Blanc and Schlenker, 2020; Olper et al., 2021). Irrespective of the selected proxy, the debate on whether to estimate climate impacts on economic activity measured in levels or growth rates is still open, as pointed out by Newell et al. (2021). On the one hand, estimating the effects in levels leads to an overall reduction of uncertainty (Newell et al., 2021). On the other hand, models of GDP growth allow to overcome possible nonstationarity issues and provide estimates that reflect permanent and irreversible effects, whereas the effects estimated in levels reflect most likely a temporary phenomenon and therefore should be considered as "static" (Letta and Tol, 2019).

In the choice of climate variables, a key issue is the distinction between "climate change" and "weather variations". As pointed out by Hsiang (2016), climate concerns some deep characteristics that hardly and only in very long time spans change; on the contrary, weather variations we observe are simply realizations drawn from the climate distribution. The majority of studies focuses on variables such as temperature and rainfall (and possibly some nonlinear transformations of them). However, short-run weather fluctuations can not be a proxy of climate change, because they provide a conceptually different information. Long-run changes in the climate conditions should rather be captured by weather variables measured over long time horizons (e.g., "long" differences).

As for the geographical focus, the literature can be split between cross-country analyses (Cashin et al., 2017; Pretis et al., 2018; Acevedo et al., 2020; Alessandri and Mumtaz, 2021; Kahn et al., 2021) and country-specific studies (Deschênes and Greenstone, 2007; Sheng et al., 2022). Since climate change impacts on different economies are expected to vary across space and to exacerbate the already existing income disparities, we find it crucial to focus on a multi-country setup. For the same reason, a large number of studies rely on panel data models. Although panel regressions lead to several advantages, such as the possibility to control for omitted variables bias and the relatively easy way to include non-linearities in the model, nevertheless the specifications adopted in climate econometrics literature suffer from several limitations. First, panel data models as proposed in the studies on this topic, lack of proper structural dynamics to observe the propagation of climate shocks through time.[1] On the contrary, a structural model would allow for an

[1]See Pesaran and Smith (1995) for a discussion on dynamic analysis drawbacks in panel models.

explicit identification of the shocks and provide a very useful tool to study climate effects dynamically. Second, climate variables which enter in the panel specifications as regressors, are considered fully exogenous with respect to the dependent variable. As pointed out by Pretis (2020, 2021), economic and environmental systems are determined with a feedback in both directions, so we believe it is essential to endogenize climate variables within the adopted model.[2] Third, the heterogeneity among different countries in their net responses to structural climate shocks is hard to capture via panel data regressions, apart from considering the estimated country-specific fixed effects. A common finding is that weather effects are unequally distributed in space, with hot and poor countries being the most adversely affected. In contrast, there is no consensus for the effects regarding rich and cold countries.[3] Some studies suggest that climate change may be beneficial for countries located in colder regions (Mendelsohn et al., 2006; Acevedo et al., 2020), some others find an overall negative effect for both rich and poor countries, regardless of the geographical area (Burke et al., 2015; Alessandri and Mumtaz, 2021; Kahn et al., 2021) and a third group of studies does not find a statistically significant effect apart for hot and poor countries (Dell et al., 2012; Newell et al., 2021).[4] Fourth, another important aspect which is not properly considered within the panel data literature is the economic interdependence between countries. As argued in Di Mauro and Pesaran (2013), macroeconomic policy analysis requires taking into account the interconnections across different economic systems, with trade as one of the main channels driving the spillover effects. Countries

[2]Consistent with this, Acevedo et al. (2020) find that the median temperature over the first 15 years of this century, compared with the first 15 years of the past century, was 1.4°C higher in advanced economies, 1.3°C higher in emerging market economies, and only 0.7°C higher in low-income countries, meaning that most of the warming happened in advanced economies.

[3]Note that, in general, rich economies are also those located in colder regions; the debate on whether poor countries are less developed *because* they are hot, suggesting economic output is pre-determined by geographical starting endowment, is still ongoing.

[4]The relationship between climate and economic activity is stronger in the case of temperature, whereas the effect of precipitation is less clear and seldom investigated.

cannot be considered as isolated since shocks occurring to some particular region could spill over and affect other regions through their economic interdependence.

Our study contributes to the literature by overcoming these limitations. Accounting for endogeneity of climate, identifying structural climate and economic shocks within a dynamic context and, at the same time, considering economic interdependence across countries are demanding tasks from a methodological point of view. We face this challange by introducing a new model, in the vein of the Global VAR (GVAR) proposed by Pesaran et al. (2004), that allows us to take into account all these elements. The GVAR model represents an approach to describe the country-specific economic systems accounting for interconnections in a global perspective. Climate change represents a global phenomenon. However, several features are related to country-specific dynamics because the intrinsic climate conditions and their effects on economic output are different according to the geographical region. The standard GVAR model is designed specifically to capture the domestic characteristics of different economies and to simultaneously include interlinkages among the countries under scrutiny. Hence, a similar setup represents the natural way of modelling the climate-economy relationship. The model is based on two steps. The first step deals with the estimation of separate, country-specific VARX models where the interlinkages are expressed via the so-called foreign variables, which are treated as weakly exogenous. In the second step, the estimated country-specific models are stacked to form one single large global model and to obtain the global solution. It is worth noting that the canonical GVAR is a reduced form specification, that is, there is no a structural estimation in the second step. Given that formal identification is not contemplated, the dynamic analysis is usually performed through the Generalized Impulse Response Functions (GIRFs).[5]

[5]The GIRF approach does not aim at identifying the shocks according to some canonical system or *a*

We propose a Bayesian Structural Global VARX (BS-GVARX) model based on the algorithm developed by Baumeister and Hamilton (2015), to identify the effects of climate shocks on economic growth. Our approach is novel in several respects. We perform a structural analysis where the country-specific VAR models are nested in a single global specification where the identification of the structural parameters involves interdependence across countries by including joint prior information derived through the equilibrium impact of the structural shocks. This explicitly allows for spillover effects without the use of any data-shrinkage approach and solves the dimensionality issue of large VARs. Furthermore, identification via equilibrium impacts allows us to preserve a mapping between the reduced form and the structural form of the model. To our knowledge, this paper is the first embedding a Bayesian structural dynamic analysis in a GVAR and, besides Cashin et al. (2017), there are no other examples of a GVAR model employed to study the climate-economy relationship.[6]

Our main findings can be summarized as follows. First, there is a feedback effect that goes in both directions, from the economy to the environment and viceversa suggesting the importance of endogenizing climate variables in modelling the climate-economy relationship. Second, although the impact effects of climate shocks on economic growth in different countries are mixed, for most of the countries the responses become negative in the subsequent periods. More interestingly, we find no precise regularities in the differences of this effect between poor, rich, hot and cold countries. Third, the trade linkage

priori economic theory, but considers a counterfactual exercise where the historical correlations of shocks are assumed as given. GIRFs are independent of the variables order, because they integrate the effects of other shocks out of the response. This tool is very useful in the case of large systems, where structural relationships are hard to identify. However, these cannot really be interpreted as structural impulse responses, even if providing an accurate depiction of the historic development of the variables (Pesaran and Shin, 1998).

[6] There are other articles proposing structural analyses in a GVAR framework: Mohaddes and Pesaran (2016), for instance, focus on the identification of country-specific oil supply shocks; however, their results are still based on GIRFs.

between countries plays a role in amplifying or dampening their responses to the climate shocks, depending on the country-specific trade structure and trade partners network, as well as on its level of development.

The rest of the paper is structured as follows. Section 2 describes the data and the countries included in the analysis. Section 3 explains the methodology and introduces the BS-GVARX model. Section 4 presents and discusses the results and Section 6 concludes.

2 Data description

We perform our analysis relying on macroeconomic and climate data for 33 countries. Specifically, we focus on the economies included in the classic GVAR framework, as illustrated in Mohaddes and Raissi (2020), which account for more than 90% of world GDP and cover all the regions of the world from a geographical perspective. The sample includes economies at different stages of development and with heterogeneous climatic conditions (see Table 1). Since most of the relevant studies agree on the negative effects of rising temperatures on economic performance in poor and hot regions, whereas impacts are less clear for the rich and cold areas, the focus on this particular sample of countries, including several developed economies, is of paramount interest.

For each country, we consider three endogenous domestic variables, specifically temperature, precipitations and real GDP growth ($\mathcal{T}_{it}$, $\mathcal{P}_{it}$ and $\mathcal{Y}_{it}$), at annual frequency. To take into consideration the difference between climate change and simple weather realizations, the two climate variables are expressed in the deviations from their historical norms. As argued in Kahn et al. (2021) and Tol (2021), this way of measuring allows for estimation of unbiased weather effects, introduces an interaction between weather and climate and, crucially, represents an implicit way of including adaptation in the model.

The vector of the endogenous country-specific variables is defined as $\mathbf{y}_{it} = [\mathcal{T}_{it}, \mathcal{P}_{it}, \mathcal{Y}_{it}]'$, where $i = 1, \ldots, N$ is the country index and $t = 1, \ldots, T$ is the time index. We collect climate data, provided by the World Bank Climate Knowledge Portal, from 1960 to 2019, and compute their respective deviations from the norm defined as the moving average of the past 30 years.[7] We then compute $\mathcal{T}_{it}$ and $\mathcal{P}_{it}$ as the difference between the observed temperature and precipitations at time t and the respective 30-years moving average at time $t-1$. Real GDP growth rates are computed as the logarithmic differences of constant-prices GDP in levels obtained from Penn World Tables for the same time span.[8].

One intrinsic feature of the GVAR model is the inclusion of the so-called foreign variables, capturing the interconnections between each country and the rest of the world. Foreign variables, considered as weakly exogenous, are constructed as weighted averages of all the other countries' variables. We define weights via a $N \times N$ trade matrix, as proposed in Dees et al. (2007) and Chudik and Pesaran (2016). Each element of the trade matrix is defined as $w_{ij} = \frac{T_{ij}}{T_i}$, where T_{ij} is the bilateral trade of country i with country j, computed as the sum of exports and imports, and T_i is the total trade of country i. All weights are constructed for each year of the selected period and then the simple average of all weights is computed. Since real GDP growth is the only economic variable in our model, we compute one foreign exogenous variable, defined as $x^*_{it} = W_i \mathcal{Y}_{it}$. Including non-granular (local) cross-sectional weighted averages of $\mathcal{Y}_{it}$ helps to deal with omitted variable bias in the form of unobserved common shocks that may affect the set of the endogenous variables of the GVAR model (see Chudik and Pesaran, 2011; Chudik et al., 2021). Note that, as in Chudik et al. (2021), the foreign variable enters in our model with one lag. This relaxes the potential problem of high correlation between the domestic real

[7] https://climateknowledgeportal.worldbank.org/download-data

[8] https://www.rug.nl/ggdc/productivity/pwt/

GDP growth variable, $\mathcal{Y}_{it}$, and the foreign variable, x^*_{it}.

Table 1: Countries in the BS-GVARX model

	Income classification	Structure of output			Climate conditions	
	Income	Agriculture (% of GDP)	Industry (% of GDP)	Services (% of GDP)	Mean annual temperature (1991-2020)	Mean annual precipitation (1991-2020)
Asia and Pacific						
Australia	High	2	25.5	72.5	22.14 °C	482.33 mm
China	Upper-Middle	7.7	37.8	54.5	7.43 °C	610.67 mm
India	Lower-Middle	18.3	23.5	58.2		
Indonesia	Lower-Middle	13.7	38.3	48	26.14 °C	2857.01 mm
Japan	High	1	28.7	70.3	11.31 °C	1658.05 mm
Korea	High	1.8	32.6	65.6	11.41 °C	1394.50 mm
Malaysia	Upper-Middle	8.2	35.9	55.9	25.74 °C	3135.52 mm
New Zealand	High	5.7	20.4	73.9	10.21 °C	1770.29 mm
Philippines	Lower-Middle	10.2	28.4	61.4	25.83 °C	2461.35 mm
Singapore	High	0	24.4	75.6	27.60 °C	2254.07 mm
Thailand	Upper-Middle	8.6	33.1	58.3	26.80 °C	1549.85 mm
North America						
Canada	High	1.7	24.6	73.7	-4.23 °C	532.87 mm
Mexico	Upper-Middle	3.8	29.7	66.5	21.36 °C	758.59 mm
United States	High	0.9	18.2	80.9	9.47 °C	722.19 mm
South America						
Argentina	Upper-Middle	5.9	23.3	70.8	14.88 °C	590.11 mm
Brazil	Upper-Middle	5.9	17.7	76.4	25.58 °C	1755.82 mm
Chile	High	3.9	31.4	64.7	8.99 °C	530.14 mm
Peru	Upper-Middle	7.5	30.5	62	19.77 °C	1542.43 mm
Middle East and Africa						
Saudi Arabia	High	2.6	41.4	56	25.50 °C	75.67 mm
South Africa	Upper-Middle	2.5	23.4	74.1	18.32 °C	455.96 mm
Europe						
Austria	High	1.1	25.5	73.4	7.23 °C	1210.84 mm
Belgium	High	0.6	19.5	79.9	10.67 °C	885.45 mm
Finland	High	2.5	24	73.5	2.72 °C	558.75 mm
France	High	1.6	16.4	82	11.70 °C	838.18 mm
Germany	High	0.7	26.5	72.8	9.62 °C	711.41 mm
Italy	High	2	21.6	76.4	12.94 °C	879.10 mm
Netherlands	High	1.6	17.8	80.6	10.40 °C	790.94 mm
Norway	High	1.8	26	72.2	2.11 °C	1152.66 mm
Spain	High	3.1	20.4	76.5	13.98 °C	596.29 mm
Sweden	High	1.4	21.1	77.5	2.99 °C	663.81 mm
Switzerland	High	0.7	25.2	74.1	6.06 °C	1631.54 mm
Turkey	Upper-Middle	6.7	28	65.3	11.69 °C	576.82 mm
United Kingdom	High	0.6	17	82.4	9.13 °C	1198.08 mm

Sources: World Bank's World Development Indicators and Climate Knowledge Portal. Notes: country classification by income refers to 2022. Low-income economies are defined as those with a per capita Gross National Income (GNI) of $1,045 or less; lower middle-income economies are those with a GNI per capita of $1,046 to $4,095; upper middle-income economies are in the range $4,096 to $12,695; high-income economies are those with a value higher than $12,696. GDP shares by sectors refer to 2020. Services as a share of GDP are computed as difference between the total and the combined share of Agriculture and Industry.

3 Methodology

We propose a Bayesian Structural Global VARX (BS-GVARX) model that encompasses in a standard GVAR framework a Bayesian identification structure. The GVAR model, originally proposed by Pesaran et al. (2004), provides an attractive way of modeling the dynamic relationship between the variables and the interconnections across countries in a high-dimensional system. However, this methodology is not designed to perform structural analysis for two reasons. First, global reduced-form parameters are not estimated, but derived from a re-parametrization of the first-step estimated coefficients, using the link matrix defined in terms of the country-specific weights. Second, this solution of the global model depends on the way that static and dynamic interdependencies are taken into account in the country-specific analysis. It is worth noting that, in case of static interdependence, the global vector of reduced-form solution residuals are obtained from a linear combination of the residuals coming from the estimation of the country-specific VARX models and the measure of interlinkage.[9] Instead, assuming only dynamic interdependence, the stacked country-specific residuals and those obtained from the solution coincide. However, there is an implicit assumption that the estimated VARX and a model with only endogenous variables are coincident. Thus, the main contribution of our work on the GVAR literature is that we draw structural interpretation from the correlations we observe in the data without imposing a data-shrinkage approach. Moreover, we apply a Bayesian perspective, which consists in a statistical method of combining prior probability distribution, that describes our degree of beliefs about the structural parameters, with the probability distribution of the sample, that is the likelihood function of the observed data. In this way, it is possible to solve the problem of identification by bringing in additional information from multiple sources, for instance relying on the literature, and contribute to form the identifying assumptions of the structural model.

[9]The interlinkages are measured by the product of the trade weights and the coefficients associated with the foreign variables. The former are deterministic components, which are designed to capture political and cultural interconnections across countries (see Gross, 2019; Chudik and Pesaran, 2016). The latter represent stochastic components, which are estimated in the first-stage.

Our structural analysis nests country-specific models in a single global specification, by performing the algorithm proposed by Baumeister and Hamilton (2015). For what concerns country-specific analysis, the VAR model of each country, augmented by the exogenous (foreign) variable, is straightforwardly estimated. Then, all individual country Structural VARX models are stacked to form one large global system. At this point, the identification of the structural shocks are no longer independent across countries, since it accounts for some joint prior information about the interaction of the responses of country-specific economic activity to climate shocks. Thus, the idea of modelling the economic spillovers between different countries through the equilibrium impacts of structural shocks allows us to deal with the curse of dimensionality without the help of data-shrinkage methods and to preserve a clear mapping from structural to reduced-form parameters of the BS-GVARX model.

3.1 Country-specific climate-economy relationship

The endogenous variables of each country-specific Structural VARX models, collected in the vector $\mathbf{y}_{it}$, are temperature ($\mathcal{T}_{it}$), precipitations ($\mathcal{P}_{it}$) and real GDP growth ($\mathcal{Y}_{it}$). The exogenous foreign variable, x^*_{it}, captures the role of the global economy. The nested SVARX model for a generic country i is:

$$\mathbf{A}_i \mathbf{y}_{it} = \mathbf{B}_i \mathbf{x}_{it-1} + \mathbf{u}_{it} \tag{1}$$

where $\mathbf{A}_i$ is a $k_i \times k_i$ matrix of simultaneous structural coefficients, $\mathbf{y}_{it}$ is a $k_i \times 1$ vector of endogenous variables, $\mathbf{x}_{it-1}$ is a $(lk_i + 2) \times 1$ vector containing a constant, the lags of the country and foreign variables, that is $\mathbf{x}'_{it-1} \equiv \left[\mathbf{y}'_{it-1}, \mathbf{y}'_{it-2}, \cdots, \mathbf{y}'_{it-l}, 1, x^*_{it-1}\right]'$ and

$\mathbf{B}_i \equiv [\mathbf{B}_{i1}, \mathbf{B}_{i2}, \mathbf{b}_{i0}, \mathbf{c}_i]$ a $k_i \times (lk_i + 2)$ matrix of structural coefficients.[10] Specifically, $\mathbf{b}_{i0}$ is a $k_i \times 1$ vector of intercepts, $\mathbf{B}_{i1}$, $\mathbf{B}_{i2}$ are $k_i \times k_i$ matrices of lagged structural coefficients and $\mathbf{c}_i$ is a $k_i \times k_i^*$ vector that governs the relationship between the foreign and the country variables. The vector of structural shocks $\mathbf{u}_{it} \equiv [u_{i,1t}, u_{i,2t}, u_{i,3t}]'$ is assumed to be normally distributed with zero mean and diagonal variance-covariance matrix $\mathbf{D}_i \equiv E\left[\mathbf{u}_{it}\mathbf{u}_{it}'\right]$. Consequently, the likelihood of the observed data $\mathbf{Y}_{i,T} = (\mathbf{y}_{i,T-1}', \mathbf{y}_{i,T-2}', \cdots, \mathbf{y}_{i,1}')'$ conditional on the pre-sample observations $\mathbf{x}_{i0}$ is given by:

$$
\begin{aligned}
p\left(\mathbf{Y}_{iT}|\boldsymbol{\theta}_i, \mathbf{x}_{i0}\right) = (2\pi)^{-Tk_i/2} \left|\det\left(\mathbf{A}_i\right)\right|^T \left|\mathbf{D}_i\right|^{-T/2} \times \\
\exp\left[-(1/2)\sum_{t=1}^{T}\left(\mathbf{A}_i\mathbf{y}_{it} - \mathbf{B}_i\mathbf{x}_{it-1}\right)' \mathbf{D}_i^{-1}\left(\mathbf{A}_i\mathbf{y}_{it} - \mathbf{B}_i\mathbf{x}_{it-1}\right)\right]
\end{aligned}
\tag{2}
$$

where $\left|\det\left(\mathbf{A}_i\right)\right|$ denotes the absolute value of the determinant of $\mathbf{A}_i$ and $\boldsymbol{\theta}_i$ is a vector collecting the unknown structural coefficients in $\mathbf{A}_i$, $\mathbf{B}_i$ and $\mathbf{D}_i$. We use the following specification for $\mathbf{A}_i$ to set-identify the structural shocks of interest:

$$
\mathbf{A}_i = \begin{bmatrix} 1 & 0 & -a_{i,\mathcal{T}\mathcal{Y}} \\ 0 & 1 & -a_{i,\mathcal{P}\mathcal{Y}} \\ -a_{i,\mathcal{Y}\mathcal{T}} & -a_{i,\mathcal{Y}\mathcal{P}} & 1 \end{bmatrix}
\tag{3}
$$

The structural matrix $\mathbf{A}_i$ implies that temperature and precipitation variables are endogenous to the economic system, via the parameters $a_{i,\mathcal{T}\mathcal{Y}}$ and $a_{i,\mathcal{P}\mathcal{Y}}$. Moreover, real economic activity is simultaneously affected by both temperature and precipitation through the parameters $a_{i,\mathcal{Y}\mathcal{T}}$ and $a_{i,\mathcal{Y}\mathcal{P}}$. We use two exclusion restrictions on the elements of matrix (3), that are, $a_{i,\mathcal{T}\mathcal{P}} = 0$ and $a_{i,\mathcal{P}\mathcal{T}} = 0$. These restrictions imply that climate variables affect

[10] We set the number of lags $l = 2$ for each country. This choice takes into account both the Information Criteria selected lag order, equal to 1 for all countries according to the HQN and BIC IC, and the 2-year duration of a global business cycle (see Kilian and Lütkepohl, 2017; Hamilton, 2021).

each other only after one period. Literature has not identified a scheme of transmission from one "most exogenous" to another "more endogenous" weather variable; rather, climate is a complex system resulting from the combination of different contemporaneous conditions. The two zero-restrictions are further motivated by the fact that both temperature and precipitation are expressed as long-term deviations in the model, rather than being sudden weather shocks. The structural representations of (1) can be written as:

$$\begin{cases} \mathcal{T}_{it} = a_{i,\mathcal{T}\mathcal{Y}}\mathcal{Y}_{it} + \mathbf{b}'_{i1}\mathbf{x}_{it-1} + u_{i,1t} & \text{(4a)} \\ \mathcal{P}_{it} = a_{i,\mathcal{P}\mathcal{Y}}\mathcal{Y}_{it} + \mathbf{b}'_{i2}\mathbf{x}_{it-1} + u_{i,2t} & \text{(4b)} \\ \mathcal{Y}_{it} = a_{i,\mathcal{Y}\mathcal{T}}\mathcal{T}_{it} + a_{i,\mathcal{Y}\mathcal{P}}\mathcal{P}_{it} + \mathbf{b}'_{i3}\mathbf{x}_{it-1} + u_{i,3t} & \text{(4c)} \end{cases}$$

where $\mathbf{b}'_{ij}$ contains all structural coefficients on the lagged variables of the j^{th} equation and corresponds to the j^{th} row of $\mathbf{B}_i$. The vector $\boldsymbol{u}_{it}$ consists of three different country-specific structural shocks, namely a temperature shock $\boldsymbol{u}_{1,it}$, a precipitation shock $\boldsymbol{u}_{2,it}$ and an economic activity shock $\boldsymbol{u}_{3,it}$.

The reduced form of the SVARX model for each country is given by:

$$\mathbf{y}_{it} = \mathbf{\Pi_i}\mathbf{x}_{it-1} + \boldsymbol{\varepsilon}_{it} \tag{5}$$

where $\mathbf{\Pi}_i \equiv [\mathbf{\Phi}_{i1}, \mathbf{\Phi}_{i2}, \boldsymbol{\phi}_i, \boldsymbol{\lambda}_i]$, is a $k_i \times (k_i l + 2)$ matrix of the reduced-form coefficients and $\boldsymbol{\varepsilon}_{it}$ is a vector of zero-mean white noise process with variance-covariance matrix $E\left[\boldsymbol{\varepsilon}_{it}\boldsymbol{\varepsilon}'_{it}\right] \equiv \mathbf{\Omega}_i$, such that $\boldsymbol{\varepsilon}_{it} \sim \mathcal{N}\left(\mathbf{0}, \mathbf{\Omega}_i\right)$.

The Maximum Likelihood estimators of $\mathbf{\Pi}_i$ and $\mathbf{\Omega}_i$ are given by:

$$\widehat{\mathbf{\Pi}}_i = \left(\sum_{t=1}^{T} \mathbf{y}_{it}\mathbf{x}'_{it-1}\right)\left(\sum_{t=1}^{T} \mathbf{x}_{it}\mathbf{x}'_{it-1}\right)^{-1}. \tag{6}$$

$$\widehat{\mathbf{\Omega}}_i = \frac{1}{T}\sum_{t=1}^{T} \widehat{\boldsymbol{\varepsilon}}_{it}\widehat{\boldsymbol{\varepsilon}}'_{it} \tag{7}$$

where $\widehat{\boldsymbol{\varepsilon}}_{it} = \mathbf{y}_{it} - \widehat{\mathbf{\Pi}}_i \mathbf{x}_{it-1}$ denotes a $(k_i \times 1)$ vector of country-specific reduced-form errors.

3.2 The global climate-economy relationship

At this point, all single-country SVARX specifications are stacked to form one large global structural model. Using the $k_i \times k$ and $(k_i l + 2) \times N(k_i l + 2)$ dimensional selection matrices that select $\mathbf{y}_{it}$ and $\mathbf{x}_{it}$, equation (1) can be re-written as:

$$\mathbf{A}_i \mathbf{E}'_i \mathbf{y}_t = \mathbf{B}_i \tilde{\mathbf{E}}'_i \mathbf{x}_{t-1} + \mathbf{u}_{it} \tag{8}$$

where $\mathbf{y}_t = (y'_{1t}, y'_{2t}, \cdots, y'_{Nt})'$ is a $(k \times 1)$ vector containing all the endogenous country-specific variables, with $k = \sum_{i=1}^{N} k_i$ and $\mathbf{x}_{t-1} = \left[\mathbf{x}'_{1,t-1}, \mathbf{x}'_{2,t-1}, \cdots, \mathbf{x}'_{N,t-1}\right]'$ is a $N(k_i l + 2) \times 1$ vector consisting of all country-specific variables. If we stack these models for each country, we will end up with the BS-GVARX model:

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{u}_t \tag{9}$$

where $\mathbf{A}$ is a $k \times k$ contemporaneous structural matrix and $\mathbf{B}$ is a $k \times N(k_i l + 2)$ matrix of lagged parameters, that is:

$$\mathbf{A} \equiv \begin{bmatrix} \mathbf{A}_1\mathbf{E}'_1 \\ \mathbf{A}_2\mathbf{E}'_2 \\ \vdots \\ \mathbf{A}_N\mathbf{E}'_N \end{bmatrix}, \mathbf{B} \equiv \begin{bmatrix} \mathbf{B}_1\tilde{\mathbf{E}}'_1 \\ \mathbf{B}_2\tilde{\mathbf{E}}'_2 \\ \vdots \\ \mathbf{B}_N\tilde{\mathbf{E}}'_N \end{bmatrix} = \begin{bmatrix} \mathbf{B}_1\left[\mathbf{I}_{(k_1 l+2)}, \mathbf{0}_{(k_1 l+2)}, \cdots, \mathbf{0}_{(k_1 l+2)}\right] \\ \mathbf{B}_2\left[\mathbf{0}_{(k_2 l+2)}, \mathbf{I}_{(k_2 l+2)}, \cdots, \mathbf{0}_{(k_2 l+2)}\right] \\ \vdots \\ \mathbf{B}_N\left[\mathbf{0}_{(k_N l+2)}, \mathbf{0}_{(k_N l+2)}, \cdots, \mathbf{I}_{(k_N l+2)}\right] \end{bmatrix}.$$

Let $\mathbf{u}_t = (\mathbf{u}'_{1t}, \mathbf{u}'_{2t}, \cdots, \mathbf{u}'_{Nt})'$ denote a $k \times 1$ vector of the stacked country-specific structural innovations, assumed to be normally distributed with zero mean and a $k \times k$ diagonal covariance matrix $E[\mathbf{u}_t \mathbf{u}'_t] = \mathbf{D}$. It is worth noting that the structural innovations account for the interdependence across countries.[11] If we assume that the likelihoods of the observed data are independent for each county, then the likelihood function of the global model is given by:

$$p(\mathbf{Y}_T | \boldsymbol{\theta}, \mathbf{x}_0) = p(\mathbf{Y}_{1,T} | \boldsymbol{\theta}_1, \mathbf{x}_{1,0}) \times p(\mathbf{Y}_{2,T} | \boldsymbol{\theta}_2, \mathbf{x}_{2,0}) \times \cdots \times p(\mathbf{Y}_{N,T} | \boldsymbol{\theta}_N, \mathbf{x}_{N,0}) \tag{10}$$

where $\mathbf{Y}_T$ is a vector of stacked country-specific observed data, $\mathbf{x}_0$ is a vector collecting the pre-sample observations for each country and $\boldsymbol{\theta}$ is a vector containing all the unknown parameters of $\mathbf{A}$, $\mathbf{D}$ and $\mathbf{B}$. If the block-diagonal matrix $\mathbf{A}$ is non-singular, the reduced form of the BS-GVARX model can be obtained, multiplying equation (9) by $\mathbf{A}^{-1}$, that is:

$$\mathbf{y}_t = \mathbf{\Pi} \mathbf{x}_{t-1} + \boldsymbol{\varepsilon}_t \tag{11}$$

where $\mathbf{\Pi} = \mathbf{A}^{-1}\mathbf{B}$ is a $(k \times N(k_i l + 2))$ matrix of reduced-form coefficients and $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}'_{1t}, \boldsymbol{\varepsilon}'_{2t}, \cdots, \boldsymbol{\varepsilon}'_{Nt})'$ is a $(k \times 1)$ vector of the stacked country-specific reduced-form errors, with a $(k \times k)$ variance-covariance matrix $E[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_t] \equiv \mathbf{\Omega} = \mathbf{A}^{-1}\mathbf{D}(\mathbf{A}^{-1})'$, such that $\boldsymbol{\varepsilon}_{it} \sim \mathcal{N}(\mathbf{0}, \mathbf{\Omega})$. The Maximum Likelihood estimates for this representation are given by:

$$\hat{\mathbf{\Pi}} = \left(\sum_{t=1}^{T} \mathbf{y}_t \mathbf{x}'_{t-1} \right) \left(\sum_{t=1}^{T} \mathbf{x}_t \mathbf{x}'_{t-1} \right)^{-1}. \tag{12}$$

$$\widehat{\mathbf{\Omega}} = T^{-1} \sum_{t=1}^{T} \widehat{\boldsymbol{\varepsilon}}_t \widehat{\boldsymbol{\varepsilon}}'_t \tag{13}$$

[11] The interdependence is modelled through equilibrium impact of the structural shocks, as we explain later.

where $\widehat{\boldsymbol{\varepsilon}}_t = \mathbf{y}_t - \hat{\boldsymbol{\Pi}}\mathbf{x}_{t-1}$ denotes a $(k \times 1)$ vector of stacked country-specific residuals. In order to obtain a positive definite matrix $\widehat{\boldsymbol{\Omega}}$, we adopt the naive shrinkage approach, which considers all the cross-country covariances equal to zero. This is not an issue since we do not consider static interdependence in the reduced-form GVAR model, and we expect the cross-country covariances to be reduced by including the foreign variables.

We estimate model (9) using the methodology proposed by Baumeister and Hamilton (2015), which relies on Bayesian inference for set-identified structural VAR models. The identification of the structural parameters is based on two steps. In the first step, priors are assigned to the contemporaneous structural coefficients $\mathbf{A}$, the equilibrium impacts of structural shocks $\mathbf{H} \equiv \mathbf{A}^{-1}$, the lagged structural coefficients $\mathbf{B}$ and the variances of the structural shocks $\mathbf{D}$. The identification algorithm discussed in Baumeister and Hamilton (2015) and extended in Baumeister and Hamilton (2019) allows for any type of distribution that represents adequately the existing knowledge on the contemporaneous structural parameters. Therefore, the functional form of the probability density function for $\mathbf{A}$, denoted by $p(\mathbf{A})$, is not restricted. The priors information for the other coefficients, denoted by $p(\mathbf{D}|\mathbf{A})$ and $p(\mathbf{B}|\mathbf{A}, \mathbf{D})$, are selected from natural conjugate families in order to ensure a closed-form analytic expression for the Bayesian posterior distribution and thus reducing the computational effort. The second step relies on sampling S=3 million draws $\{\mathbf{A}, \mathbf{D}, \mathbf{B}\}_{s=1}^{S}$ from the posterior distribution of the unknown structural coefficients $p(\mathbf{A}, \mathbf{D}, \mathbf{B}|\mathbf{Y_T})$, with 2 million draws of burn-in. Specifically, we generate draws from the posterior distribution $p(\mathbf{A}|\mathbf{Y}_T)$ using a random walk Metropolis-Hastings algorithm and next we revise $\mathbf{A}$ to taking into account the information we set on $\mathbf{H}$. Finally, we make draws of the structural shocks and the lagged structural parameters from posterior distributions $p(\mathbf{D}|\mathbf{A}, \mathbf{Y}_T)$ and $p(\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y}_T)$.

3.2.1 Prior information about the structural parameters

The overall prior is given by:

$$p(\mathbf{A}, \mathbf{D}, \mathbf{B}) = p(\mathbf{A}) \prod_{i=1}^{N} p(d_i|\mathbf{A}) \prod_{i=1}^{N} \prod_{j=1}^{k_i} p(\mathbf{b}_{ij}|\mathbf{A}, \mathbf{D}) \tag{14}$$

whose components are discussed below.

<u>*Prior for the contemporaneous structural coefficients.*</u> Let $\boldsymbol{\theta}_{A_i}$ be the vector of the free parameters in matrix $\mathbf{A}_i$. Assuming independence across countries and structural equations, the unconditional prior distribution of $\mathbf{A}$, denoted by $p(\mathbf{A})$, is:

$$p(\mathbf{A}) = \prod_{i=1}^{N} p(\boldsymbol{\theta}_{A_i}) \tag{15}$$

where $p(\boldsymbol{\theta}_{A_i}) = p(a_{i,\mathcal{TY}})p(a_{i,\mathcal{PY}})p(a_{i,\mathcal{YT}})p(a_{i,\mathcal{YP}})p(\boldsymbol{\theta}_{H_i})$. It is worth noting that, the resulting prior $p(\mathbf{A})$ takes into account the prior information about the general equilibrium impacts of the structural shocks within and across countries, via $p(\boldsymbol{\theta}_{H_i})$. The priors for the unknown elements of matrix $\mathbf{A}_i$ are Student t distributions, with mode, scale parameters and degrees of freedom as reported in Table 2.[12] The priors for the parameters $a_{i,\mathcal{TY}}$ and $a_{i,\mathcal{PY}}$, corresponding to the economic effects on climate, are imposed equal across all countries, whereas for $a_{i,\mathcal{YT}}$ and $a_{i,\mathcal{YP}}$, denoting how climate affects the economy, we differentiate the priors by considering groups of countries with similar features. The first choice is consistent with the view that it is reasonable to expect that, on impact, climate is mildly affected by real economic activity. Beware of this, we opt for an informative prior,

[12] Here $\tilde{\phi}_\nu(x)$ denotes the probability density function of a standard Student t variable with location parameter c, scale parameter σ and ν degrees of freedom evaluated at the point x, that is:

$$\tilde{\phi}_\nu(x) = \frac{\Gamma\left[(\nu+1)/2\right]}{(\nu\pi)^{1/2}\,\Gamma(\nu/2)}\left(1+\frac{x^2}{\nu}\right)^{-(\nu+1)/2}.$$

with mode $c_{a_{i,\mathcal{T}\mathcal{Y}}} = c_{a_{i,\mathcal{P}\mathcal{Y}}} = 0$, standard deviation $\sigma_{a_{i,\mathcal{T}\mathcal{Y}}} = \sigma_{a_{i,\mathcal{P}\mathcal{Y}}} = 0.01$ and 3 degrees of freedom. Instead, since the two parameters capturing the effects of climate shocks on real GDP growth are the main focus of the analysis, we opt for different settings considering three groups of countries. We divide countries combining the information we have about multi-country empirical studies, country-specific analyses and descriptive statistics about weather conditions and income levels. The priors are reported in Table 2. The prior modes of $a_{i,\mathcal{Y}\mathcal{T}}$ are equal to those for $a_{i,\mathcal{Y}\mathcal{P}}$ within the country groups. This choice is determined by two main motivations. First, whereas there is plenty of analyses focusing on the temperature effect on economic performance, there are less considering the effects of precipitation, and still if both variables are included, there is greater uncertainty in estimating the effects of rainfall at country-level (Damania et al., 2020). Second, we make the assumption that both climate variables have the same importance in explaining economic activity, so we opt for the same magnitude.

The groups of countries we define are split in order to identify regions with different on-impact effects of climate shocks according to the disposable prior knowledge. Bearing in mind that colder countries, such as Canada, Finland, Norway and Sweden, are associated with positive temperature effects in terms of economic growth in the majority of empirical literature (see, among others Acevedo et al., 2020), we set for this group the mode at $c_{a_{i,\mathcal{Y}\mathcal{T}}} = c_{a_{i,\mathcal{Y}\mathcal{P}}} = 0.005$. The second and third groups are defined as one containing poor and hot countries and the other containing all the rich economies which are not part of the first group. There are however some exceptions: when detailed analyses about one particular country are available, we rely on them and privilege that information with respect to multi-country set ups. Due to this, the second group, in the bottom panel of Table 2, consists in a mix of poor and hot countries, found to be the more damaged

Table 2: Prior distributions specifications for the structural parameters in $\mathbf{A}_i$

		Student t		
List of countries	Parameter	mode (c)	scale (σ)	d.o.f.
Canada, Finland, Norway, Sweden	$a_{i,\mathcal{YT}}$	0.005	0.01	3
	$a_{i,\mathcal{YP}}$	0.005	0.01	3
Austria, Belgium, China, France Germany, Italy, Netherlands,	$a_{i,\mathcal{YT}}$	0.001	0.01	3
New Zealand, Spain, Switzerland, Turkey, United Kingdom	$a_{i,\mathcal{YP}}$	0.001	0.01	3
Argentina, Australia, Brazil, Chile, India, Indonesia, Japan, Korea, Malaysia, Mexico,	$a_{i,\mathcal{YT}}$	-0.005	0.01	3
Peru, Philippines, Saudi Arabia, Singapore, South Africa, Thailand, USA	$a_{i,\mathcal{YP}}$	-0.005	0.01	3

Notes: $a_{i,\mathcal{YT}}$ and $a_{i,\mathcal{YP}}$ denote the effect of temperature and precipitation, respectively, on economic growth in country i. The location and scale parameters of the t distribution are the mode and its standard deviation; d.o.f. denotes the degrees of freedom.

ones in economic terms, and a small set of countries which, even if rich, are expected to be negativelly affected by climate shocks: Australia, Japan and the United States.A work by Acevedo et al. (2020) finds that the Austrialian economy is strongly negatively affected by increasing temperature. They do not find statistically significant effects for the cases of the USA and Japan. However, US is too big and characterized by a variety of climatic conditions across the different regions. Since data for the US is available in a very disaggregated detail, estimating several models in which within-country data are used leads to the conclusion that the effects are negative and significant, as discussed by Kahn et al. (2021). The same disaggregated analysis is performed for Japan by Kurachi et al. (2022), who conclude that rising temperature has a detrimental effect in economic outcome over the long run. Thus, our prior for the parameter's mode is $c_{a_{i,\mathcal{YT}}} = c_{a_{i,\mathcal{YP}}} = -0.005$. The third group, in the middle panel of Table 2, is composed by those cold-rich countries in which the effect of climate variations is still unclear, often statistically not significant and for which the evidence is mixed (see Dell et al., 2012; Burke et al., 2015; Acevedo et al., 2020). We put in this group the European countries, New Zealand, China and Turkey.We consider China too big and heterogeneous to put it in the former group; indeed, evidence considering micro data of Chinese firms performance conclude that the effect of rising temperature is U-shaped (Zhang et al., 2018). Turkey is included here as part of Europe from a geographical and climatic point of view, and because Acevedo et al. (2020) find statistically not signficant effects of temperature on its economic activity. In this case, we set $c_{a_{i,\mathcal{YT}}} = c_{a_{i,\mathcal{YP}}} = 0.001$, slightly positive but very close to zero, considering the effect of climate change on economic growth rather marginal.

Prior information about impacts of structural shocks. Given the impact multiplier matrix $\mathbf{H}$, define with $\boldsymbol{\theta}_{H_i}$ the vector collecting the elements of $\mathbf{H}$ for country i. The resulting prior is:

$$p(\mathbf{H}) = \prod_{i=1}^{N} p(\boldsymbol{\theta}_{H_i}) \tag{16}$$

where $p(\boldsymbol{\theta}_{H_i}) = p(\boldsymbol{\theta}_{H_i^D})p(\boldsymbol{\theta}_{H_i^F})$. Note that $\mathbf{H} = \frac{1}{\det(\mathbf{G}_0)}\tilde{\mathbf{H}}$, where $\tilde{\mathbf{H}}$, as $\mathbf{A}$, is block-diagonal, with each block equal to:

$$\tilde{\mathbf{H}}_i = \begin{bmatrix} 1 - a_{i,\mathcal{PY}}a_{i,\mathcal{YP}} & a_{i,\mathcal{TY}}a_{i,\mathcal{YP}} & a_{i,\mathcal{TY}} \\ a_{i,\mathcal{PY}}a_{i,\mathcal{YT}} & 1 - a_{i,\mathcal{TY}}a_{i,\mathcal{YT}} & a_{i,\mathcal{PY}} \\ a_{i,\mathcal{YT}} & a_{i,\mathcal{YP}} & 1 \end{bmatrix}. \tag{17}$$

Thus, $p(\boldsymbol{\theta}_{H_i^D})$ collects the prior information about the domestic impacts of the structural shocks on the economic growth and it is defined as $p(\boldsymbol{\theta}_{H_i^D}) = p(h^D_{i,\mathcal{YT}})p(h^D_{i,\mathcal{YP}})$, where $h^D_{i,\mathcal{YT}} = \frac{a_{i,\mathcal{YT}}}{\det(A_i)}$ and $h^D_{i,\mathcal{YP}} = \frac{a_{i,\mathcal{YP}}}{\det(A_i)}$. Specifically, we incorporate prior information on the country-specific response of GDP growth to temperature and precipitation shocks using

Student t variables with location, scale parameters and degrees of freedom identical to those imposed on $\mathbf{A}$.

Moreover, in our identification strategy interdependence is considered via $\boldsymbol{\theta}_{H_i^F}$, a (2×1) vector collecting the spillover effects from foreign countries to country i, which is defined as $h^F_{i,y\mathcal{T}} = \sum_{j=1}^{N} h^D_{i,y\mathcal{T}} \omega_{ij}$ for temperature shocks and $h^F_{i,y\mathcal{P}} = \sum_{j=1}^{N} h^D_{i,y\mathcal{P}} \omega_{ij}$ for precipitation shocks, where ω_{ij} is the trade weight relating country i and j, with $j \neq i$. For these priors we employ Student t distributions with location parameter equals to the weighted average of the country specific priors as reported in table 2, scale parameters set at 0.01 and degrees of freedom set at 3. This implies relatively informative priors over the response of GDP growth to climate shocks that are perfectly consistent with values set for $\mathbf{A}$. It also implies that the direct (i.e., domestic) prior on $\mathbf{A}$ is combined with the instantaneous spillover effects, which are weighted by the correspondent trade weights, consistently with the study of De Santis and Zimic (2018), using absolute magnitude restrictions to identify the shocks in presence of spillovers. These assumptions account for the importance of trade and of spillover effects, both exhaustively documented in the literature. As argued in Chudik and Pesaran (2016), when the number of countries is moderate, spillover effects are important and it is advisable to use trade weights that also capture political and cultural interlinkages across countries. Dellink et al. (2017) also find that in response to climate shocks, the trade linkage between regions is an important source of spillover. When studying climate change effects on agricultural yields, Gouel and Laborde (2021) find a strong role of international trade in balancing the new domestic supply and demand schedules and consequently in responding to climate shocks. Finally, Dall'Erba et al. (2021) investigate the role of U.S. interstate trade in the response of U.S. crop profit to climate shocks and find that crop growers' profits depend on both local and trade partners' weather conditions.

Prior for the structural variances conditional on $\mathbf{A}$. Let $d_{i,jj}^{-1}$ denote the reciprocal of the j^{th} element on the diagonal of $\mathbf{D}$, the variance-covariance matrix of the structural shocks. We assume that, conditional on $\mathbf{A}$, the priors for the structural variances of country i follow an inverse-Gamma distribution and are independent across countries and equations, so that:

$$p(\mathbf{D}|\mathbf{A}) = \prod_{i=1}^{N} p(d_i|\mathbf{A}) \tag{18}$$

where $d_i = \prod_{j=1}^{k_i} p(d_{i,jj})$.[13]

Prior for the lagged structural coefficients conditional on $\mathbf{A}$ *and* $\mathbf{D}$. These priors are assumed to be independent across countries and structural equations:

$$p(\mathbf{B}|\mathbf{A}, \mathbf{D}) = \prod_{i=1}^{N} \prod_{j=1}^{k_i} p(\mathbf{b}_{ij}|\mathbf{A}, \mathbf{D}). \tag{19}$$

where $\mathbf{b}_{ij}'$ is a row vector of $\mathbf{B}_i$, collecting the random parameters which follow a multivariate Normal distribution with mean $\mathbf{m}_{ij}$ and variance $d_{i,jj}\mathbf{M}_{ij}$.[14] Consistent with the fact that climatic and economic variables are not easy to predict, we set prior expected values for all parameters equal to zero, $\mathbf{m}_{ij}' = \mathbf{a}_{ij}' \left(\mathbf{0}_{k_i \times 1}\ \mathbf{0}_{k_i \times k_i l_i + 2}\right)$, where $\mathbf{a}_{ij}$ denotes the

[13]We can write the conditional prior distribution for $d_{i,jj}^{-1}$ as:

$$p\left(d_{i,jj}^{-1}|\mathbf{A}\right) = \frac{\tau_j^{\kappa_j}}{\Gamma(\kappa_j)} \left(d_{i,jj}^{-1}\right)^{\kappa_j - 1} \exp\left(-\tau_j d_{i,jj}^{-1}\right), \text{for } d_{i,jj}^{-1} \geq 0$$

where κ/τ_j and κ/τ_j^2 represent the first and second moments of $d_{i,jj}^{-1}$, respectively. Following Baumeister and Hamilton (2015, 2019), we set the prior mean for $d_{i,jj}^{-1}$ equal to the reciprocal of the diagonal element of matrix $\mathbf{A}_i \mathbf{\Sigma}_i \mathbf{A}_i'$, where $\mathbf{\Sigma}_i$ represents the sample variance-covariance matrix of the residuals, from univariate first-order autoregressive models estimated on each endogenous variable. Moreover, we set $\kappa = 0.5$, which weights the prior as identical to the information that would come from a single observation.

[14]The conditional prior distribution for the lagged structural coefficients can be expressed as follows:

$$p\left(\mathbf{b}_{ij}|\mathbf{A}, \mathbf{H}, \mathbf{D}\right) = (2\pi)^{-k/2} \left|d_{i,jj}\mathbf{M}_{ij}\right|^{-1/2} \times \exp\left[-(1/2)\left(\mathbf{b}_{i,j} - \mathbf{m}_{i,j}\right)' \left(d_{i,jj}\mathbf{M}_{ij}\right)^{-1} \left(\mathbf{b}_{ij} - \mathbf{m}_{ij}\right)\right]$$

where $\mathbf{m}_{ij}$ is the best guess about $\mathbf{b}_{ij}$ before looking at the data and $\mathbf{M}_{ij}$ is our confidence in this prior information.

j-th row of $\mathbf{A}_i$. We define:

$$\mathbf{v}_{i1} \equiv \left(1^{-2\lambda_1} \ \cdots \ l^{-2\lambda_1}\right)'$$

$$\mathbf{v}_{i2} \equiv \left(s_{11}^{-1} \ s_{22}^{-1} \ s_{33}^{-1}\right)'$$

$$\mathbf{v}_{i3} \equiv \lambda_0^2 \begin{bmatrix} \mathbf{v}_{i1} \otimes \mathbf{v}_{i2} \\ \lambda_{i3}^2 \\ \lambda_{i4}^2 \end{bmatrix}$$

where s_{11}, s_{22} and s_{33} denote the diagonal elements of matrix $\mathbf{\Sigma}_i$ and λs are the hyper-parameters about the prior coefficients of the lagged structural coefficients as reported in note 15. Then the variance-covariance matrix $\mathbf{M}_{ij}$ is diagonal, whose *r-th* diagonal element is the *r-th* element of $\mathbf{v}_{i3}$. For $\mathbf{M}_{ij}$, we set a standard Minnesota prior assigning large confidence that coefficients related to higher lags are zero (see Doan et al. (1984)).[15]

3.2.2 Posterior distributions of the structural parameters

We adapt the closed-form analytical expression for the marginal posterior distribution of the contemporaneous structural parameters $\mathbf{A}_i$ in the context of the BS-GVARX, as follows:

$$p(\mathbf{A}|\mathbf{Y}_T) = \frac{\kappa_T p\left(\mathbf{A}\right)\left[\det\left(\mathbf{A}\mathbf{\Omega}_T\mathbf{A}'\right)\right]^{T/2}}{\prod_{i=1}^{N}\prod_{j=1}^{k_i}\left[\left(2/T\right)\tau_{ij}^{*}\right]^{\kappa_{ij}^{*}}} \prod_{i=1}^{N}\prod_{j=1}^{k_i}\tau_{ij}^{k_{ij}} \tag{20}$$

with: $\kappa_{ij}^{*} = \kappa_i + (T/2)$, $\tau_{ij}^{*} = \tau_i + (\xi_{ij}^{*}/2)$. and κ_T is a constant term for which (20) integrates to unity. Note that, $p\left(\mathbf{A}\right)$ is the prior density for the contemporaneous structural parameters and $\mathbf{\Omega}_T$ denotes the sample variance-covariance matrix for the reduced-from

[15] According to Baumeister and Hamilton (2015), four values for the hyper-parameters of the prior for $\mathbf{M}_{ij}$ are chosen. First, a parameter controlling the overall tightness of the prior, λ_0, which is set to 0.5. Second, a parameter governing how quickly the prior of the past coefficients tightens to zero as the lags increase, λ_1 which is set to 1. Finally, the parameters governing the tightness of the prior for the constant term λ_3 and the exogenous variable λ_4, are both set to 100. The latter imply uninformative priors over the exogenous variable and the constant term.

residuals in the global system. Analogously to Baumeister and Hamilton (2019), we use a random-walk Metropolis Hastings algorithm to generate different draws of the unknown elements of the contemporaneous structural matrix $\mathbf{A}_i$. Specifically, for each draw, $\mathbf{A}_i$ is numerically revised to account for the spillover effects to country i. This can be easily calculated in three steps. First, we compute the impact multiplier matrix implied by $\mathbf{A}_i$, which is denoted by $\mathbf{H}_i$. Second, we add to $\mathbf{H}_i$ the foreign effects of climate shocks on GDP growth rate of country i, namely $\mathbf{H}_i = \mathbf{H}_i + \mu \mathbf{H}_i^F$, where μ denotes the relative importance of trade and $\mathbf{H}_i^F$ is a (3×3) matrix, defined as follows:

$$\mathbf{H}_i^F = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ h_{i,\mathcal{YT}}^F & h_{i,\mathcal{YP}}^F & 0 \end{bmatrix}.$$

Third, defining $\mathbf{A}_i = \mathbf{H}_i^{-1}$, we show how information about the equilibrium impacts can be used to generate draws for $\mathbf{A}_i$ that are consistent with domestic and foreign impact responses.[16] From now on, the Baumeister and Hamilton's approach allows us to derive the posterior distributions of $\mathbf{D}$ and $\mathbf{B}$ using well known formulas (see Baumeister and Hamilton (2022)). Specifically, let ξ_{ij}^* be the sum of squared residuals of a regression of $\tilde{\mathbf{Y}}_{ij}$ on $\tilde{\mathbf{X}}_{ij}$, where $\tilde{\mathbf{Y}}_{ij}$ and $\tilde{\mathbf{X}}_{ij}$ represent augmented vectors defined as $\tilde{\mathbf{Y}}_{ij} \equiv \left[\mathbf{y}_{i1}'\mathbf{a}_{ij} \ \cdots \ \mathbf{y}_{iT}'\mathbf{a}_{ij} \ \mathbf{m}_{ij}'\mathbf{P}_{ij}\right]'$ and $\tilde{\mathbf{X}}_{ij} \equiv \left[\mathbf{x}_{i0}' \ \cdots \ \mathbf{x}_{i,T-1}' \ \mathbf{P}_{ij}\right]'$, with $\mathbf{P}_{ij}$ denoting the Cholesky factor of $\mathbf{M}_{ij}^{-1}$. Then, the posterior distribution of diagonal elements of $\mathbf{D}$ given $\mathbf{A}$ turns out to be $IG\ (\kappa_{ij}^*, \tau_{ij}^*)$. Finally, the posterior distribution for the jth row of $\mathbf{B}_i$ conditional on $\mathbf{D}$ is normal with mean and variance-covariance matrix equal to $\mathbf{m}_{i,j}^* = (\tilde{\mathbf{X}}_{ij}\tilde{\mathbf{X}}_{ij})^{-1}(\tilde{\mathbf{X}}_{ij}'\tilde{\mathbf{Y}}_{ij})$ and $\mathbf{M}_{ij}^* = (\tilde{\mathbf{X}}_{ij}\tilde{\mathbf{X}}_{ij})^{-1}$ respectively.

[16]In our application, the scalar parameter μ takes value on 1, consistent with the idea that foreign impact response is equally important to domestic impact response. In contrast, if we set $\mu = 0$, we will end up with a global model that provides same results of country-specific SVAR modes.

4 Empirical results

Although our empirical approach produces two set of results, coming from the estimation of the country-specific models and of the single global specification, we will mainly focus on the latter, as it includes all the information embedded into the former models, but also add role for interdependence. The difference between the two sets is given by the way interactions among countries are modeled. Since we model interdependence via *trade*, we can analyze how imports and exports act to mitigate or amplify the effects of climate shocks. In the rest of this Section we will focus on the impact and dynamic effects of temperature and precipitation shocks on economic activity growth.

4.1 Economic effects of climate shocks

4.1.1 Priors and posterior distributions of the contemporaneous structural parameters

Figure 1 and 2 show the prior and posterior distributions of the estimated model, referring to the parameter $a_{i,\mathcal{YT}}$. Whereas Figure 1 reports the countries for which we get a negative median, Figure 2 focuses on economies positively responding on impact to a temperature shock (in median). In all panels, the prior distribution we set are represented by the blue lines. The green, pink and orange histograms show different posterior distributions, specifically the green ones refer to the estimation of the global model in which interdependence is included ($\mu = 1$) and the $\mathbf{A}_i$ matrix is updated with information of the equilibrium impacts, as explained in Section 3.2, the pink one come instead from estimating the global model with $\mu = 1$ but without updating of $\mathbf{A}_i$ and the orange ones are associated to country-specific models, or equivalently to a global model in which we set $\mu = 0$. We report also the three median values for the posterior distributions, denoted with "Median 1", "Median 2" and "Median 3", representing the median values for

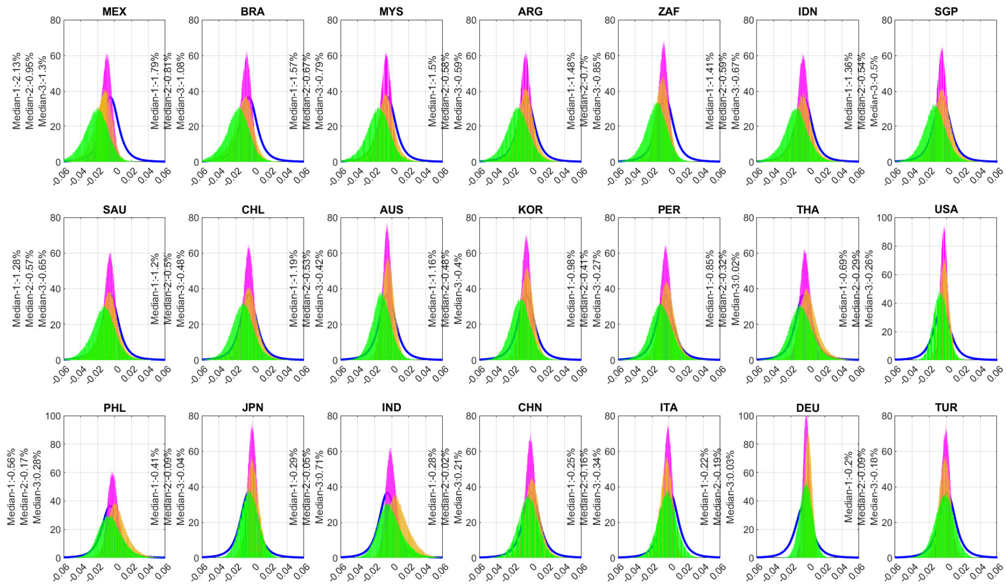


Figure 1: Prior and posterior distribution for the $a_{i,\mathcal{YT}}$ structural parameters: negative median responses

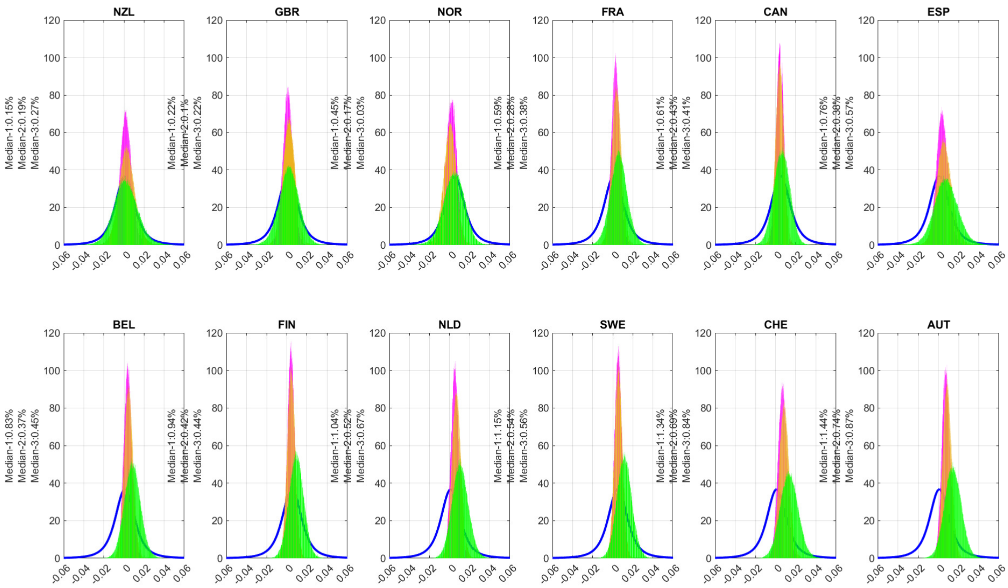


Figure 2: Prior and posterior distribution for the $a_{i,\mathcal{YT}}$ structural parameters: positive median responses

the green, orange and pink distributions, respectively. Figures 4 and 3 show the equivalent comparison between the prior and posterior distributions in different setups, but focusing on the instantaneous effect of precipitation on real GDP growth, captured by $a_{i,\mathcal{YP}}$.

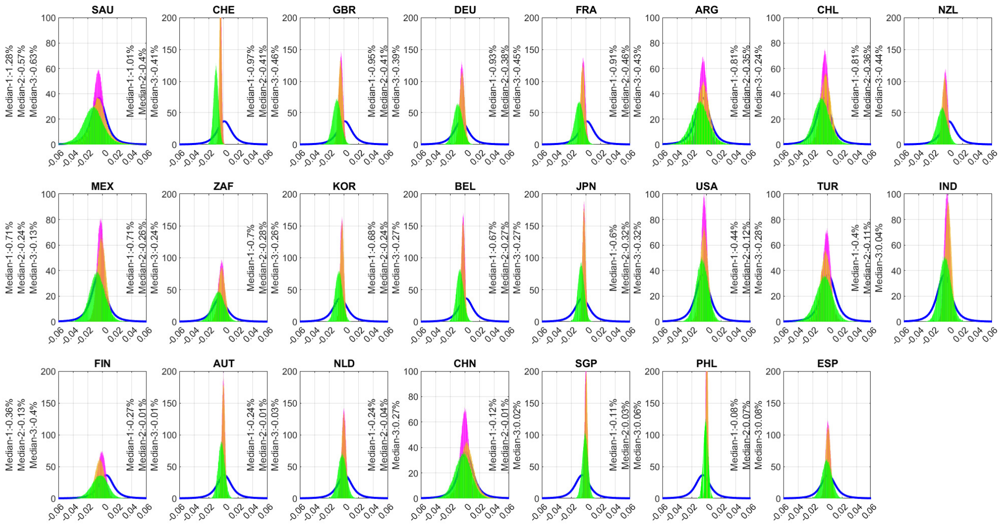


Figure 3: Prior and posterior distribution for the $a_{i,\mathcal{YP}}$ structural parameters: negative median responses

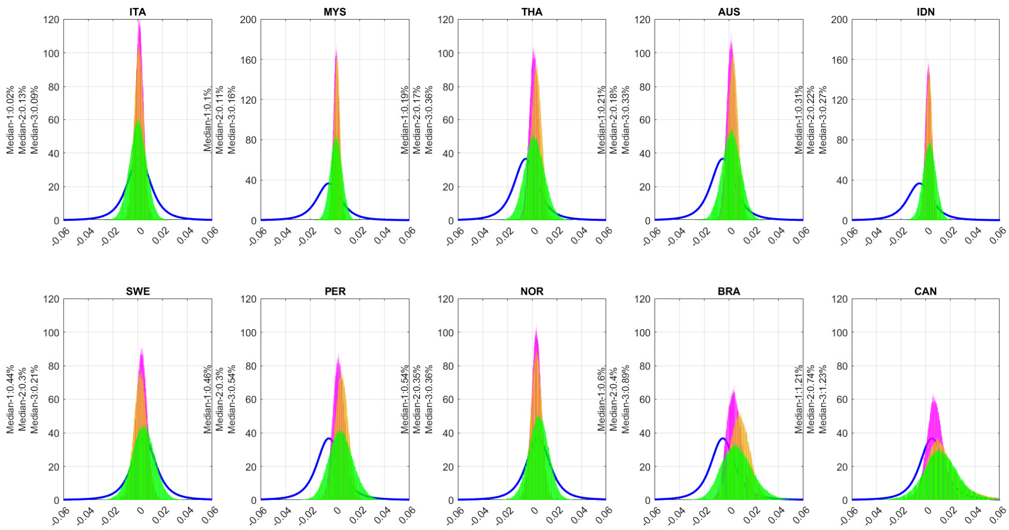


Figure 4: Prior and posterior distribution for the $a_{i,\mathcal{YP}}$ structural parameters: positive median responses

As shown by Figures 1, 2, 3 and 4, we get more countries overall negatively affected than positively from climate shocks, both in the case of a positive temperature or a positive precipitation shocks. Interestingly, by comparing the median value of the green posterior distributions with the medians for the orange distribution (that is, the model with $\mu = 1$ to the one with $\mu = 0$) we notice that trade may act as an amplifier of the climate effects in some countries, specifically those exhibiting the higher effects in magnitude, in absolute terms. This suggests that the trade openness is additionally detrimental because it helps spreading the adverse effects on the economies of climate shocks, whereas the (fewer) positively affected countries strengthen the benefic effects they get from increases in temperature and precipitation with import and export. We will further discuss the role of trade in the climate-economy relationship in Section 5. The remainder of this Section focuses on the results obtained via estimating the global model in which we allow for full interdependence setting $\mu = 1$.

4.1.2 Dynamic responses

Our estimation procedure allows to perform a structural dynamic analysis in a very natural way, to assess how climate affects economic activity through time. Figures 5 and 6 analyze the dynamic responses of GDP growth to temperature shocks at different time horizons, with countries divided among those reporting negative and positive effects on impact. The red lines and shaded areas represent the medians of the responses from the estimation of the global model and the credible regions comprehending the 68% of the distribution, respectively.

Conversely, Figures 7 and 8 focus on the impulse responses of countries' real GDP to a positive precipitation shock, again split between those exhibiting negative and positive impact responses.

The picture emerging from the analysis of the impulse responses splits countries for which the effect is rather uncertain or disappear rather quickly with those exhibiting a persistent significant effect that does not vanish after 5 years. One of the most important result we get is that countries with economic growth negatively affected by a temperature shock on impact also tend to be associated with a negative effect in the dynamics, whereas

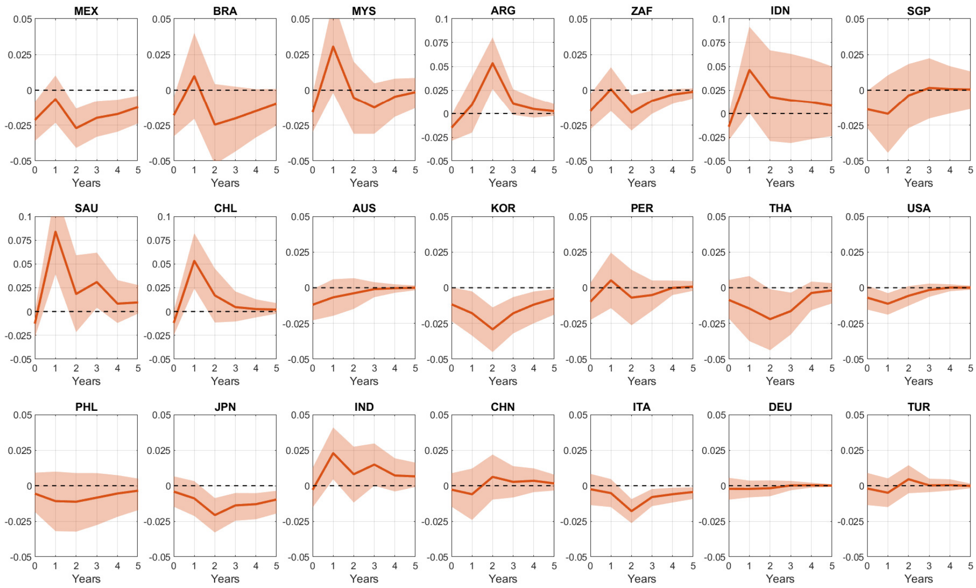


Figure 5: IRFs of real GDP growth to temperature shocks: on impact negatively affected countries

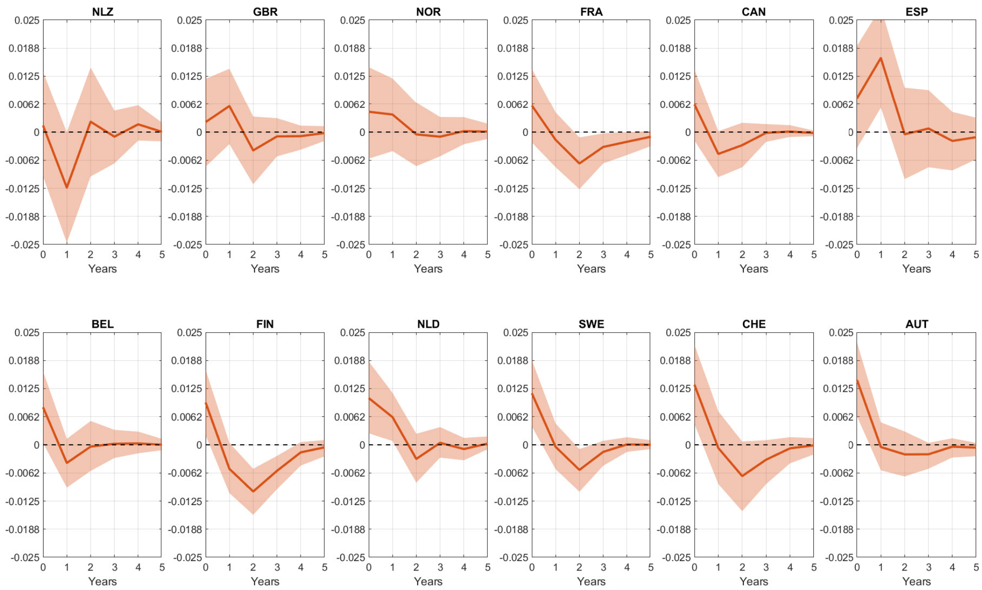


Figure 6: IRFs of real GDP growth to temperature shocks: on impact positively affected countries

on the contrary most countries whose economic growth contemporaneously benefit from a temperature shock are then exhibiting a negative effect in the long-run.[17] This finding is

[17]Some economies show a short-term "rebound effect", meaning they show a negative impact effect, then becoming positive after one year, and thereafter it dampens.

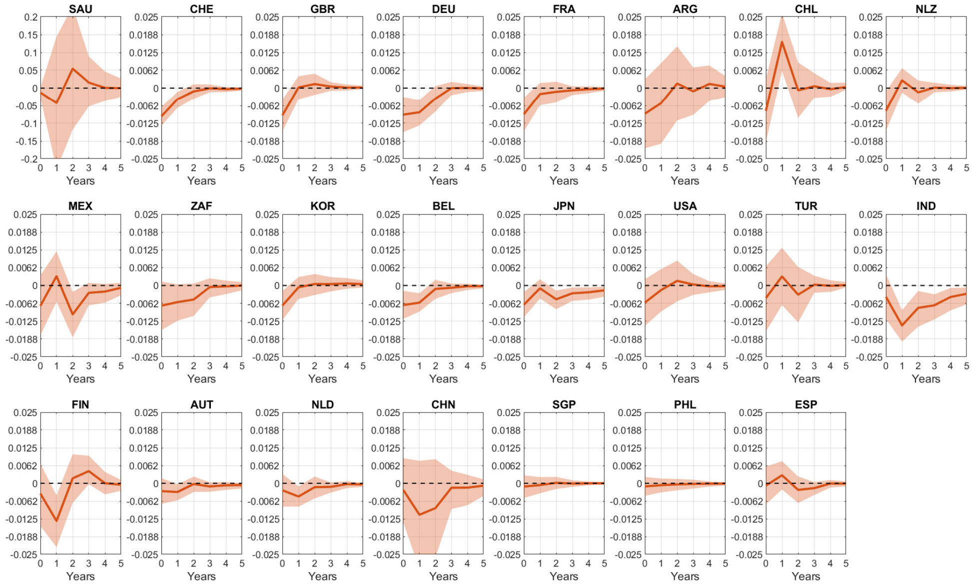


Figure 7: IRFs of real GDP growth to precipitation shocks: on impact negatively affected countries

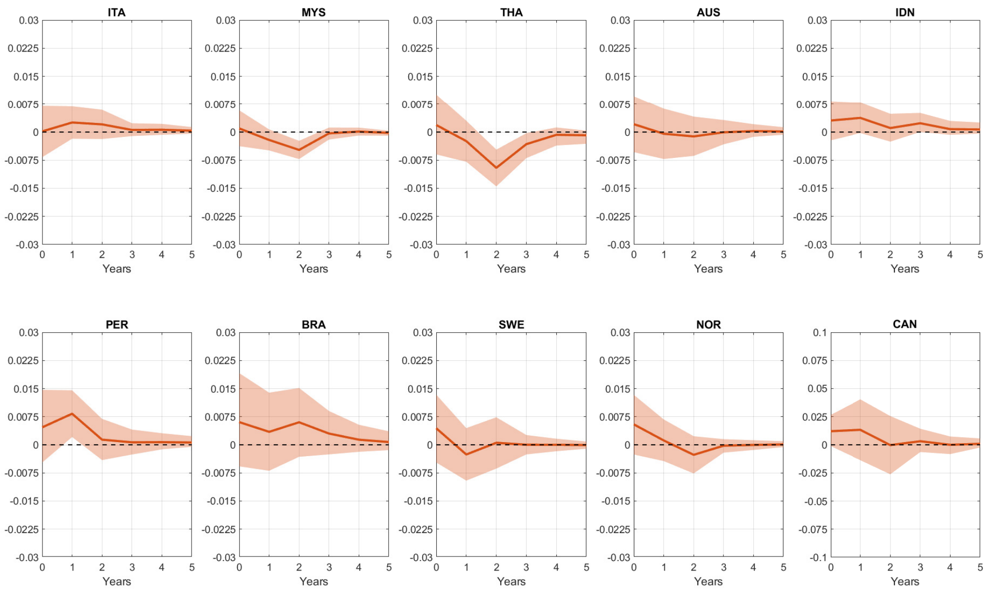


Figure 8: IRFs of real GDP growth to precipitation shocks: on impact positively affected countries

of paramount importance because it reveals that *all* economies are going to be negatively exposed to temperature increases, no matter what happens in the short-run: sooner or later, the detrimental effects of climate change hit the economic growth for the majority of the countries in our sample. By looking at the responses of GDP growth to precipitation shocks, the picture is similar, but the effects tend to be on average more stable in the dynamics (there is less evidence for rebound effects), and overall the shocks revert to zero after 5 years, suggesting rainfall shocks are more easily absorbed by economies than temperature increments.

Finally, uncertainty of the estimated effects needs to be considered. Whereas for some countries the responses of economic activity to climate shocks are estimated with small variability, for some others the mass of the distributions is much concentrated on the tails, suggesting the effect is estimated with more uncertainty. This could reflect the different characteristics of specific countries, as for example the multiple geographic conditions that may coexist in a single very extended country, as well as other considerations associated with the quality of data.

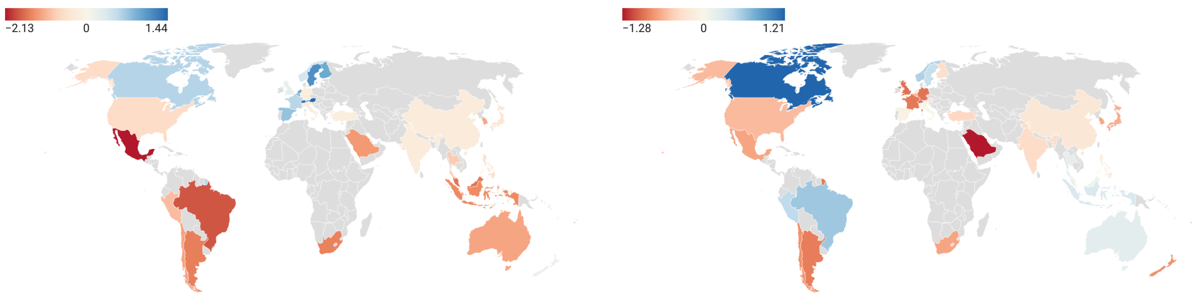
5 Discussion of the empirical evidence

In this Section we make some comparisons with the results obtained in the empirical studies on the climate-economy relationship, and we discuss our findings in order to draw a schematic picture of how climate effects are distributed among countries. Since our results can mostly be interpreted in relation to geographical and income dissimilarities among different economies and to the role of trade spillovers, we will focus on these two aspects.

5.1 Disentangling geographical and income heterogeneity

Both in case of temperature and precipitation shocks, as well as in terms of on impact and dynamic effects, it is not an easy task to identify regular patterns with respect to geographical or climate areas. The on impact responses to climate shocks are negative for the majority of countries, and the number of negatively affected economies is greater in the case of precipitation shocks. Following the literature, we have tried to identify some similar patterns by grouping countries according to the effects we have estimated. According to the majority of the empirical studies, temperature is expected to negatively affect economic performance at least in less developed countries and in hotter areas of the world. Our results, however, are mixed in both dimensions, that is hot vs cold regions and rich vs poor countries.[18] In our setup, clustering countries in specific groups, for instance using criteria such as geographical homogeneity or level of development, requires greater care and comes after estimation of the model.

Figure 9 reports the same information of the impulse responses at horizon 0, but allows to see in a more intuitive way how the effects we estimate are distributed in space. Figure



(a) Temperature shocks

(b) Precipitation shocks

Figure 9: Percentage effects at horizon 0 of climate shocks to real GDP growth from the global model

9a, interestingly, groups the positive impact effects of temperature shocks on economic growth only between part of Europe, Canada and New Zealand. The rest of the world is associated with economic losses from temperature shocks, or with effects indistinguishable from zero. Thus, not all the richer economies are positively affected by temperature

[18]We remind that in panel regression specifications, the overall effect regarding poor or rich (hot or cold) countries is obtained by splitting the sample among richer and poorer economies (hotter or colder areas) *before* the estimation.

shocks, but all the positively affected countries *are*, in facts, rich. The most adversely affected countries are Mexico and Brazil, located in the American continent. Conversely, the highest effects in magnitude are associated with cold European countries. Figure 9b shows that the most adverse effect of precipitation shocks is registered in Saudi Arabia, whose economic growth loss is estimated at -1.28%. Interestingly, Saudi Arabia is also the less rainy country of the sample (see Table 1). In general, we note that the starting rainfall conditions matter, in the sense that countries less exposed to rainfall are more adversely impacted by precipitation shocks. We explain this empirical evidence with the fact that countries with lower levels of rainfall have less capacity to face and to absorb unexpected precipitation shocks. On the opposite, we find Canada, with a +1.21% effect on real GDP growth. Interestingly, moreover, some countries are negatively (or positively) affected by both climate shocks, whereas some others are positively affected by one of the two shocks and negatively by the other, adding another difficulty in our clustering.

Nevertheless, some similarities between our results and the findings of other studies with a multi-country focus do emerge. Kahn et al. (2021) find an adverse effect of temperature shock on output growth in most of the countries, albeit to different degrees, without distinction between poor, rich, hot and cold countries. They argue that economic growth is affected not only by persistent increases in temperatures but also by the degree of climate variability. They point out the faster pace with which temperatures are rising in colder regions and argue that not only the temperature, but also its deviation from the historical norm, together with the climate conditions to which countries are accustomed, determine the size of income loss. Colacito et al. (2018), examining the US economy, find that the economic effects of rising temperature differs across states and highly depend on the industrial composition of each area. Therefore, the negative effect of higher temperatures is not necessarily linked with the predominance of the agricultural sector or with a lower level of income, as instead is generally suggested by the literature. Importantly, they find that the negative impact of temperature on GDP growth is more pronounced in the recent period, despite the advances in measures for adaptation.

As far as precipitations are concerned, it is well estabilished in the literature that low income countries are facing sharper effects with respect to rich countries,[19] and that the key channel for the transmission of the shock is agriculture. Our results are mixed in this respect, as there is no clear distinction in terms of income or agriculture shares.

5.2 The role of trade

To disentangle the role that trade plays in our results, we report the "foreign" posterior distribution of the model, that is, the posterior distribution associated with $\boldsymbol{H}_i^F$. These distributions are reported in Figures 10 and 11, in which we split countries associated with a negative or positive traded spillover for the temperature effect on economic growth. Figures 12 and 13 focus instead on trade spillover posterior distributions associated to a precipitation shock on economic activity.

In Figures 10, 11, 12 and 13 the blue lines represent the "prior" distributions and the green histograms the corresponding posterior distributions.[20]

By construction, the medians of these distributions represent the pure effect of trade spillovers, and we can order countries from the most negatively affected to the most

[19]See, for example, Damania et al. (2020), who explains, among other things, that the reason for which many studies fail to detect a significant role for precipitation in explaining economic output is given by the aggregation at a country level, since rainfall is much more heterogeneous from a spatial point of view with respect to temperature. However, it is worth noting that the relationship between rainfall and GDP is found to be concave, which may explain why for developed countries an additional unit of precipitation may be associated with negative economic growth.

[20]Notice that we do not impose a prior associated with spillovers in a proper sense. Conversely, the prior distribution of $\boldsymbol{H}_i$ is given by the sum of two components, namely the domestic and the foreign part for each country i. The prior for the trade spillover is simply obtained as the weighted average of domestic priors in all the other countries with the exception of the ith one.

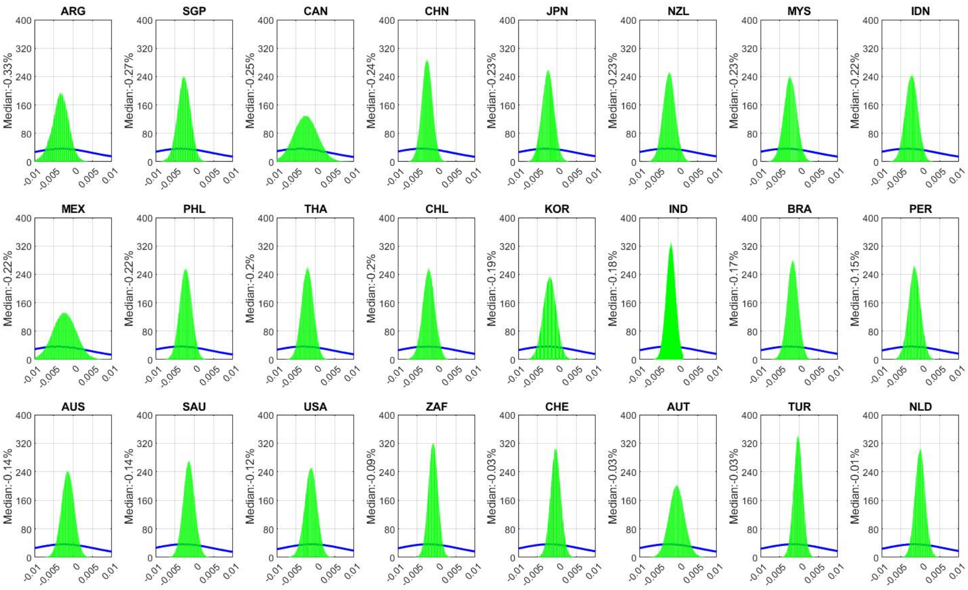


Figure 10: Impact of temperature shocks on real GDP growth coming from the foreign component; negative spillovers

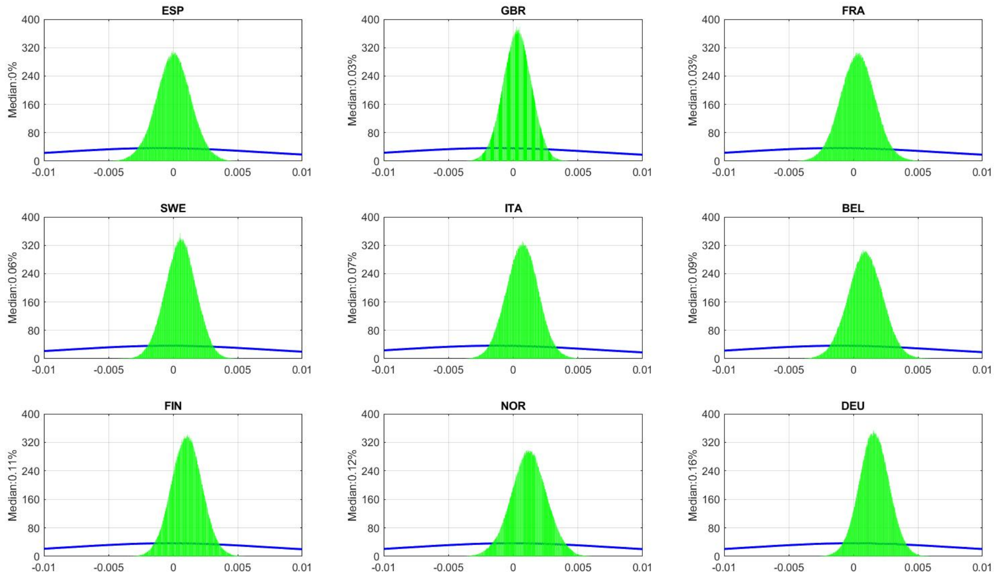


Figure 11: Impact of temperature shocks on real GDP growth coming from the foreign component; positive spillovers

positively affected by the inclusion of trade interdependence. For the majority of countries, namely 24 in the case of temperature shocks, and 31 in the case of precipitation ones, trade as a detrimental effect, whereas only few countries benefit from the inclusion of

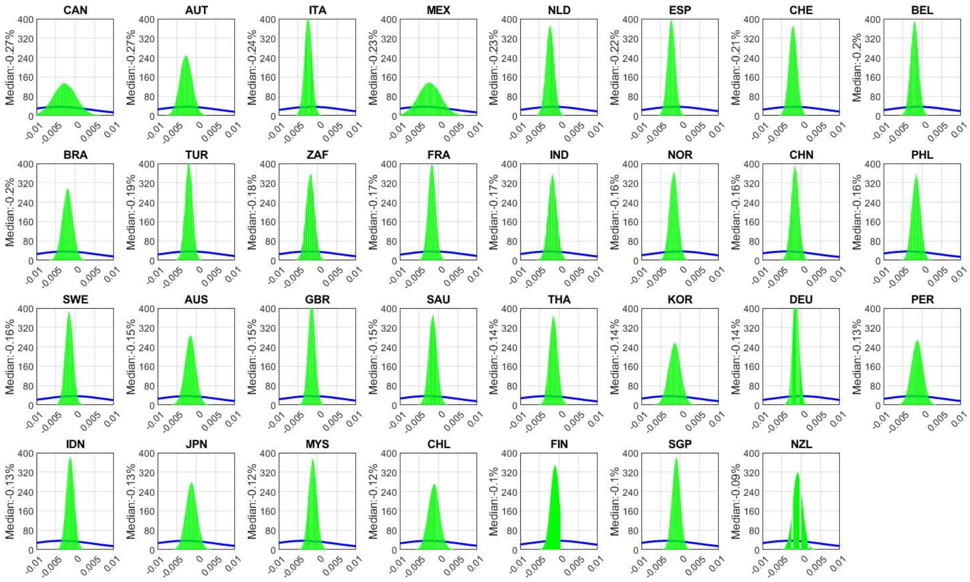


Figure 12: Impact of precipitation shocks on real GDP growth coming from the foreign component; positive spillovers

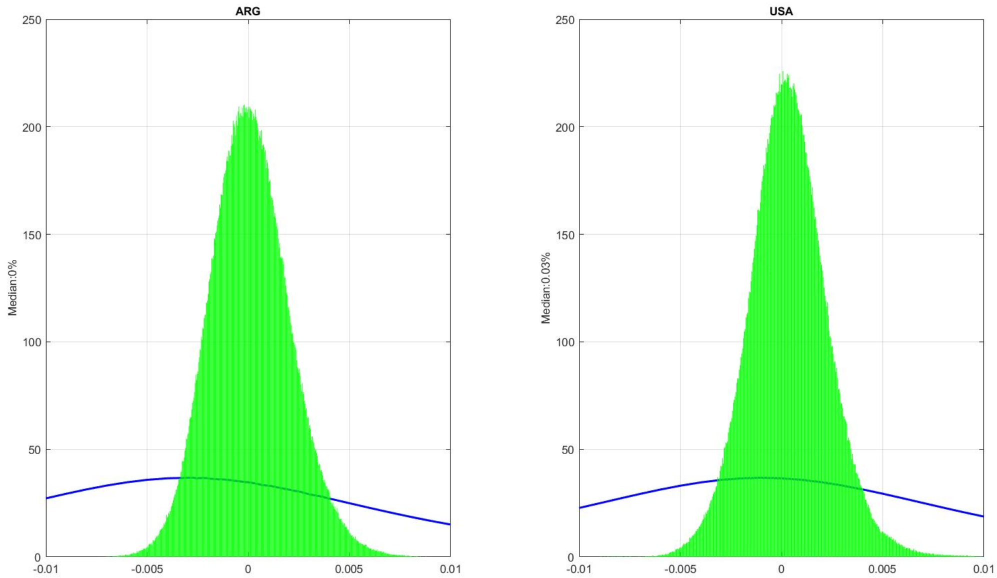


Figure 13: Impact of precipitation shocks on real GDP growth coming from the foreign component; negative spillovers

interdependence.

Focusing on the temperature shocks trade spillover, it is interesting to note that the few countries gaining from trade are located in Europe. However, not all the EU countries are associated with a positive trade spillover, so that this result must be handled with care and in order to make further considerations, additional analyses on this respect are necessary. Curiously, the spillover associated with precipitation shocks is always negative, apart for the two cases of Argentina and the United States. Finding regularities in the geographical distribution of the trade effects and understanding the different results we get is of paramount usefulness. Thus, these will be the focus of our forthcoming analyses.

6 Concluding remarks

We have studied the effects of climate shocks on real economic activity, both at country level and global setup. To perform our analysis, we have employed the BS-GVARX model to disentangle the net effect of temperature and precipitation shocks to real GDP growth, as well as the role of economic interdependence between countries.

Three are the novelties of our paper. First, the inclusion of a formal identification structure in a GVAR model. Second, the endogenization of the climate variables, temperature and precipitations. Third, the incorporation of economic interdependencies among countries.

Three main conclusions emerge from our analysis. First, we find evidence that climate and economic growth are mutually influenced, suggesting the importance of fully endogenizing of the system. Second, climate change plays a role both from local and global perspectives. Whereas the local aspects are usually highlighted by the literature, the focus on a global system, where climatic and economic interconnection is explicitly modeled, is a novelty. Third, accounting for the economic interdependence across countries, we find that, in response to the temperature and precipitation shocks, the majority of countries are overall negatively exposed to trade, suggesting that even if climate change may have different effects on economic growth at a local level, in a global perpective the interconnection among all the economies exacerbates the impacts of temperature and precipitation shocks.

Finally, we remark that the majority of countries are negatively affected in terms of economic growth when exposed to climatic shocks, if not immediately when the shock occurs, at least at a higher horizon. Climate change consequences may be severe and the effects of temperature and precipitation anomalies should be handled with care.

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