Economic Modelling 148 (2025) 107082

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

Climate shocks, economic activity and cross-country spillovers: Evidence from a new global model

Maryam Ahmadi [a], Chiara Casoli [b,c,*], Matteo Manera [d,c], Daniele Valenti [e,c]

[a] Rabobank, Utrecht, Netherlands
[b] InsIDE lab, Department of Economics (DiEco), University of Insubria, Varese, Italy
[c] Fondazione Eni Enrico Mattei (FEEM), Milano, Italy
[d] Department of Economics, Management and Statistics (DEMS), University of Milano-Bicocca, Milano, Italy
[e] Department of Management, Economics and Industrial Engineering (DIG), Politecnico di Milano, Milano, Italy

ARTICLE INFO

Dataset link: Codes and data: replication material of the article "Climate shocks, economic activity and cross-country spillovers: evidence from a new global model" (Original data)

JEL classification:
C11
C32
O44
Q51
Q54

Keywords:
Bayesian structural VARs
Identification
Global VARs
Climate shocks
Economic spillovers

ABSTRACT

This study investigates the impact of climate shocks on economic activity, addressing the gap in the literature of climate change economics. Using data covering a time span of 59 years, from 1960 to 2019, we employ a new global model to examine the effects of temperature and precipitation shocks on real output across 33 countries, accounting for more than 90% of the world's gross domestic product. Our analysis reveals that hotter and less-developed countries are more exposed to temperature shocks. Moreover, only some colder and more developed countries show a contraction of output in the medium-long run. Our results highlight trade interconnections as the main channel of propagation of climate shocks into the economic system. This study offers new insights into the transmission mechanism of climate shocks and suggests the adoption of climate policies at both global and local levels.

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 this century. However, the impact of climate shocks on economic activity is still unclear for some countries, including the majority of the most developed economies. Climate change can influence economic performance through various channels, including the destruction or degradation of ecosystems, damage to infrastructure, loss of human capital, reduced labor productivity, and increased macroeconomic instabilities (Bowen et al., 2012). The quantification of these effects is of paramount importance for policymakers to dampen the adverse economic implications of global warming.

In recent years, many econometric analyses have focused on assessing the relationship between climate variables and economic output. However, the different setups and methodologies adopted within this literature have led to very heterogeneous results, so 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).

In this article, we present new evidence on how climate shocks affect economic activity across different regions of the world. Our analysis focuses on 33 countries over a 59 year period (1960–2019). Specifically, we disentangle the direct effects of temperature and precipitation shocks on real GDP from spillover effects transmitted through cross-country trade. In fact, cross-country interdependence redistributes climate impacts across regions (see e.g. Jones and Olken, 2010; Kemfert et al., 2004; Reilly and Hohmann, 1993).

* Correspondence to: Fondazione Eni Enrico Mattei, Corso Magenta 63, 20123 Milan, Italy.
E-mail address: chiara.casoli@feem.it (C. Casoli).

https://doi.org/10.1016/j.econmod.2025.107082
Received 2 June 2024; Received in revised form 14 March 2025; Accepted 17 March 2025
Available online 25 March 2025

To capture climate's causal impact on economic activity while incorporating trade spillovers and feedback effects, we develop a novel Bayesian Structural Global Vector Autoregressive model (BS-GVARX) and provide new insights into the economic effects of climate shocks across world regions.

The literature on climate impacts on economic activity is rapidly evolving and highly heterogeneous in the variable selection, geographical focus, and modeling design. This diversity leads to varying findings, with few common conclusions.

From a methodological perspective, many studies rely on panel data models, reflecting the view that climate change impacts vary across space and exacerbate existing income disparities.

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, most of the panel data models proposed on this topic lack proper structural dynamics to describe the propagation of climate shocks through time.[1] On the contrary, structural models allow for an explicit identification of the shocks and provide a very useful tool to study climate effects dynamically. Second, climate variables entering panel specifications as regressors are considered fully exogenous with respect to the dependent variable. Since, as pointed out by Pretis (2020) and Pretis (2021), economic and environmental systems are determined with a feedback in both directions, it is crucial to endogenize climate variables. The feedback between climate and economic activity is also considered in Chen et al. (2024) and by Ciccarelli and Marotta (2024). Third, heterogeneity among different countries in their responses to structural climate shocks is hard to capture via panel data regressions. 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.[2] Fourth, another important aspect which is not systematically addressed within the climate panel data literature is the economic interdependence among countries. As argued in Di Mauro and Pesaran (2013), macroeconomic policy analysis requires to take into account the interconnections across different economic systems, where trade is one of the main channels driving the spillover effects. Countries 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 the endogeneity of climate, identifying structural climate and economic shocks within a dynamic context and, at the same time, considering economic interdependence across different countries are demanding tasks from a methodological point of view. We face these challenges by introducing a new BS-GVARX model, that extends the Global Vector Autoregressive (GVAR) approach proposed by Pesaran et al. (2004).

The standard GVAR model describes interconnections among country-specific economic systems in a global perspective. Although climate change represents a global phenomenon, several features are related to country-specific dynamics, because the intrinsic climate conditions and their effects on economic output are geographically heterogeneous. The classical GVAR model is designed specifically to capture the domestic characteristics of different economies and to simultaneously include interlinkages among the countries under scrutiny. Hence, this model represents the natural way of describing the climate-economy relationship. The standard GVAR model is based on two steps. The first step deals with the estimation of separate, country-specific VAR models with exogenous variables (VARX), 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. This requires to incorporate the estimated country-specific coefficients associated to foreign variables within the global matrix of parameters, thus preventing the estimation of the large global model. It is worth noting that the canonical GVAR is a reduced form specification, that is there is no structural estimation in the second step.[3]

With the idea of extending this framework, we propose a new BS-GVARX model, based on the algorithm developed by Baumeister and Hamilton (2015), that allows to identify the causal effects of climate shocks on economic performance. Our structural approach brings to several advantages and can be extended to a variety of applications accounting for dynamic multi-country analysis and cross-country interdependence. The BS-GVARX model is designed to allow for a fully structural interpretation of the shocks, that is, to capture causal relationships among variables.

The main idea behind our BS-GVARX model can be synthetized as follows. First, we perform a structural analysis where the country-specific VARX models are nested in a single global specification, which can be directly estimated. Second, identification of the global model via equilibrium impacts allows us to preserve a mapping between the reduced form and the structural form of the model. Third, the identification of the global structural parameters exploits the interdependence across countries by considering joint prior information derived through the impact multipliers of the country-specific structural shocks. This framework explicitly allows for spillover effects without the use of any data shrinkage approach and provides a solution for the dimensionality issue of large VARs. To our knowledge, this paper is the first embedding a Bayesian fully structural dynamic analysis in a GVAR and one of the few examples employing a GVAR model to study the climate-economy relationship (see e.g. Cashin et al., 2017, for GVAR models with climate and economic variables).

Our findings can be summarized in three main points. First, for most of the countries showing a positive contemporaneous economic effect after an unexpected temperature increase, the responses become negative or negligible in the subsequent periods. Second, the adverse economic effects from positive temperature shocks are highly correlated with higher shares of agriculture on total GDP and in a lesser extent with lower levels of economic development. In contrast, less precise regularities across countries are found in the estimated effects from precipitation shocks, but countries with higher shares of agriculture over total output are associated with positive economic responses to precipitation shocks. Finally, spillovers play a detrimental role for almost all countries. The interdependence effects depend on the country-specific trade structure, consisting in the trade partners network and the mix of exported and imported products.

The rest of the paper is structured as follows. Section 2 provides an overview of the literature about the effects of climate change on economic output. Section 3 describes the data and the countries included in the analysis. Section 4 explains the methodology and introduces the BS-GVARX model. Section 5 presents the empirical results, which are discussed in Section 6. Section 7 assesses the robustness of our findings by proposing two alternative model specifications and focusing on the climate effects on agriculture and the manufacturing sector. Section 8 concludes.

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

[2] In general, rich economies are also located in colder regions. The debate on whether poor countries are less developed *because* they are hot is still ongoing.

[3] Given that formal identification is not contemplated, the dynamic analysis is usually performed through the Generalized Impulse Response Functions (GIRFs). The GIRF approach considers a counterfactual exercise where the historical correlations of the shocks are assumed as given. GIRFs are independent of the variables order, because they integrate the effects of other shocks out of the response, and are useful in the case of large systems, where structural relationships are hard to identify. However, GIRFs cannot be interpreted as structural impulse responses (Pesaran and Shin, 1998).

2. Literature review

A large part of the literature on climate impacts on economic systems is based on regression models, where the outcome variable is a proxy of economic activity, chosen in general among GDP, in levels or growth rates (Dell et al., 2012; Burke et al., 2015; Newell et al., 2021), Total Factor Productivity (Letta and Tol, 2019), agricultural output (Deschênes and Greenstone, 2007; Auffhammer and Schlenker, 2014; Blanc and Schlenker, 2020), firms access to credit (Lai et al., 2022), efficiency at firm level (Agostino et al., 2025) and conflicts (Conigliani et al., 2024).[4]

In the choice of climate variables, some studies examine extreme events, such as droughts, floods or hurricanes (see e.g. Botzen et al., 2019), some contributions consider El Niño climate patterns (e.g. Cashin et al., 2017; Dufrénot et al., 2024), whereas others focus on weather variations proxied by temperature and precipitation (see Dell et al., 2014; Damania et al., 2020; Newell et al., 2021). Kahn et al. (2021) model climate variations around long-term trends, which capture temperature and precipitation anomalies that can be thought as technologically neutral (i.e. if climate variables do not deviate with respect to their historical norms, there should be no effect on productivity). As for the geographical focus, the literature can be split between cross-country analyses (e.g. Cashin et al., 2017; Pretis et al., 2018; Acevedo et al., 2020; Kalkuhl and Wenz, 2020; Kahn et al., 2021) and country-specific studies (e.g. Deschênes and Greenstone, 2007; Sheng et al., 2022).

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; Kahn et al., 2021) and a third group of studies does not find a statistically significant effect for cold and rich countries (Dell et al., 2012; Newell et al., 2021). In the majority of these cases, the relationship between climate and economic activity is stronger in the case of temperature, whereas the effect of precipitation is less clear (Damania et al., 2020, are among the few quantifying a relevant and significant role for precipitation shocks).

There is broad consensus that higher temperatures, increased precipitation, and more extreme weather events significantly impact economic performance. Climate-economy analyses are crucial for assessing the economic costs of current and future climate damages, quantifying climate risks, and developing targeted mitigation and adaptation policies (see Dell et al., 2014).

As previously mentioned, climate shocks do not affect all economies equally, with low-income and hotter countries experiencing the most severe impacts (Burke et al., 2015; Dell et al., 2012; Kalkuhl and Wenz, 2020). This is particularly concerning from a policy perspective, as developing countries not only suffer greater economic losses but must also allocate significant resources to climate policies. This dynamic exacerbates income inequality and increases exposure to climate risk. Additionally, as noted by Kumar and Mallick (2024), climate shocks can disrupt oil supply chains, leading to volatile energy prices. Given the oil market's role in global production and trade, some economies face both direct climate shocks and indirect shocks through fluctuating energy costs.

Effective climate policies must balance adaptation and mitigation efforts to limit climate-induced income disparities and equitably distribute policy costs across countries. As highlighted in Kotsogiannis and Woodland (2025), financial transfers from developed to developing nations could help offset adverse climate effects and trade spillovers.

Moreover, low-income countries not only bear the burden of climate-related economic losses but also face high mitigation costs, which can further slow development (Taconet et al., 2020). This pattern reinforces global income inequalities, as confirmed by Diffenbaugh and Burke (2019), who find that poorer countries suffer the most from global warming while wealthier economies are more resilient. Similarly, Rezai et al. (2018) document that climate damage negatively impacts the evolution of the economy in the long-run and reduces the potential income level. Fankhauser and Tol (2005) further emphasize that countries negatively affected by climate change reduce investments, leading to lower capital accumulation and future economic outcome.

Addressing these disparities is critical. As Bowen et al. (2012) argues, economic growth, especially through investments in skills and financial access, can reduce vulnerability to climate change in developing nations. This highlights the need for an accurate quantification of climate damages to design effective policy strategies.

Since countries face diverse climatic and economic conditions, aggregate analyses may fail to capture country-specific climate effects on economic activity. Our multi-country structural analysis estimates the economic effects of temperature and precipitation shocks across a broad set of countries, providing crucial insights for designing tailored climate policies.

3. Data description

We perform our analysis relying on macroeconomic and climate data for 33 countries included in the classical GVAR framework, as illustrated in Mohaddes and Raissi (2020), which account for more than 90% of global GDP and cover all the geographical regions of the world. The sample considers economies at different stages of development and with heterogeneous climatic conditions, as reported in Table 1. Since in most of the relevant studies the impacts are less clear for rich and cold areas, the focus on this particular sample of countries, including several developed economies, is of paramount interest. For each country, our analysis covers 59 years, spanning from 1960 to 2019.

For each country, we consider three endogenous domestic variables, namely temperature ($\mathcal{T}_{it}$), precipitation ($\mathcal{P}_{it}$) – both expressed as long-run deviations from the norm – and real GDP growth ($\mathcal{Y}_{it}$), at annual frequency. Temperature and precipitation variables are mostly used within the climate econometrics literature, as they are directly observable and available at a very granular and high-frequency level. We focus on temperature and precipitation data to make our findings directly comparable to the majority of empirical works investigating the effects of climate variables on economic activity.[5] Real GDP is used because it is the most relevant measure of economic output and it is widely employed in other climate-economy applications.[6]

The two climate variables are expressed as anomalies with respect to their long-run behaviors (climatologies) to take into consideration the difference between weather realizations and long-term climate change-driven dynamics. Climatologies are usually computed as simple or moving averages of monthly values over a period of reference. Anomalies are simply the differences between the observed temperature (precipitation) monthly values and the corresponding monthly climatology. In this work, we focus on anomalies with respect to 30 year moving averages, to account for a time variation in the cli-

[4] Another growing strand of literature focuses on the relationship between energy price shocks and climate change (see e.g. Blanz et al., 2025; Kumar and Mallick, 2024; Salisu et al., 2024).

[5] As highlighted in Dell et al. (2014), it is important to include both temperature and precipitation in the model, because their correlation tends to vary by region. Therefore, avoiding to consider one of the two may result in an omitted variable bias.

[6] As a robustness check, we investigate the effects of climate shocks on the decomposition of the aggregate output into agriculture and manufacture value added (see Section 7).

Table 1
Countries in the BS-GVARX model.

	Income classification	Structure of output				Climate condition	
	Income	Agriculture (% of GDP)	Industry (% of GDP)	Services (% of GDP)	Economic complexity index	Mean annual temperature (1991–2020)	Mean annual precipitation (1991–2020)
Asia and Pacific							
Australia	High	2	25.5	72.5	−0.52	22.1 °C	482 mm
China	Upper-Middle	7.7	37.8	54.5	1.3	7.4 °C	611 mm
India	Lower-Middle	18.3	23.5	58.2	0.42	na	na
Indonesia	Lower-Middle	13.7	38.3	48	−0.07	26.1 °C	2857 mm
Japan	High	1	28.7	70.3	2.27	11.3 °C	1658 mm
Korea	High	1.8	32.6	65.6	1.95	11.4 °C	1395 mm
Malaysia	Upper-Middle	8.2	35.9	55.9	1.12	25.7 °C	3136 mm
New Zealand	High	5.7	20.4	73.9	0.17	10.2 °C	1770 mm
Philippines	Lower-Middle	10.2	28.4	61.4	0.84	25.8 °C	2461 mm
Singapore	High	0	24.4	75.6	1.87	27.6 °C	2254 mm
Thailand	Upper-Middle	8.6	33.1	58.3	1.11	26.8 °C	1550 mm
North America							
Canada	High	1.7	24.6	73.7	0.57	−4.2 °C	533 mm
Mexico	Upper-Middle	3.8	29.7	66.5	1.22	21.4 °C	759 mm
United States	High	0.9	18.2	80.9	1.47	9.5 °C	722 mm
South America							
Argentina	Upper-Middle	5.9	23.3	70.8	−0.22	14.9 °C	590 mm
Brazil	Upper-Middle	5.9	17.7	76.4	0.03	25.6 °C	1756 mm
Chile	High	3.9	31.4	64.7	−0.24	9.0 °C	530 mm
Peru	Upper-Middle	7.5	30.5	62	−0.83	19.8 °C	1542 mm
Middle East and Africa							
Saudi Arabia	High	2.6	41.4	56	0.62	25.5 °C	76 mm
South Africa	Upper-Middle	2.5	23.4	74.1	−0.15	18.3 °C	456 mm
Europe							
Austria	High	1.1	25.5	73.4	1.7	7.2 °C	1211 mm
Belgium	High	0.6	19.5	79.9	1.13	10.7 °C	886 mm
Finland	High	2.5	24	73.5	1.4	2.7 °C	559 mm
France	High	1.6	16.4	82	1.29	11.7 °C	838 mm
Germany	High	0.7	26.5	72.8	1.96	9.6 °C	711 mm
Italy	High	2	21.6	76.4	1.34	12.9 °C	879 mm
Netherlands	High	1.6	17.8	80.6	0.99	10.4 °C	791 mm
Norway	High	1.8	26	72.2	0.69	2.1 °C	1153 mm
Spain	High	3.1	20.4	76.5	0.77	14.0 °C	596 mm
Sweden	High	1.4	21.1	77.5	1.59	3.0 °C	664 mm
Switzerland	High	0.7	25.2	74.1	2.14	6.1 °C	1632 mm
Turkey	Upper-Middle	6.7	28	65.3	0.63	11.7 °C	577 mm
United Kingdom	High	0.6	17	82.4	1.54	9.1 °C	1198 mm

Notes: data sources are World Bank's World Development Indicators and Climate Knowledge Portal. 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 the difference between total and combined shares of Agriculture and Industry. The Economic Complexity Index is developed by Harvard University and takes higher values for countries with larger export and more diversified complex products (https://atlas.cid.harvard.edu/rankings). Mean annual temperatures and precipitation are not available (na) for India.

mate variables.[7] As argued in Kahn et al. (2021), the computation of anomalies 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 $t = 1, \ldots, T$ denotes the time index. We collect climate data, provided by the World Bank Climate Knowledge Portal, from 1960 to 2019, and compute $\mathcal{T}_{it}$ and $\mathcal{P}_{it}$. Specifically, we express $\mathcal{T}_{it}$ and $\mathcal{P}_{it}$ as the difference between the observed temperature and precipitation at time t and the respective backward-looking 30 year moving average at time $t-1$.[8] 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.[9]

One feature of GVAR models is the inclusion of foreign variables, capturing the interconnections between each country and the rest of the world. In general, foreign variables are considered as weakly exogenous and constructed as weighted averages of all the other countries' endogenous variables. Since real GDP growth ($\mathcal{Y}_{it}$) is the only economic variable in our model, we define only one foreign exogenous variable computed as $x^*_{it} = \sum_{\imath \neq i} \omega_{i\imath} \mathcal{Y}_{\imath t}$, where each $\omega_{i\imath}$ is an element of a trade matrix, as proposed in Dees et al. (2007) and Chudik and Pesaran (2016).[10]

Specifically, $\omega_{i\imath} = \frac{T_{i\imath}}{T_i}$, where $T_{i\imath}$ is the bilateral trade of country i with country $\imath$, computed as the sum of exports and imports, and T_i is

[7] A wide set of climate institutions and data providers suggest to consider climate variables expressed as anomalies. Examples include the NOAA monitoring and indices construction (see https://www.ncei.noaa.gov/access/monitoring/global-temperature-anomalies/anomalies) and the IEA Weather, Climate and Energy Tracker (see https://www.iea.org/data-and-statistics/data-tools/weather-for-energy-tracker?tab=Weather+for+energy+tracker).

[8] Data available from https://climateknowledgeportal.worldbank.org/download-data.

[9] Data available from https://www.rug.nl/ggdc/productivity/pwt/.

[10] Alternative approaches consider geographical or economic proximity to construct weights (see e.g. Mastromarco et al., 2016). This weighting scheme based on contiguity is appealing to model interconnections of climate variables, however we prefer to focus only on economic spillovers, since they represent the main interest of our analysis.

the total trade of country i. All weights are constructed for each year of the selected period and their simple average is computed. Including local cross-sectional weighted averages of $\mathcal{Y}_{it}$ helps to deal with the omitted variable bias in the form of unobserved common shocks that may affect the endogenous variables of the model (see Chudik and Pesaran, 2011). Note that, as in Chudik et al. (2021), the foreign variable enters in our model with one lag. This mitigates the potential problem of high correlation between the domestic real GDP growth variable ($\mathcal{Y}_{it}$) and the foreign variable (x^*_{it}).

4. Methodology

We propose a Bayesian Structural Global VARX (BS-GVARX) model that encompasses a standard GVAR framework within a Bayesian identification structure. The classical GVAR model is not designed for a fully structural analysis, for two main reasons. First, global reduced-form parameters are not estimated, rather derived from a re-parametrization of the first-step estimated coefficients, using a link matrix defined in terms of the country-specific weights. Second, the solution of the global model depends on how static and dynamic interdependence are taken into account within the country-specific analysis. In case of static interdependence, the global vector of reduced-form residuals is obtained using a linear combination of the residuals from the estimation of the country-specific VARX models and the interlinkages.[11]

We depart from the existing structural GVAR approaches (e.g. Eickmeier and Ng, 2015; Mohaddes and Pesaran, 2016; Feldkircher and Huber, 2016; Cuaresma et al., 2019), where the identification of the shocks is based on the solution of the model. In contrast, the main contribution of our work on the GVAR literature is to fully estimate the global specification. In particular, we are able to provide a structural interpretation of the model without "endogenizing" the foreign variables in the global specification, under a Bayesian perspective. In other words, our structural analysis nests country-specific models in a single global specification. For the country-specific analysis, a Structural VARX (SVARX) model of each country is estimated. Then, all local models are stacked to form one large global system. At this point, the identification of the structural shocks is 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. The interdependence is modeled via the impact multiplier matrix at the global level, which is defined as the inverse of the matrix of contemporaneous structural coefficients. As pointed out in Baumeister and Hamilton (2021), it is possible to incorporate the prior beliefs in both matrices. The contemporaneous matrix of coefficients embeds information about elasticities, policy rules or behavioral relationships from economic theory. Moreover, we inform the model about cross-country spillovers via the impact multiplier matrix, which is often preferred from a policy perspective, as it describes the responses of country-specific variables to global shocks. The idea of modeling the economic spillovers between different countries through the equilibrium impacts of structural shocks allows us to deal with the curse of dimensionality and to preserve a clear mapping from structural to reduced-form parameters of the BS-GVARX model.[12]

[11] The interlinkages are measured as the product of the trade weights and the coefficients associated to 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 are estimated in the first stage.

[12] In this context, the curse of dimensionality refers to the fact that any cross-country spillover directly modeled would result in an additional parameter to estimate.

4.1. The BS-GVARX model

Considering the vector of endogenous variables, $\mathbf{y}_{it}$, and the exogenous foreign variable x^*_{it}, the SVARX model for a generic country i is given by:

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

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-specific and foreign variables, that is $\mathbf{x}'_{it-1} \equiv \left[\mathbf{y}'_{it-1}, \mathbf{y}'_{it-2}, \dots, \mathbf{y}'_{it-l}, 1, x^*_{it-1}\right]'$ and $\mathbf{B}_i \equiv \left[\mathbf{B}_{i1}, \mathbf{B}_{i2}, \mathbf{b}_{i0}, \mathbf{c}_i\right]$ a $k_i \times (lk_i+2)$ matrix of structural coefficients.[13] 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 relationships between foreign and the country-specific variables. The vector of structural shocks $\mathbf{u}_{it} \equiv \left[u_{i,1t}, u_{i,2t}, u_{i,3t}\right]'$ is assumed to be normally distributed with zero mean and diagonal variance–covariance matrix $\mathbf{D}_i$.

The structural representations of (1) can be expressed as:

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

where $\mathbf{b}'_{ij}$ contains all structural coefficients on the lagged variables of the jth equation and corresponds to the jth row of $\mathbf{B}_i$. The contemporaneous structural parameters and the imposed exclusion restrictions are further discussed in Section 4.2. The three different country-specific structural shocks are defined as: (i) a positive temperature shock $u_{i,1t}$, expressing an unexpected change in a given country's temperature anomaly of 1°C; (ii) a precipitation shock $u_{i,2t}$, denoting a positive shift of 100 mm in country-specific precipitation anomalies; (iii) an economic activity shock $u_{i,3t}$, associated with a 1% unexpected increase in domestic real GDP growth.

The structural global model stacks all single-country SVARX specifications as follows:

$$\underbrace{\begin{bmatrix} \mathbf{A}_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}_N \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} \mathbf{y}_{1t} \\ \mathbf{y}_{2t} \\ \vdots \\ \mathbf{y}_{Nt} \end{bmatrix}}_{\mathbf{y_t}} = \underbrace{\begin{bmatrix} \mathbf{B}_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{B}_N \end{bmatrix}}_{\mathbf{B}} \underbrace{\begin{bmatrix} \mathbf{x}_{1t-1} \\ \mathbf{x}_{2t-1} \\ \vdots \\ \mathbf{x}_{Nt-1} \end{bmatrix}}_{\mathbf{x_{t-1}}} + \underbrace{\begin{bmatrix} \mathbf{u}_{1t} \\ \mathbf{u}_{2t} \\ \vdots \\ \mathbf{u}_{Nt} \end{bmatrix}}_{\mathbf{u_t}} \tag{3}$$

We estimate model (3) using the methodology proposed by Baumeister and Hamilton (2015) and extended in Baumeister and Hamilton (2019) (thereafter BH), which relies on Bayesian inference for set-identified SVAR models. Note that the BH algorithm directly estimates the structural form of the model and does not require the estimation of the reduced form model.

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 $\mathbf{B}$; the variances of the structural shocks $\mathbf{D}$.[14] Information on $\mathbf{H}$ is directly added in $p(\mathbf{A})$, by means of a

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

[14] The BH identification algorithm accommodates any type of prior distribution 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. Priors information for the other coefficients, denoted by $p(\mathbf{D}|\mathbf{A})$

composite prior, as illustrated in Section 4.3. The second step relies on sampling S = 3 million draws on the set $\{\mathbf{A}, \mathbf{D}, \mathbf{B}\}_{s=1}^{S}$, 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. Finally, we generate draws of the structural shocks and of the lagged structural parameters from posterior distributions $p(\mathbf{D}|\mathbf{A}, \mathbf{Y}_T)$ and $p(\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y}_T)$.[15]

4.2. The simultaneous climate-economy relationship

We use the following recursive specification for $\mathbf{A}_i$ to identify the structural shocks of interest:

$$\mathbf{A}_i = \begin{bmatrix} 1 & 0 & 0 \\ -a_{i,\mathcal{PT}} & 1 & 0 \\ -a_{i,\mathcal{YT}} & -a_{i,\mathcal{YP}} & 1 \end{bmatrix}. \tag{4}$$

The structural matrix $\mathbf{A}_i$ implies that temperature anomalies influence precipitation within the year, through the parameter $a_{i,\mathcal{PT}}$, while the opposite is not true. Moreover, real economic growth is simultaneously affected by both temperature and precipitation through the parameters $a_{i,\mathcal{YT}}$ and $a_{i,\mathcal{YP}}$.

We impose three exclusion restrictions on the elements of matrix (4), that is $a_{i,\mathcal{TP}} = a_{i,\mathcal{TY}} = a_{i,\mathcal{PY}} = 0$.

The first exclusion restriction implies that the instantaneous relationship between the two climate variables is asymmetric. This choice reflects, on the one hand, the information available from climatic studies, and, on the other hand, the necessity of reducing model uncertainty.[16] Specifically, temperature and precipitation are related via the dependence on the atmospheric moisture. It is generally recognized that higher temperature is associated with an increase in average precipitation at a global scale. Conversely, increasing rainfall is expected to affect surface water availability, winds, ocean currents, evaporation and humidity. However, it is less clear if these factors would in turn cause an increase or decrease in temperature. In other words, the effect of precipitation on temperature is less direct and difficult to disentangle. The climate literature typically indicates that the correlation between precipitation and temperature is negative during summers and positive during cool months, at least at higher latitudes (see e.g. Trenberth and Shea, 2005). The rationale is that drier summers result in warmer temperature, whereas winters affected by heavier precipitation are also colder. Therefore, it is reasonable to expect that the two opposite seasonal effects should compensate within the year. We conclude that restricting $a_{i,\mathcal{TP}}$ to zero is plausible and realistic when modeling the effect of precipitation on temperature at an annual frequency.

Additionally, the other two exclusion restrictions imply that feedbacks from economic activity to the two climate variables occur after some time. Note that these assumptions do not prevent economic growth to influence temperature and precipitation, but this influence is distributed over a longer horizon. A similar assumption is made by Kim et al. (2022) and Ciccarelli and Marotta (2024), as they stress that economic growth is unlikely to immediately affect weather conditions. This is consistent with the fact that the link between economic activity and global warming is related with cumulative carbon emissions rather than current emissions (Frölicher and Paynter, 2015).

4.3. Prior information about the contemporaneous structural parameters

The marginal prior distribution of the global matrix $\mathbf{A}$, denoted by $p(\mathbf{A})$, is:

$$p(\mathbf{A}) = \prod_{i=1}^{N} p(\mathbf{A_i})p(h_1)p(h_{i2}^{\star}). \tag{5}$$

Therefore, the joint prior distribution of $\mathbf{A}$ is obtained as the product of all country-specific priors for $\mathbf{A}_i$, the prior for the determinant (as in BH setup) and the spillover effects collected in $h_{i2}^{\star}$.

The priors on parameters in $\mathbf{A}_i$ are assumed to be Student t distributions, with mode, scale parameters and degrees of freedom as reported in Table 2. Additional details on these priors and the criteria used to cluster countries can be found in Section A of the Online Appendix.

Our model implies that the global matrix $\mathbf{A}$ is block diagonal, as shown in Eq. (3). We do not include our prior beliefs about static interdependence in the extra-diagonal blocks, rather we add information about the spillover effects via the impact multiplier matrix $\mathbf{H}$.

Our approach is implemented building on the BH algorithm, which shows that prior beliefs about $\mathbf{A}$ and $\mathbf{H}$ can be incorporated jointly via a so-called composite prior, that is a single unified prior combining the two separate prior beliefs. As illustrated in Baumeister and Hamilton (2021), analytical computation of the density of the unified prior can be complex because the likelihood is specified in terms of the structural coefficients, whereas priors on $\mathbf{H}$ are set on the space of impact responses. For this reason, it is more convenient to enter the product numerically in the likelihood and let the algorithm draw the correct posterior distribution. Nevertheless, as derived in Kocięcki (2010), the Jacobian of transformation to link the two prior spaces and to map structural coefficients and impulse responses is exactly equal to 1 when the matrix of structural coefficients is lower triangular with 1s on the main diagonal, as in our case.

The impact multiplier matrix $\mathbf{H}$ is defined as $\mathbf{H} = \frac{1}{\det(\mathbf{A})}\tilde{\mathbf{H}}$, where $\tilde{\mathbf{H}}$, as $\mathbf{A}$, is block-diagonal, with each block equal to:

$$\tilde{\mathbf{H}}_i = \begin{bmatrix} 1 & 0 & 0 \\ a_{i,\mathcal{PT}} & 1 & 0 \\ a_{i,\mathcal{YT}} + a_{i,\mathcal{PT}} * a_{i,\mathcal{YP}} & a_{i,\mathcal{YP}} & 1 \end{bmatrix}. \tag{6}$$

Since $\frac{1}{\det(\mathbf{A})} = 1$ in our recursive setup, it follows that $\mathbf{H_i} = \tilde{\mathbf{H}}_\mathbf{i}$.

We distinguish between prior information about both the “domestic” and “foreign” impacts of the structural shocks. The “domestic” part reflects the country-specific prior information about the structural parameters. We define the “foreign” equilibrium impacts of the structural shocks as the country-specific weighted averages of all the other countries’ domestic responses. Therefore, the domestic priors of country i are assigned to the elements of A_i, as they correspond to the direct causal climate-economy effects. Moreover, we add prior information on the foreign impacts of structural shocks, designed to capture the interdependence between country i and all other countries.

The weights are computed via bilateral trade flows, and coincide with the weights used to construct the foreign variables. Since real economic growth is our main variable of interest, we only add prior information about the foreign effects of the elements $\tilde{h}_{i,31}$ and $\tilde{h}_{i,32}$ of $\tilde{\mathbf{H}}_i$, corresponding to the responses of GDP growth to temperature and precipitation shocks. Therefore, we can define the foreign impacts $h_{i,31}^{\star} = \sum_{\imath\neq i} \frac{\tilde{h}_{\imath,31}}{det(\mathbf{A})} w_{i\imath}$ and $h_{i,32}^{\star} = \sum_{\imath\neq i} \frac{\tilde{h}_{\imath,32}}{det(\mathbf{A})} w_{i\imath}$ as the spillover effects from all countries’ temperature and precipitation shocks to economic growth of country i. We consider $h_{i2}^{\star} = \left\{h_{i,31}^{\star}, h_{i,32}^{\star}\right\}$ and specify the spillover effects’ density function as $p(h_2^{\star}) = \prod_{i=1}^{N} p(h_{i2}^{\star})$. Then, we incorporate

and $p(\mathbf{B}|\mathbf{A}, \mathbf{D})$, is selected from natural conjugate families in order to ensure a closed-form analytic expression for the Bayesian posterior distribution and thus reducing the computational burden.

[15] Under the Bayesian framework, to ensure the stability of the model, the eigenvalues of the companion form of the GVAR must lie within the unit circle. This condition implies that shocks have no permanent impact on the system in the very long run. Technically, this can be obtained by discarding posterior draws of the companion matrix where the maximum eigenvalue exceeds unity. In our study, 99% of the draws deliver stationary structural models.

[16] In fact, an alternative would have been to relax the assumption of $a_{i,\mathcal{TP}} = 0$ and model the effect of precipitation anomalies on temperature by assuming a completely non-informative prior, given the lack of information on this effect within a yearly horizon. However, this alternative would have significantly increased model uncertainty and would have weakened the identification of structural shocks.

Table 2
Prior distribution specifications for the structural parameters of $\mathbf{A}_i$.

Parameter	List of countries	Student t			
		mode	scale	d.o.f.	sign
$a_{i,\mathcal{PT}}$	*All*	0	10	3	()
$a_{i,\mathcal{YT}}$	Argentina, Australia, Brazil, India, Indonesia, Malaysia, Mexico, Philippines, Saudi Arabia, Singapore, South Africa, Thailand	−0.005	0.05	3	−
	Austria, Canada, Finland, Norway, Sweden, Switzerland	0.005	0.05	3	+
	Belgium, Chile, China, France, Germany, Italy, Japan, Korea, Netherlands, New Zealand, Peru, Spain, Turkey, UK, US	−0.001	0.05	3	()
$a_{i,\mathcal{YP}}$	Argentina, Australia, Brazil, China, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Saudi Arabia, South Africa, Thailand, Turkey	0.005	0.05	3	()
	Austria, Belgium, Canada, Chile, Finland, France, Germany, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, UK, US	0	0.05	3	()

Notes: $a_{i,\mathcal{PT}}$ denotes the effect of temperature on precipitation, referred to country i; $a_{i,\mathcal{YT}}$ and $a_{i,\mathcal{YP}}$ denote the effect of temperature and precipitation 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. Sign indicates whether a distribution is truncated on the positive (+) or negative (−) domain; when no sign restrictions are imposed, this is indicated with ().

prior information on these responses using Student t distributions with location, scale parameters and degrees of freedom according to the approach used to set the prior on the determinant (Baumeister and Hamilton, 2018). Specifically, we generate 50000 random draws from prior distributions of elements in $\mathbf{A_i}$ and $\mathbf{H_i}$ allowing to compute $h^{\star}_{i2}$. The means and standard deviations derived in the simulation represent our guesses for the location and scale parameters of both $p(h_1)$ (i.e. the prior for the determinant) and $p(h^{\star}_2)$. After setting prior distributions on $p(\mathbf{A_i})$, the determinant $p(h_1)$ and the country-specific foreign impact responses $p(h^{\star}_{i2})$, we derive the joint prior distribution of the global matrix as specified in Eq. (5).

The overall prior for model (3) is given by:

$$p(\mathbf{A}, \mathbf{D}, \mathbf{B}) = p(\mathbf{A}) \prod_{i=1}^{N} p(d_i|\mathbf{A}) \prod_{i=1}^{N} \prod_{j=1}^{k_i} p(\mathbf{b}_{ij}|\mathbf{A}, \mathbf{D}) \tag{7}$$

where priors on $\mathbf{D}$ and $\mathbf{B}$ are discussed in details in Section A of the Online Appendix.

4.4. 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:

$$p(\mathbf{A}|\mathbf{Y}_T) = \frac{\kappa_T p(\mathbf{A}) \left[\det\left(\mathbf{A}\boldsymbol{\Omega}_T\mathbf{A}'\right)\right]^{T/2}}{\prod_{i=1}^{N}\prod_{j=1}^{k_i}\left[(2/T)\,\tau^*_{ij}\right]^{\kappa^*_{ij}}} \prod_{i=1}^{N}\prod_{j=1}^{k_i} \tau_{ij}^{k_{ij}}, \tag{8}$$

with $\kappa^*_{ij} = \kappa_i + (T/2)$, $\tau^*_{ij} = \tau_i + (\xi^*_{ij}/2)$ and κ_T being a constant term for which (8) integrates to unity.

We use a random-walk Metropolis Hastings algorithm to generate different draws of the unknown elements of the global contemporaneous structural matrix $\mathbf{A}$. Note that, for each draw, $\mathbf{A}$ is numerically revised to account for the spillover effects to country i. The BH approach allows to derive the posterior distributions of $\mathbf{D}$ and $\mathbf{B}$. 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 $\mathbf{M}^{-1}_{ij}$. 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.

5. Empirical results

5.1. Priors and posterior distributions of the contemporaneous structural parameters

Figs. 1 and 2 show the prior and posterior distributions obtained from estimation of model (3), focusing on the economic effects of positive climate shocks in different countries. Specifically, Fig. 1 plots the temperature effects and Fig. 2 the precipitation effects.

The prior beliefs on the structural parameters are revised for almost all countries. The most notable exception is the precipitation effect on economic growth of Saudi Arabia, where data are not informative to identify the structural parameter.

Considering the medians of the posterior distributions, 18 countries show a negative temperature effect on economic growth, whereas 16 countries exhibit positive effects. Nevertheless, the positive medians are always below 1%, while, in the case of negatively affected countries, some effects are remarkable. The largest detrimental roles of temperature on economic activity are registered for Malaysia (−3.34%), Indonesia (−3.33%), Saudi Arabia (−2.93%), Mexico (−2.81%) and Brazil (−2.79%). Moving to the effects of precipitation on real GDP growth, the majority of countries registers a negative median effect, whereas 14 countries are associated with positive medians. However, only in three countries the median in absolute value is higher than 1%, namely Saudi Arabia (−2.31%), Brazil (1.25%) and Canada (4.61%), confirming the established finding that the effect of precipitation on economic output is milder than the effect of temperature, at least at country-level.

5.2. Dynamic responses

Fig. 3 plots the dynamic impulse responses of GDP to positive temperature shocks of 1°C at different time horizons. Analogously, Fig. 4 focuses on the impulse responses of countries' real GDP to a positive 100 mm precipitation shock.

The picture emerging from the analysis classifies countries in different clusters according to the dynamics and significance of the estimated responses. There is large heterogeneity among the examined economies, ranging from countries where the economic response to climate shocks is more uncertain, to countries displaying more clear-cut dynamics. With reference to the responses to temperature shocks (Fig. 3), all countries with positive contemporaneous median effects display

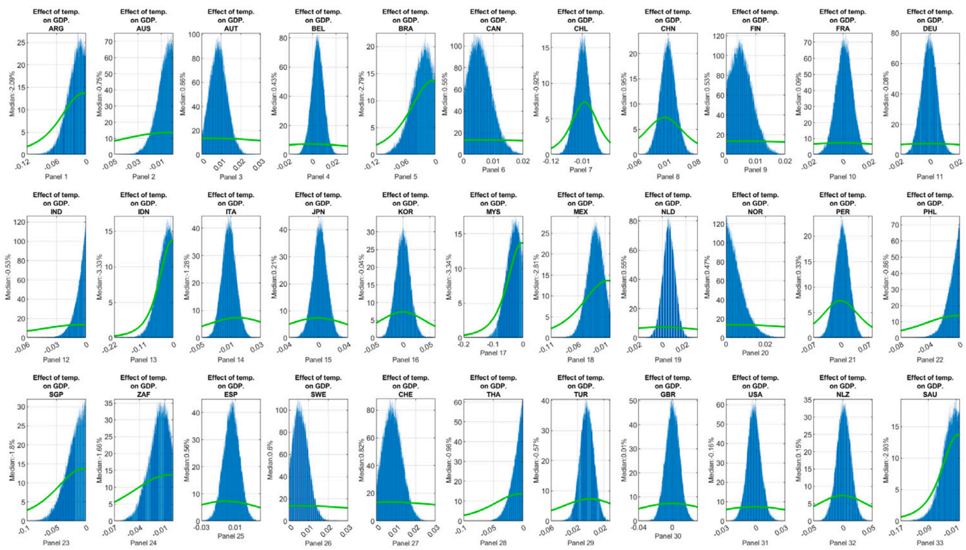

Fig. 1. Prior and posterior distributions for $a_{i,\mathcal{Y}\mathcal{T}}$.
Notes: green lines denote the prior distributions. Blue histograms refer to posterior distributions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

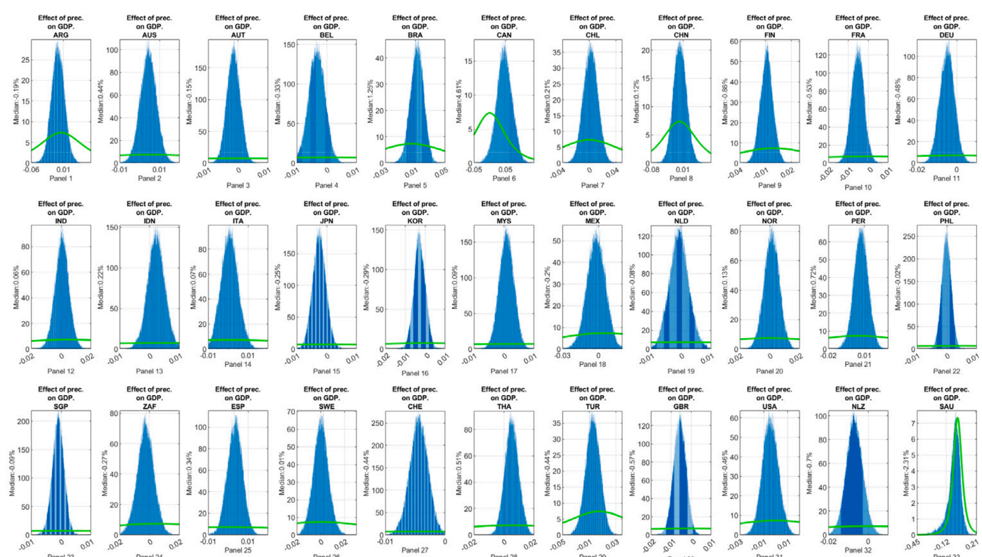

Fig. 2. Prior and posterior distributions for $a_{i,\mathcal{Y}\mathcal{P}}$.
Notes: green lines denote the prior distributions. Blue histograms refer to posterior distributions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

a negative or zero effect after 5 years, with the only exception of Norway. This result is of paramount importance as it shows that, whereas some cold economies are positively affected by additional warming on a short horizon, still this effect vanishes or becomes negative over a longer period. In particular, in the case of Finland and France, the positive impact response reverses its sign and becomes negative and statistically significant up to 5 years. Regardless of the initial responses within the first year, 25 out of 33 responses are negative after 5 years. Moreover, the responses of some countries are always negative and always statistically different from zero, namely: Australia, Brazil, Italy, Mexico, Philippines and Thailand. All these countries are associated with economic losses induced by temperature increments in the climate econometrics literature (see e.g. Acevedo et al., 2020). Conversely, for the following countries we do not find any clear result, as the responses are uncertain at all the horizons considered: Belgium, China, Germany, India, Peru, Spain, Turkey, UK and New Zealand. Comparing this evidence with previous analyses, these counties are either part of the group of rich economies for which the effect is unclear (see Acevedo et al., 2020; Dell et al., 2012) or too big and heterogeneous for a net effect to be disentangled (as pointed out by Kahn et al., 2021).

Moving to economic responses to precipitation shocks, we find completely uncertain effects for 11 countries, namely Argentina, China, Italy, Mexico, Norway, Philippines, Singapore, Sweden, Turkey, the US and Saudi Arabia. The 12 countries which are negatively affected in economic terms by unexpected precipitation shocks (Austria, Belgium, Finland, France, Germany, India, Japan, Malaysia, Netherlands, South Africa, Switzerland and the UK) are mostly located in the areas exposed to flooding risk, i.e. Northern Europe and South-Eastern Asia.[17] For Brazil, Canada and Peru, the response is always positive and significant. One possible explanation is that these three countries have in common

[17] See https://www.visualcapitalist.com/countries-highest-flood-risk/.

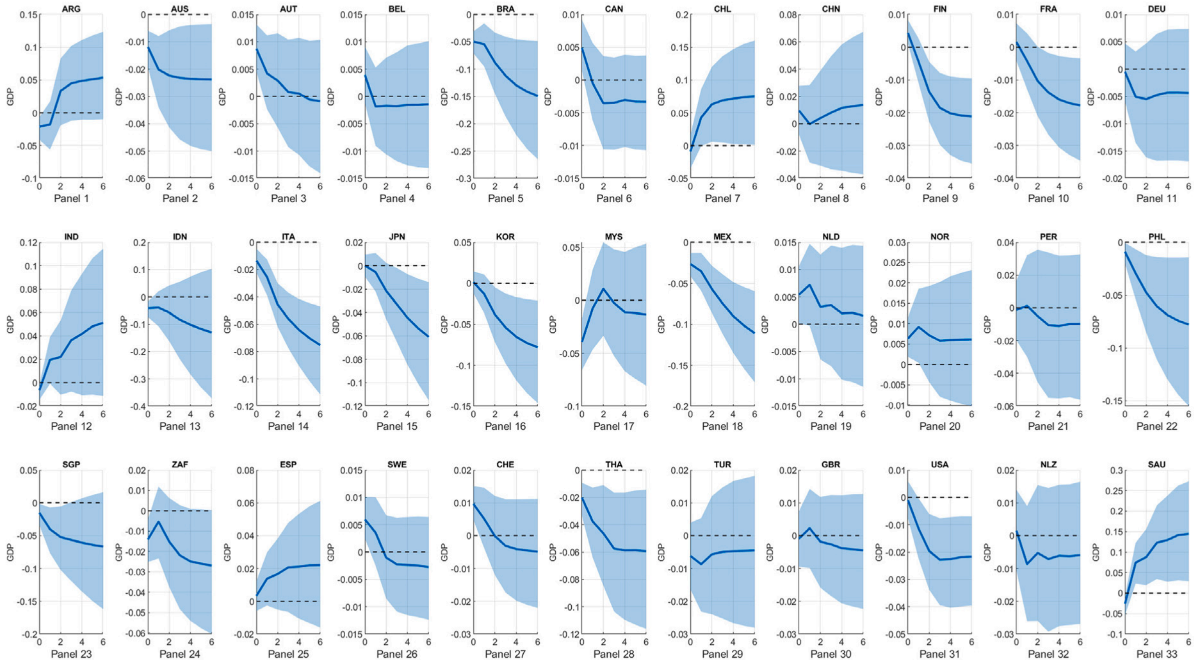

Fig. 3. Cumulated impulse response functions of real GDP to temperature shocks.
Notes: blue lines represent the medians of the responses from the estimation of the global model. Shaded areas denote the credible regions comprehending the 68% of the distributions.

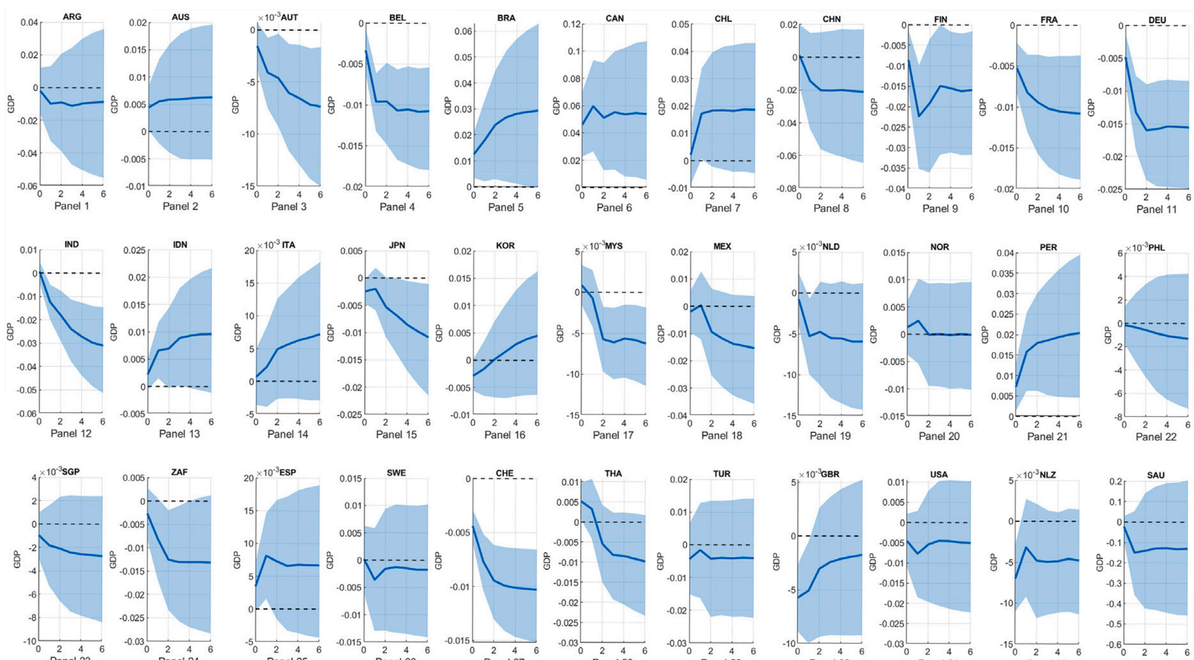

Fig. 4. Cumulated impulse response functions of real GDP to precipitation shocks.
Note: blue lines represent the medians of the responses from the estimation of the global model. Shaded areas denote the credible regions comprehending the 68% of the distributions.

the large share of hydro-power electricity, which can justify the relative economic benefit of additional precipitation.[18]

Overall, the results from the dynamic analysis bring us to the conclusion that, in general, climate change is a harmful phenomenon for the majority of countries, despite some of them may benefit in economic terms from climate shocks, especially in the very short term.

6. Discussion

The relationship between climate and the economy can be better understood if examined across different regions focusing on the role of spillovers across countries. In this section we discuss our findings by

[18] See https://www.hydropower.org/region-profiles/south-america and https://www.iea.org/reports/climate-impacts-on-latin-american-hydropower/climate-impacts-on-latin-american-hydropower for South-American countries and https://www.statcan.gc.ca/o1/en/plus/5776-hydroelectricity-generation-dries-amid-low-precipitation-and-record-high-temperatures for the Canadian case.

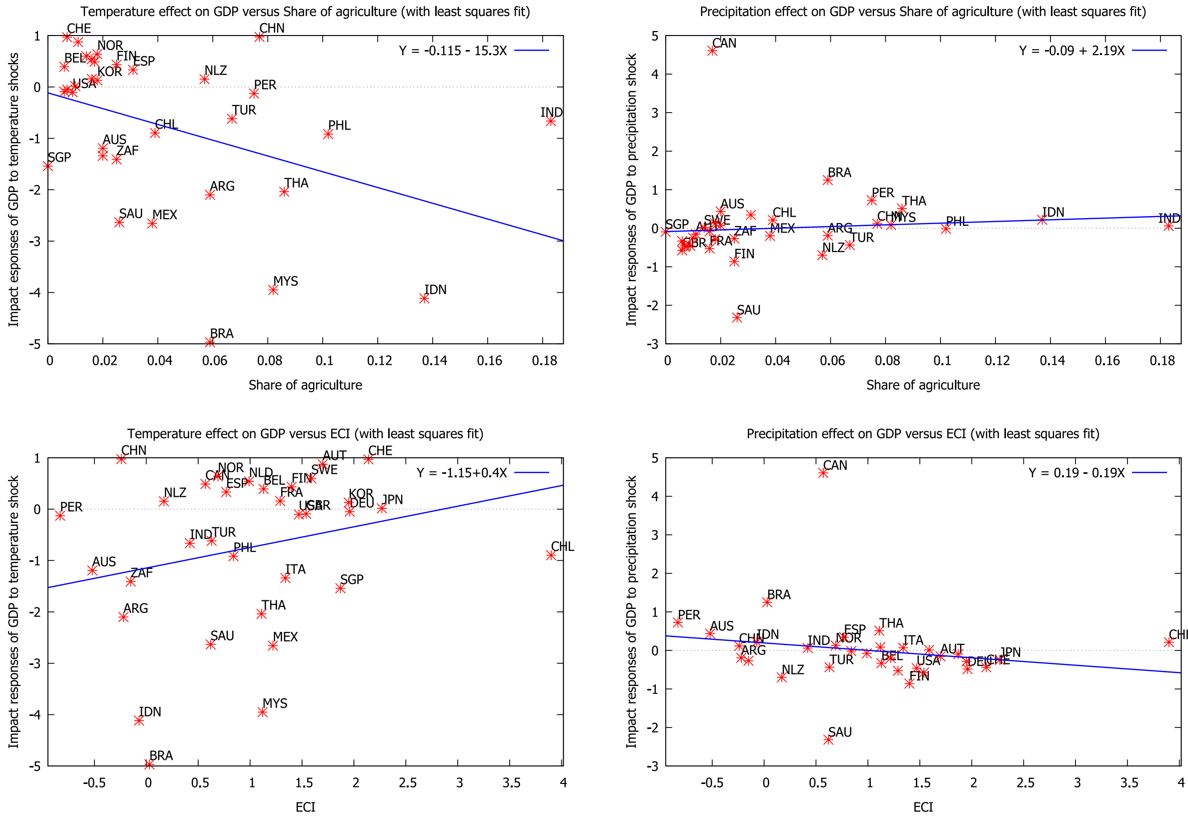

Fig. 5. Correlation of temperature and precipitation median impact responses and country-specific economic features.
Note: Some country labels are dropped to improve readability.

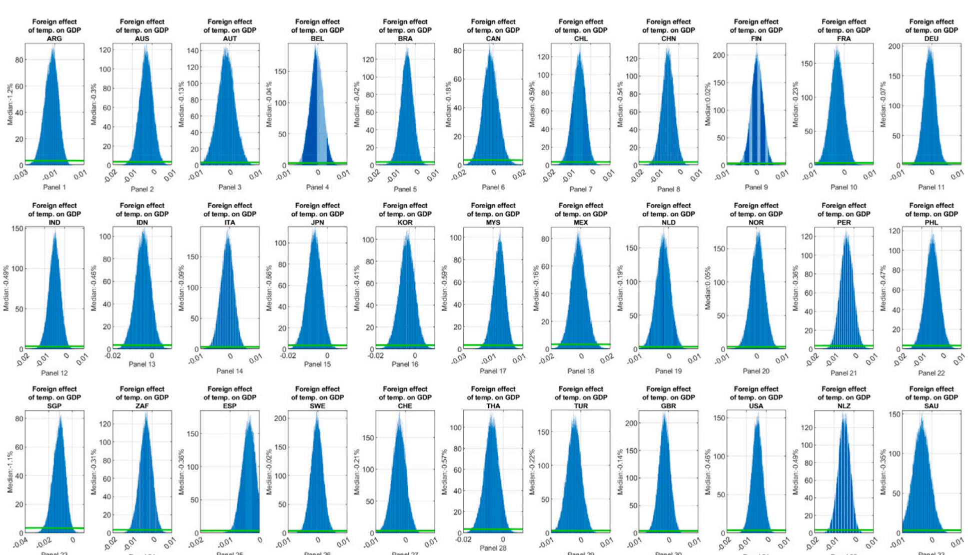

Fig. 6. Prior and posterior distribution of the foreign temperature effects.
Note: green lines denote the prior distributions. Blue histograms refer to posterior distributions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

looking at: (*i*) the distribution and heterogeneity of the economic responses to climate shocks among countries with different geographical and economic characteristics; (*ii*) the importance of spillovers and the role of trade in spreading climate shocks.

6.1. Disentangling geographical and income heterogeneity

The high degree of cross-sectional heterogeneity among the economic responses to temperature and precipitation shocks suggests to

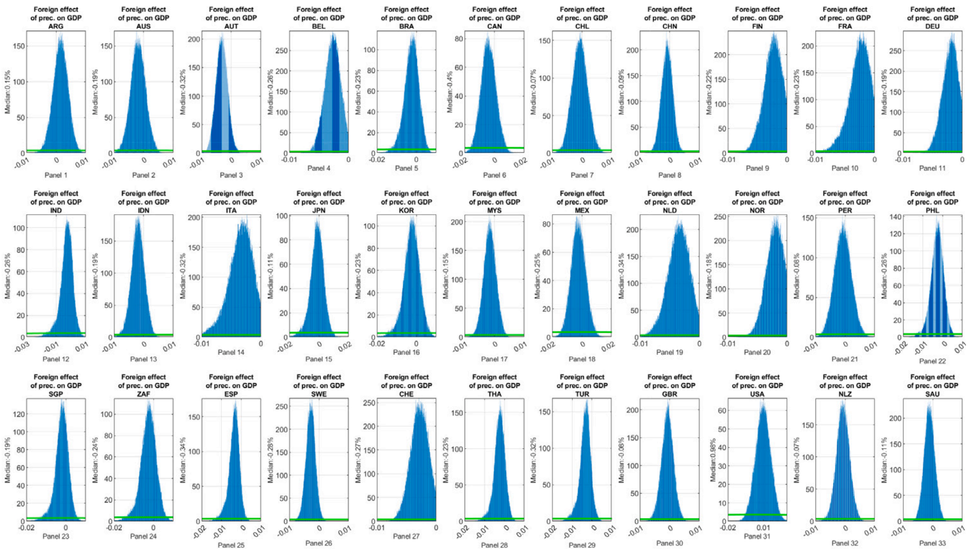

Fig. 7. Prior and posterior distribution of the foreign precipitation effects.
Note: green lines denote the prior distributions. Blue histograms refer to posterior distributions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

identify some regular patterns with respect to geographic and climate areas and country-specific economic features.

In line with the literature, we find that higher temperature is detrimental for economic output in hot and tropical areas, although it may boost growth in colder countries in the short run (see Acevedo et al., 2020; Burke et al., 2015; Kahn et al., 2021).[19] At the same time, a higher level of development is commonly associated with higher responses of economic output to climate shocks. All countries recording a positive on-impact response to a temperature shock are located in temperate or cold regions (Europe and Canada) and classified as high income countries. Nevertheless, the contrary is not necessarily true, as the US, Japan, Italy and Australia show negative responses even within the first year. On average, emerging markets suffer the most, as there is no country within this group that positively reacts to an increase of 1°C in temperature. Thus, not all the developed economies are positively affected by temperature shocks, but all the positively affected countries are actually high-income. This results have paramount economic implications, as it is well documented that the unbalance in climate shocks exposure is associated with an increase in income inequalities (Diffenbaugh and Burke, 2019; Taconet et al., 2020). As discussed in Section 2, the distributional implications of climate change can be severe and the heterogeneity of cross-country effects from climate shocks is expected to exacerbate the already existing disparities.

It is also worth stressing that the (few) positive effects are short-lived, as they become indistinguishable from zero after one year, or, in the case of Finland and France, even negative. Moreover, an interesting finding from our analysis is the presence of significant effects among some cold and developed countries, which adds fresh evidence to the previous empirical studies.

To deepen the interpretation of our results, we study the relation between the responses of economic activity to climate shocks and some key elements which capture the heterogeneity of the analyzed countries, such as the relative importance of the agricultural sector, economic development and international trade (see Dell et al., 2014).

The first variable we consider is a dummy which is equal to 1 if the ith country is a high-income economy and is 0 otherwise. We regress the median impact responses of real GDP to temperature and precipitation shocks on this dummy in order to assess if the level of development positively or negatively correlates with the average estimated climate effect. The second variable is the share of agriculture on total GDP. The choice of this variable is motivated by the existing literature which documents the exposure of agriculture to climate shocks. As before, we regress the previous impact responses on the share of agriculture. We interpret the estimated coefficients as the impacts of an increase in the agriculture share on the median climate responses. The third variable is the Economic Complexity Index (ECI), which reflects the number and complexity of products a country exports. We employ this variable as a summary of the main features of an economic system. We regress the climate impact responses on this third variable. The coefficients associated with the ECI quantify the effect on the median climate impacts of a one-unit increase in the index.

Fig. 5 summarizes the results of this analysis by showing the correlations of the responses to climate shocks and (i) share of agriculture in top panels, (ii) ECI in bottom panels. The left-hand side of the figure refers to temperature shocks, while the right-hand side considers precipitation shocks.

We find that countries classified as high income economies exhibit 0.9%-higher responses of economic activity to temperature shocks. Moreover, a 1% increase in the share of agriculture over total GDP corresponds to a reduction of 15.35% of the median GDP response to temperature shocks. The ECI is positively correlated with the impact GDP responses to temperature shocks: a one-unit increase in the index yields a 0.4% higher median response.

Moving to the economic responses to precipitation shocks, a high-income economy is associated with a lower average impact (−0.07%). An increasing ECI translates to a lower median response of economic activity to a precipitation shock (−0.19%), whereas a 1% increase in the share of agriculture corresponds to higher GDP responses (2.19%).

Overall, the correlations associated with impacts to precipitation shocks closer to zero with respect to the corresponding correlations obtained for responses to temperature shocks. As intuition suggests, countries that rely more on agriculture benefit in economic terms from precipitation shocks, whereas they are dampened and more exposed to temperature shocks. The low correlations shown for the case of responses to precipitation shocks may depend on the aggregation at country level, given that rainfall is much more heterogeneous from

[19] An exception is Saudi Arabia, for which our estimates indicate that a positive temperature shock will boost economic activity after the first year. We explain this result with the country's relatively peculiar economic structure: Saudi Arabia is in fact one of the most oil-dependent economies in the world. Thus, for Saudi Arabia energy shocks are likely to dominate climate shocks.

a spatial point of view with respect to temperature (as stressed in Damania et al., 2020).

6.2. The role of trade

International trade represents one of the most important sources of spillovers among countries. With our model we can easily disentangle the role of trade in spreading the effects of climate shocks to different economies. In this respect, we compute the "foreign" posterior distributions of the model for each country (i.e. the posterior distribution associated with $h^{\star}_{i2}$).[20] These distributions are reported in Figs. 6 and 7, where the economic responses to foreign temperature and precipitation shocks are shown. As it is displayed, the simulated prior distributions for these spillovers are completely flat relative to the posterior distributions, which implies that the results are data-driven.

By construction, the medians of these distributions represent the pure effect of trade spillovers, so that it is possible to state if countries are positively or negatively affected by trade. In our sample, the average spillover from economic responses to foreign temperature shocks is -0.36%, with all countries showing a negative median, with the exception of Finland and Norway. The most detrimental role of trade is reported for Argentina, which response to foreign temperature shocks is -1.2% in median. Similarly, in the case of precipitation shocks spillovers, 31 countries out of 33 show negative median responses. The only exceptions are Argentina and the US. The trade effect is maximum for the US (0.98%) and minimum for Canada (-0.4%).

Strikingly, in nearly all examined countries, trade amplifies the negative effects of climate shocks, although some economies suffer more from trade interdependence than others.

Given that the trade structure of the countries in our sample varies considerably, we collect a series of variables that can help in disentangling the heterogeneity of the spillover effects. In particular, we consider the number of exporting partners for each country (Number), the share of food products in total trade (Share), the Hirschman–Herfindahl Market Concentration Index (HH MCI) and the index of export market penetration (IEMP). Finally, since the European single market is the most important free trade zone within our sample, we also construct a binary variable (Europe) selecting countries member of the EU and EFTA.[21] The number of exporting countries is included to reflect the trade openness of a country. The percentage share of traded food products is selected to proxy agriculture's weight in trade of a given country, a factor that is important for explaining climate shocks economic responses. The HH MCI measures the dispersion of trade: countries with trade concentrated in few markets have an index close to 1 (the maximum), whereas countries with a more diversified trade portfolio have an index closer to zero (the minimum). The IEMP is computed as a ratio between the number of countries to which the reporting country exports a particular product and the number of countries that import the product in a given year.[22]

We estimate two regression models where the dependent variables are the economic spillovers of temperature and precipitation shocks are regressed on the set of variables described above (see Table 3).

Focusing temperature shocks, the spillover effects are positively associated with the HH MCI and Europe. Thus, European countries benefit more from cross-country interdependence than the rest of the world in terms of spillovers of temperature shocks. Share is negatively correlated with temperature shocks spillovers, as higher values of this share correspond to -2.23% of GDP growth effect coming from foreign countries. The coefficients associated with Number and the IEMP are very close to zero.

As for precipitation shocks, the coefficient of Share has a positive sign: countries trading more food products are associated with higher spillover effects (0.28%). The HH MCI and Europe exhibit negative correlations. In this case, countries with a higher HH MCI (trade concentrated in few markets and less diversified) and part of the European commercial area show negative spillover effects. The coefficients associated to temperature shocks are higher than those of precipitation spillovers, suggesting that temperature shocks propagate more with respect to precipitation shocks.

Literature on trade and climate change agrees on the importance of agriculture as a channel of transmission of weather shocks to import and export changes, but is controversial on the role of trade among countries. Some studies state that trade acts as a mitigation tool, others suggest that trade amplifies the effects of climate shocks (see, e.g., Dall'Erba et al., 2021; Gouel and Laborde, 2021; Jones and Olken, 2010; Kompas and Van Ha, 2019). In our analysis, we find that trade is detrimental in spreading climate shocks, as almost all the spillovers are negative. This could be a direct consequence of the fact that the majority of countries exhibits negative economic growth in response to climate shocks. Hence, there are few positive economic responses to climate shocks to redistribute, while there are more (and more severe) climate damages that can be spread via trade.

7. Robustness checks

We assess the robustness of our identification approach with three different exercises.[23]

In the first, we increase the uncertainty in our sets of prior distributions while maintaining the same prior modes and sign restrictions. The idea is to verify if the obtained results are similar to the findings of our main specification. The first robustness check does not modify the prior distributions for the parameters $a_{i,\mathcal{PT}}$, since the scale coefficient is already large. For the parameters $a_{i,\mathcal{YT}}$ and $a_{i,\mathcal{YP}}$ we set a standard deviation of 0.2, which is four times larger than the standard deviation reported in Table 2.

The second robustness check consists in a completely agnostic recursive model specification, as we center the parameters $a_{i,\mathcal{PT}}$, $a_{i,\mathcal{YT}}$ and $a_{i,\mathcal{YP}}$ at zero, without any truncation in the domain, and we set the scale coefficient at 100.

Figs. 8 and 9 report the impulse response functions of the first robustness analysis. We do not detect significant differences in the dynamic responses. This finding suggests that the prior beliefs in Table 2 are adequate for the identification of the structural shocks. Even if uncertainty is higher, all the shapes and trajectories of the responses to both climate shocks do not change with respect to the original impulse responses.

Figs. 10 and 11 show the cumulated dynamic responses for the second robustness check and demonstrate that, without informative priors, the responses of economic activity to climate shocks can vary considerably and are often counter-intuitive.

With these two robustness exercises we learn that informing the model with reasonable prior beliefs is crucial, and that the prior distributions we specify in our original model are not too stringent in driving the results.

For the third robustness check we consider: (i) a first specification in which the variable $\mathcal{Y}_{it}$ is replaced with manufacturing value added; (ii) a second specification in which the same variable is substituted

[20] Note that the previous posterior distributions shown in Figs. 1 and 2 are also accounting for spillovers, as they refer to the global model. In this section, we are isolating the role of spillovers without taking into account the domestic effects, since we want to focus on the role of trade.

[21] The inclusion of EFTA countries allows to select also Norway and Switzerland as part of a broader definition of the European trade area.

[22] All these variables are obtained from the World Bank's World Integrated Trade Solution country profiles, and refer to the most recent available year. Source: country profiles and trade summary at https://wits.worldbank.org/countrystats.aspx?lang=en.

[23] In this section we present the main results, whereas details are reported in Section B of the Online Appendix.

Table 3
Correlation coefficients: drivers of the spillover effects.

	Foreign temperature median effect	Foreign precipitation median effect
Number	0.0022	−0.0040
Share	−2.2287	0.2873
HH MCI	0.9470	−0.6586
IEMP	0.0005	0.0075
Europe	0.3815	−0.1682

Notes: The reported coefficients are obtained from two distinct regression models. In the first column, the dependent variable is the foreign temperature median effect. In the second column, the dependent variable is the foreign precipitation median effect. Reported values are in percentage terms.

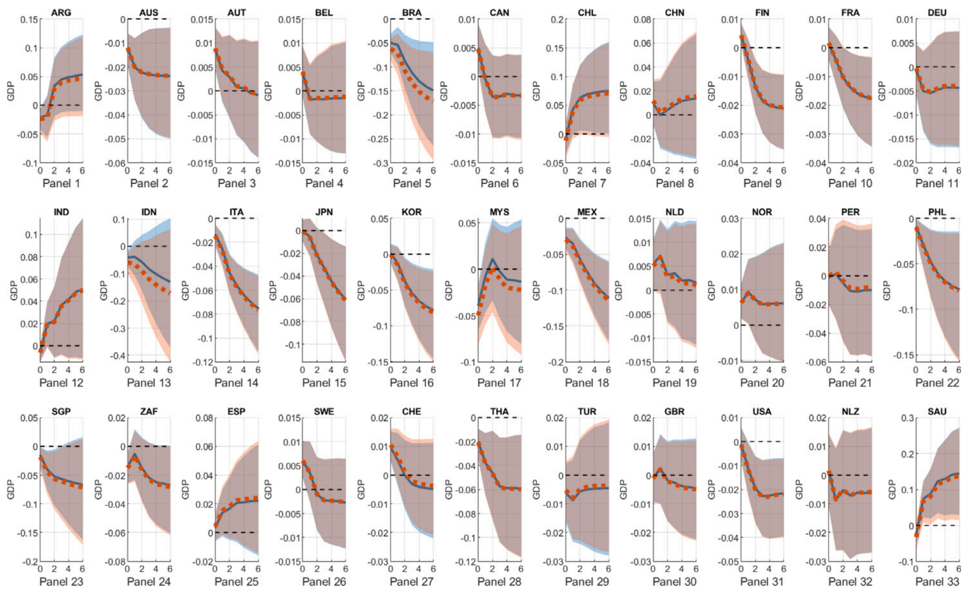

Fig. 8. Cumulated impulse response functions of real GDP to temperature shocks: first robustness check.
Note: blue lines and shaded areas represent the medians of the responses and the credible regions of the distributions of the main model. Red dotted lines and shaded areas refer instead to the first robustness check. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

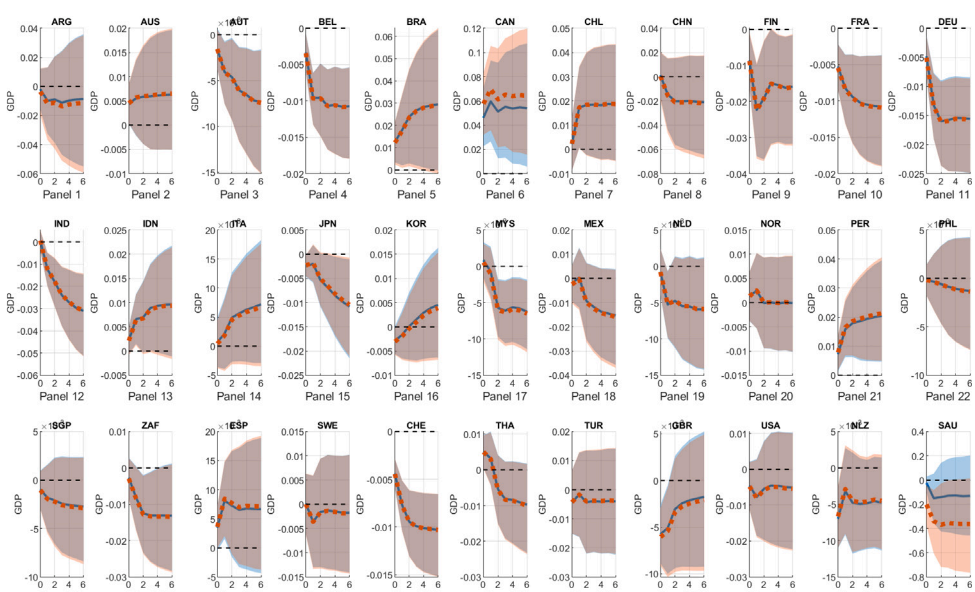

Fig. 9. Cumulated impulse response functions of real GDP to precipitation shocks: first robustness check.*Note*: See Fig. 8.

with the value added generated by agriculture; (*iii*) a third specification in which we maintain the agricultural value added as the economic variable of interest and we consider agri-food trade weights to construct both the foreign variables and the priors for the foreign effects.

With this third robustness check we aim to assess if the effects of climate shocks are more related to a specific sector, rather than affecting uniformly all the economy. Moreover, since previous results indicate that the spillover effect is correlated with the share of food products in total trade, it is crucial to verify if our findings change

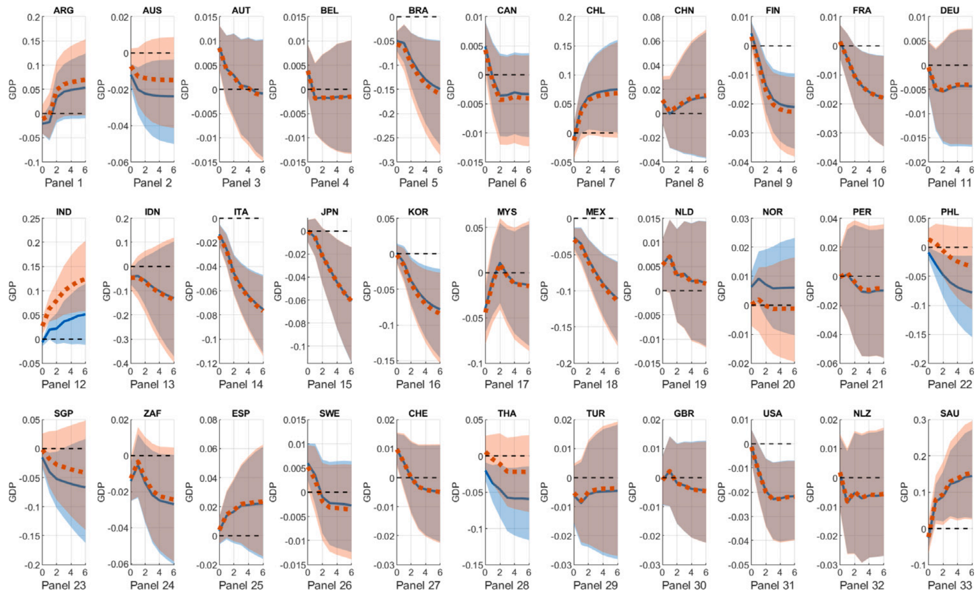

Fig. 10. Cumulated impulse response functions of real GDP to temperature shocks: second robustness check.
Note: blue lines and shaded areas represent the medians of the responses and the credible regions of the distributions of the main model. Red dotted lines and shaded areas refer instead to the second robustness check. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

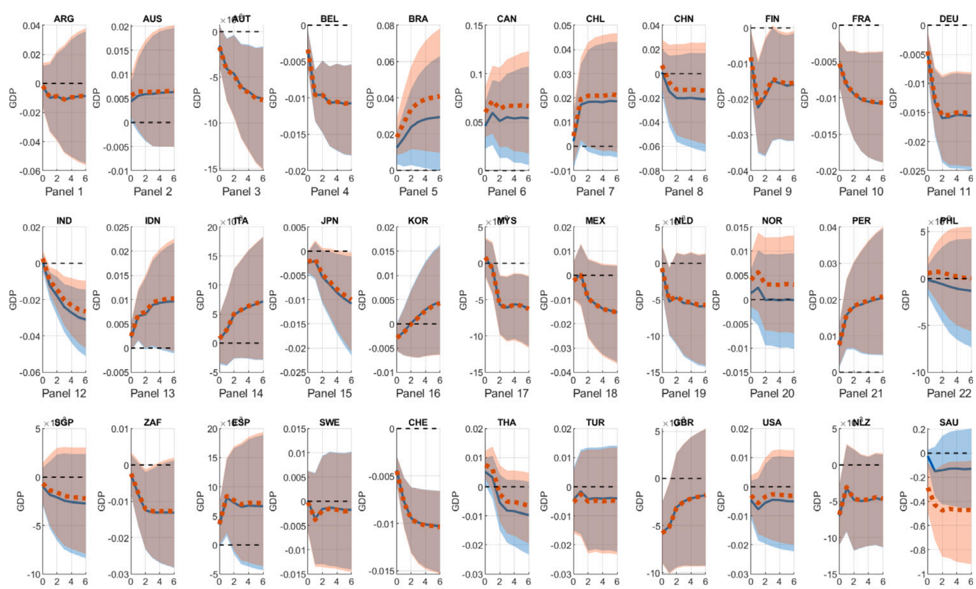

Fig. 11. Cumulated impulse response functions of real GDP to precipitation shocks: second robustness check.*Note*: See Fig. 10.

by considering a weighting scheme based on agricultural bilateral trade. We source annual data on agricultural and manufacturing value added and cross-country import and export data on crops and livestock products from FAOSTAT.[24]

Fig. 12 summarizes the results of the third robustness check. For the majority of countries, the effects of temperature shocks to agriculture are higher in absolute terms with respect to manufacture, confirming that the agricultural sector is more reactive to climate fluctuations than the industrial sector. In the case of cold countries (Austria, Canada, Finland, Sweden, Switzerland and the UK), a positive climate shock raises agricultural value added. On the contrary, for the majority of hotter countries (Argentina, Australia, Brazil, India, Indonesia, Italy, Malaysia, Mexico, Peru, Philippines, Singapore, South Africa, Saudi Arabia, Spain and Thailand) the effects are negative. For the remaining countries, the effects are uncertain. From an economic perspective, these findings are in line with the intuition that higher temperature is detrimental for agriculture when the starting temperature conditions are already high, whereas cold countries, generally less dependent on agriculture, benefit from warmer temperatures.

For seven countries (Austria, Canada, Finland, France, Sweden, Switzerland and the US) the effect of a temperature shock on manufacturing value added is positive and significant. Note that all these countries are located in cold regions and characterized by a high level of economic development. For all the other countries, the effects are either negative or not significant.

Finally, we find that there is not a remarkable difference in the results obtained with the two weighting matrices. This conclusion is

[24] See https://www.fao.org/faostat/en/#data. We consider the same time span of the original analysis (1960–2019). The new weight matrix is constructed following the same procedure reported in Section 3.

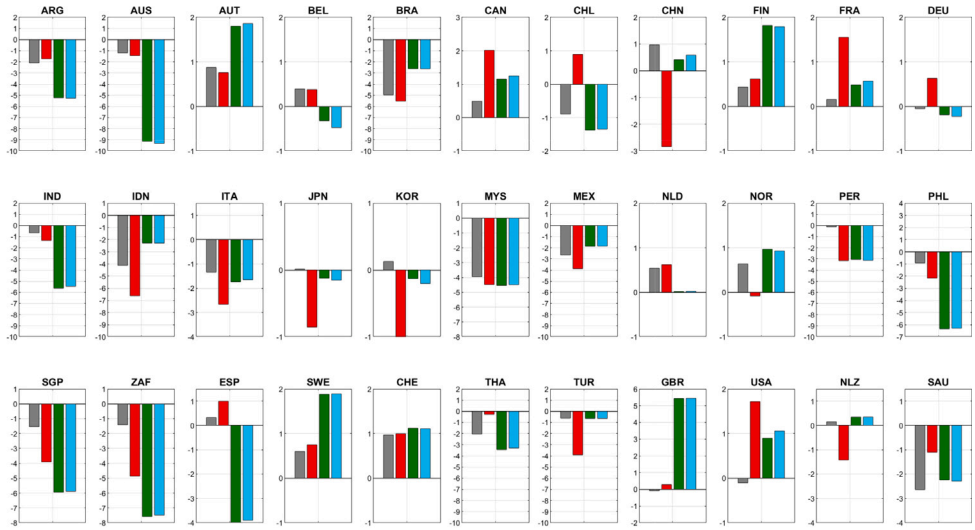

Fig. 12. Median impact responses of different economic variables to temperature shocks.
Note: Gray bars correspond to the median impact responses of real GDP. Red bars correspond to the median impact responses of manufacturing value added. Green bars correspond to the median impact responses of agricultural value added (with the total trade weights model). Blue bars correspond to the median impact responses of agricultural value added (with the agri-food trade weights model). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

supported by comparing the median impact responses of agricultural value added to temperature shocks using the total trade weights model (green bars in Fig. 12) with those using the agri-food trade weights model (blue bars in Fig. 12).

8. Concluding remarks

This article studies the effects of climate shocks on real economic activity in a global setup. Our analysis considers several regions of the world, with different economic and geographic characteristics. Specifically, we focus on the effects of temperature and precipitation shocks on real GDP in 33 countries of the world at different levels of development and with different climatic conditions for the period ranging from 1960 to 2019.

The empirical investigation is based on a new model which allows us to disentangle the temperature and precipitation effects on economic outcome and to include cross-country spillover effects that involve bilateral trade. To perform this analysis, we develop a new Bayesian Structural Global Vector Autoregressive (BS-GVARX) model, that accounts for the structural interpretation of the shocks, the interdependence across the countries and the endogenous relationship between climate and economic activity. Our model is new since it departs from the canonical reduced form GVAR (Pesaran et al., 2004; Dees et al., 2007; Chudik and Pesaran, 2016) by considering a full structural identification of the shocks. We design a single global specification which nests all the country-specific models and adds role of trade spillovers among different economies. Specifically, we achieve identification in the global model by accounting for interdependence via the impact multiplier matrix.

Our results show that the majority of countries is negatively exposed to temperature shocks, and that the few countries associated with positive economic impacts exhibit either not significant or negative responses in the medium-term. In this respect, we are in line with the findings of Kahn et al. (2021), showing that positively affected countries within a very short horizon exhibit economic losses in the medium-long term. Economic responses to precipitation shocks are more heterogeneous and less clear-cut, with a mix of not significant, positive (few) and negative (many) outcomes. Despite the larger uncertainty, the few countries that are positively affected in the first year are either characterized by a non-significant or negative economic response in the medium term. To sum up, our results suggest that the effects of climate shocks are more negative than positive, as the majority of countries experience a reduction of economic output, in line with the general findings of Acevedo et al. (2020), Burke et al. (2015) and Dell et al. (2012). Whereas for some countries this effect is instantaneous, for others it takes more than one year to manifest.

We show that these effects are linked to the agricultural sector's role in the economy. Specifically, increasing shares of agriculture are associated with decreasing economic impacts to temperature shocks, while the response to precipitation shocks intensifies.

Finally, we underline the importance of cross-country interdependence in amplifying the negative effects of climate shocks. We demonstrate that spillovers are negative for almost all countries and depend on the country-specific trade structure and product mix. Specifically, we find that the most important drivers of country interdependence are the share of food products over total country-specific trade and the Hirschman–Herfindahl market concentration index. The magnitude of the spillovers also depends on the presence of countries within the European commercial area, suggesting that the more intense is trade among countries, the larger is the role of spillover in spreading climate shocks. Moreover, we find that temperature shocks propagate across countries more than precipitation shocks.

Some additional analyses considering the sectoral decomposition of GDP reveal that the most impacted activity is agriculture, whereas the climate effect on the manufacturing sector is more limited.

Our findings have significant policy implications. Developing countries not only face greater economic losses from climate shocks, but must also devote substantial resources to climate policies. This dynamic exacerbates income inequality and increases exposure to climate risk.

To address these challenges, climate policies should find a balance between adaptation and mitigation measures, aiming to reduce climate-induced income disparities and promote a fair redistribution of climate policy costs across countries.

One limitation of the current study is that it considers only 33 countries. Future research should expand the analysis to a broader set of countries to better capture the structural climate-economy relationship across other geographical regions.

Additionally, our model examines the effects of climate shocks on an aggregate measure of economic output, but does not distinguish between supply- and demand-driven shocks. Determining whether climate change primarily affects economic activity through the supply side (e.g. productivity, infrastructure, and production) or aggregate demand (e.g. price channels) is essential for designing more targeted and effective climate policies.

Declaration of competing interest

The Authors have nothing to declare.

Acknowledgments

The authors wish to thank Emanuele Bacchiocchi, Christiane Baumeister, Paolo Nota, Luca Pedini, the Editor and two anonymous Reviewers for their valuable feedbacks. Previous versions of the paper have been presented in the 8th Conference of the Society for Economic Measurement, the 10th Italian Congress of Econometrics and Empirical Economics, the 43rd IAEE International Conference, the 6th Econometric Models of Climate Change Conference, the 14th Conference of the ESEE, the 10th IAERE Annual Conference and the RCEA Conference for Recent Developments in Economics, Econometrics and Finance. The authors are indebted to seminar participants for insightful comments and suggestions.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econmod.2025.107082.

Data availability

Data and code to replicate the findings of the article are disposable at the provided Mendeley repository

Codes and data: replication material of the article "Climate shocks, economic activity and cross-country spillovers: evidence from a new global model" (Original data) (Mendeley Data)

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., Topalova, P., 2020. The effects of weather shocks on economic activity: What are the channels of impact? J. Macroecon. 65, 103207.

Agostino, M., Rondinella, S., Ruberto, S., 2025. Extreme weather events and efficiency in Italy's food sector: Does institutional quality matter? Econ. Model. 107026.

Auffhammer, M., Schlenker, W., 2014. Empirical studies on agricultural impacts and adaptation. Energy Econ. 46, 555–561.

Baumeister, C., Hamilton, J., 2015. Sign restrictions, structural vector autoregressions, and useful prior information. Econometrica 83 (5), 1963–1999.

Baumeister, C., Hamilton, J.D., 2018. Inference in structural vector autoregressions when the identifying assumptions are not fully believed: Re-evaluating the role of monetary policy in economic fluctuations. J. Monet. Econ. 100, 48–65.

Baumeister, C., Hamilton, J., 2019. Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. Am. Econ. Rev. 109 (5), 1873–1910.

Baumeister, C., Hamilton, J.D., 2021. Advances in using vector autoregressions to estimate structural magnitudes. Econometric Theory 1–39.

Blanc, E., Schlenker, W., 2020. The use of panel models in assessments of climate impacts on agriculture. Rev. Environ. Econ. Policy 11 (2).

Blanz, A., Eydam, U., Heinemann, M., Kalkuhl, M., 2025. Market-based climate policy with fluctuating fossil energy prices. Econ. Model. 144, 106982.

Botzen, W.W., Deschenes, O., Sanders, M., 2019. The economic impacts of natural disasters: A review of models and empirical studies. Rev. Environ. Econ. Policy.

Bowen, A., Cochrane, S., Fankhauser, S., 2012. Climate change, adaptation and economic growth. Clim. Change 113, 95–106.

Burke, M., H., S.M., Miguel, E., 2015. Global non-linear effect of temperature on economic production. Nature 527, 235–239.

Cashin, P., Mohaddes, K., Raissi, M., 2017. Fair weather or foul? The macroeconomic effects of El Niño. J. Int. Econ. 106, 37–54.

Chen, Z., Wang, C., Bai, F., 2024. Greenhouse gas emissions and global real economic activities. Financ. Res. Lett. 64, 105404.

Chudik, A., Mohaddes, K., Pesaran, M.H., Raissi, M., Rebucci, A., 2021. A counterfactual economic analysis of Covid-19 using a threshold augmented multi-country model. J. Int. Money Financ. 119, 102477.

Chudik, A., Pesaran, M.H., 2011. Infinite-dimensional VARs and factor models. J. Econometrics 163 (1), 4–22.

Chudik, A., Pesaran, M.H., 2016. Theory and practice of GVAR modelling. J. Econ. Surv. 30 (1), 165–197.

Ciccarelli, M., Marotta, F., 2024. Demand or supply? An empirical exploration of the effects of climate change on the macroeconomy. Energy Econ. 129, 107163.

Conigliani, C., Costantini, V., Paglialunga, E., Tancredi, A., 2024. Forecasting the climate-conflict risk in Africa along climate-related scenarios and multiple socio-economic drivers. Econ. Model. 141, 106911.

Cuaresma, J.C., Doppelhofer, G., Feldkircher, M., Huber, F., 2019. Spillovers from US monetary policy: Evidence from a time-varying parameter GVAR model. J. R. Stat. Society: Ser. A (Stat. Society) 182, 831–861.

Dall'Erba, S., Zhangliang, C., N. Noé, J., 2021. US interstate trade will mitigate the negative impact of climate change on crop profit. Am. J. Agric. Econ. 103 (5), 1720–1741.

Damania, R., Desbureaux, S., Zaveri, E., 2020. Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014). J. Environ. Econ. Manag. 102, 102335.

Dees, S., d. Mauro, F., Pesaran, M.H., Smith, L.V., 2007. Exploring the international linkages of the euro area: A global VAR analysis. J. Appl. Econometrics 22 (1), 1–38.

Dell, M., Jones, B., Olken, B., 2012. Temperature shocks and economic growth: Evidence from the last half century. Am. Econ. J.: Macroecon. 4 (3), 66–95.

Dell, M., Jones, B., Olken, B., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52 (3), 740–798.

Deschênes, O., Greenstone, M., 2007. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. Am. Econ. Rev. 97 (1), 354–385.

Di Mauro, F., Pesaran, M.H., 2013. The GVAR Handbook: Structure and Applications of a Macro Model of the Global Economy for Policy Analysis. OUP Oxford.

Diffenbaugh, N.S., Burke, M., 2019. Global warming has increased global economic inequality. Proc. Natl. Acad. Sci. 116 (20), 9808–9813.

Dufrénot, G., Ginn, W., Pourroy, M., 2024. Climate pattern effects on global economic conditions. Econ. Model. 141, 106920.

Eickmeier, S., Ng, T., 2015. How do US credit supply shocks propagate internationally? A GVARappand roach. Eur. Econ. Rev. 74, 128–145.

Fankhauser, S., Tol, R.S., 2005. On climate change and economic growth. Resour. Energy Econ. 27 (1), 1–17.

Feldkircher, M., Huber, F., 2016. The international transmission of US shocks – evidence from Bayesian global vector autoregressions. Eur. Econ. Rev. 81, 167–188.

Frölicher, T.L., Paynter, D.J., 2015. Extending the relationship between global warming and cumulative carbon emissions to multi-millennial timescales. Environ. Res. Lett. 10 (7), 075002.

Gouel, C., Laborde, D., 2021. The crucial role of domestic and international market-mediated adaptation to climate change. J. Environ. Econ. Manag. 106, 102408.

Gross, M., 2019. Estimating GVAR weight matrices. Spat. Econ. Anal. 14 (2), 219–240.

Hamilton, J.D., 2021. Measuring global economic activity. J. Appl. Econometrics 36 (3), 293–303.

Jones, B.F., Olken, B.A., 2010. Climate shocks and exports. Am. Econ. Rev. 100 (2), 454–459.

Kahn, M., Mohaddes, K., Ng, R., Hashem Pesaran, M., Raissi, M., Yang, J., 2021. Long-term macroeconomic effects of climate change: A cross-country analysis. Energy Econ. 104, 105624.

Kalkuhl, M., Wenz, L., 2020. The impact of climate conditions on economic production, evidence from a global panel of regions. J. Environ. Econ. Manag. 103, 102360.

Kemfert, C., Lise, W., Tol, R.S., 2004. Games of climate change with international trade. Environ. Resour. Econ. 28, 209–232.

Kilian, L., Lütkepohl, H., 2017. Structural Vector Autoregressive Analysis. Cambridge University Press.

Kim, H.S., Matthes, C., Phan, T., 2022. Severe weather and the macroeconomy. Fed. Reserv. Bank Richmond Work. Pap. 21-14R.

Kocięcki, A., 2010. A prior for impulse responses in Bayesian structural VAR models. J. Bus. Econom. Statist. 28 (1), 115–127.

Kolstad, C.D., Moore, F.C., 2020. Estimating the economic impacts of climate change using weather observations. Rev. Environ. Econ. Policy 14 (1).

Kompas, T., Van Ha, P., 2019. The 'curse of dimensionality' resolved: The effects of climate change and trade barriers in large dimensional modelling. Econ. Model. 80, 103–110.

Kotsogiannis, C., Woodland, A., 2025. Climate change, strict pareto improvements in welfare and multilateral financial transfers. Oxf. Econ. Pap. 77 (1), 190–212.

Kumar, A., Mallick, S., 2024. Oil price dynamics in times of uncertainty: Revisiting the role of demand and supply shocks. Energy Econ. 129, 107152.

Lai, S., Chen, L., Wang, Q.S., Anderson, H., 2022. Natural disasters, trade credit, and firm performance. Econ. Model. 116, 106029.

Letta, M., Tol, R.S., 2019. Weather, climate and total factor productivity. Environ. Resour. Econ. 73 (1), 283–305.

Mastromarco, C., Serlenga, L., Shin, Y., 2016. Modelling technical efficiency in cross sectionally dependent stochastic frontier panels. J. Appl. Econometrics 31 (1), 281–297.

Mendelsohn, R., Dinar, A., Williams, L., 2006. The distributional impact of climate change on rich and poor countries. Environ. Dev. Econ. 11 (2), 159–178.

Mohaddes, K., Pesaran, M.H., 2016. Country-specific oil supply shocks and the global economy: A counterfactual analysis. Energy Econ. 59, 382–399.

Mohaddes, K., Raissi, M., 2020. Compilation, revision and updating of the global VAR (GVAR) database. 1979Q2-2019Q4.

Newell, R.G., Prest, B.C., Sexton, S.E., 2021. The GDP-temperature relationship: Implications for climate change damages. J. Environ. Econ. Manag. 108, 102445.

Pesaran, M.H., Schuermann, T., Weiner, S.M., 2004. Modeling regional interdependencies using a global error-correcting macroeconometric model. J. Bus. Econom. Statist. 22 (2), 129–162.

Pesaran, H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58, 17–29.

Pesaran, M., Smith, R., 1995. Estimating long-run relationships from dynamic heterogeneous panels. J. Econometrics 68, 79–113.

Pretis, F., 2020. Econometric modelling of climate systems: The equivalence of energy balance models and cointegrated vector autoregressions. J. Econometrics 214 (1), 256–273.

Pretis, F., 2021. Exogeneity in climate econometrics. Energy Econ. 96, 105122.

Pretis, F., Schwarz, M., Tang, K., Haustein, K., Allen, M.R., 2018. Uncertain impacts on economic growth when stabilizing global temperatures at 1.5 C or 2 C warming. Philos. Trans. R. Soc. A: Math. Phys. Eng. Sci. 376 (2119), 20160460.

Reilly, J., Hohmann, N., 1993. Climate change and agriculture: The role of international trade. Am. Econ. Rev. 83 (2), 306–312.

Rezai, A., Taylor, L., Foley, D., 2018. Economic growth, income distribution, and climate change. Ecol. Econom. 146, 164–172.

Salisu, A.A., Isah, K., Oloko, T.O., 2024. Technology shocks and crude oil market connection: The role of climate change. Energy Econ. 130, 107325.

Sheng, X., Gupta, R., Çepni, O., 2022. The effects of climate risks on economic activity in a panel of US states: The role of uncertainty. Econom. Lett. 213, 110374.

Taconet, N., Méjean, A., Guivarch, C., 2020. Influence of climate change impacts and mitigation costs on inequality between countries. Clim. Change 160 (1), 15–34.

Tol, R.S., 2018. The economic impacts of climate change. Rev. Environ. Econ. Policy 12 (1), 4–25.

Trenberth, K.E., Shea, D.J., 2005. Relationships between precipitation and surface temperature. Geophys. Res. Lett. 32 (14).