



## Research article

# Modeling interdependence between climatic factors, commodities, and financial markets

Fatemeh Mojtahedi<sup>a,\*</sup>, Daniel Felix Ahelegbey<sup>b,c</sup>, Mario Martina<sup>a</sup><sup>a</sup> Department of Science, Technology and Society, University School for Advanced Studies IUSS, Pavia, Italy<sup>b</sup> Department of Economics and Management, University of Pavia, Italy<sup>c</sup> School of Mathematics, Statistics, and Actuarial Science, University of Essex, UK

## ARTICLE INFO

*JEL classification:*JEL  
C01  
C11  
C32  
C52*Keywords:*Climate indices  
Natural disasters  
Network models  
Bayesian theory  
Climate risk  
Commodities

## ABSTRACT

This paper introduces a comprehensive approach to studying the impact of climate-related factors on commodity and financial markets using network analysis. We utilize a Bayesian network Vector Autoregressive model to investigate whether climate risk significantly influences commodity prices and financial market returns. Our findings provide evidence of a climate effect on major commodities and global financial markets. Specifically, we identify Crude oil, Cotton, and Sugar as the commodities most affected by climate risk, with Gold demonstrating the least susceptibility. Additionally, we observe that climate-related risk on commodities is likely propagated by patterns such as PNA, NN1, and AO. In terms of financial markets, we find that stock markets in Hong Kong, India, and Spain are the most susceptible to climate risk, while Switzerland's market appears to be the least affected. Furthermore, we document evidence that climate-related risk capable of altering financial markets is likely propagated by factors like ENP, NN1, and WH. Overall, our study underscores the intricate relationship between climate factors and market dynamics, highlighting the importance of considering climate risk in assessing market behavior and performance.

## 1. Introduction

One of the paramount challenges of our era is climate change. This phenomenon, characterized by shifts in global temperature and the occurrence of extreme weather events, has a profound and direct impact on human lives, particularly in the world's poorest and most vulnerable populations. It leads to environmental degradation and economic losses. Additionally, climate change exacerbates natural disaster events such as flooding, drought, wildfires, and storms, further intensifying their impact on the natural environment, people, and the economy [7]. This study aims to advance an econometric methodology to comprehensively analyze the direct and indirect impact of climate change on commodities and financial markets.

As highlighted in the National Climate Assessment (NCA) report, climate change introduces new risks and exacerbates existing vulnerabilities in communities. It presents growing challenges to human health, safety, and overall quality of life, while also impeding economic growth [44]. The report emphasizes that more frequent and intense extreme weather and climate-related events, along with changes in average climate conditions, will continue to cause damage to infrastructure, ecosystems, and social systems crucial for

\* Corresponding author.

E-mail addresses: [fatemeh.mojtahedi@iusspavia.it](mailto:fatemeh.mojtahedi@iusspavia.it) (F. Mojtahedi), [d.f.ahelegbey@essex.ac.uk](mailto:d.f.ahelegbey@essex.ac.uk) (D.F. Ahelegbey), [mario.martina@iusspavia.it](mailto:mario.martina@iusspavia.it) (M. Martina).<https://doi.org/10.1016/j.heliyon.2024.e36316>

Received 18 November 2023; Received in revised form 8 August 2024; Accepted 13 August 2024

Available online 19 August 2024

2405-8440/© 2024 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

community well-being. The report concluded by emphasizing the urgent need for global and regional macro-prudential policies to mitigate the adverse effects of climate change. Without such measures, the impact of changes in climate-related events on the global economy is expected to intensify further.

Climate change stands as a collective crisis for the international community, posing one of humanity's most severe challenges [22, 26,53]. Its impacts extend across various sectors, including agriculture, health, and beyond, generating concerns that are often invisible but nonetheless significant in affected regions [5,32,48,56]. Moreover, financial markets and economic systems are increasingly vulnerable to climate change-related events, with notable consequences observed [21,28]. Uncertainty and risk are inherent features of climate change, making it challenging to accurately assess its influence on the global economy [20,55]. Economic climate risk, in this context, refers to the uncertainty surrounding climate impacts on the economy, most of which inevitably affect financial performance [6].

Numerous studies have investigated the effects of different types of shocks on the economy using various methodologies [11,19,23, 24,34,36,37,47]. However, it is essential to recognize natural catastrophes, such as those arising from climate change and natural disaster events, as non-financial, exogenous shocks to the economy [35,42,46,49]. These approaches have expanded the field of studying the relationship between climate change and finance from various perspectives. These studies demonstrate that physical risks associated with climate change and natural disasters can significantly impact economies by damaging asset values, productive capacity, and overall economic activity [8,9,17,29]. These studies argue that climate change poses a significant and urgent risk that financial markets need to address. They cite empirical evidence suggesting that the equity market is already pricing in climate change and related risks, underscoring the importance of considering these factors in investment decisions. However, others raise questions about the practical implications of incorporating climate change into financial markets. They argue that while climate change may present long-term risks, the immediate impacts on financial markets are uncertain and may be overshadowed by other economic factors. In addition to scholarly literature, it's important to highlight the proactive involvement of key entities such as the European Central Bank (ECB), the Financial Stability Board (FSB), and the European Commission. These organizations are deeply invested in addressing the ramifications of climate change on the financial market and are actively engaged in seeking effective solutions. Following the acknowledged gap concerning the uncertainty of impacts, we have taken a multifaceted approach by examining various markets to fortify our findings.

In response to growing concern, financial regulators have expressed increasing interest in understanding how climate risks are reflected in the prices of financial assets and how investors can incorporate such risks into their asset allocation decisions [16]. The primary focus of current and future research lies in examining how climate risk, stemming from climate-related factors and natural disaster events, affects economic and financial systems.

Recognizing this significance, several studies have investigated the impact of climate-related phenomena on various aspects of the economy and financial markets. For instance: [14], using VAR models, examined the effects of the ENSO cycle on world prices and economic activity [38]. investigated the effect of climate uncertainty on global commodity markets using the FAVAR model [25]. studied the relationship between environmental-related variables, commodity price co-movements, and financial stability [33]. analyzed the effect of ENSO indices on commodity returns using AR models and attempted to forecast [42]. examined the effects of natural disasters on global stock market indices using the SUR model [15]. studied the effects of El Niño events on commodity prices using the wavelet approach [45]. investigated the global climate-related shocks on the prices of gold and silver in the GVAR model. In these studies, climate change, particularly events like El Niño, significantly influences commodity prices and financial markets. Historical correlations and the predictive power of climate information support incorporating climate knowledge into investment decisions, providing valuable signals for understanding financial stability dynamics. However, climate change's impact on commodity prices and financial markets should be understood in the right way. Critics raise concerns about the feasibility and effectiveness of using climate information for investment decisions, citing the uncertainty and complexity of climate models, and are searching for a better model. Once more, we recognize the necessity of conducting a more comprehensive study to achieve a deeper understanding of the impacts of climate on markets. While evidence supports the idea that climate change affects commodity prices and financial markets, ongoing debate persists regarding the extent of this influence and the efficacy of using climate information for investment decisions. This highlights the importance of further research and interdisciplinary collaboration to better understand the complex interactions between climate change, commodity markets, and financial stability.

Our contribution to the literature is manifold. Firstly, we study the impact of multiple climate indices instead of focusing on just one, as extensively discussed in many existing studies. Considering multiple climate indices allows for a comprehensive picture of global climate variability, providing a nuanced understanding of how different climate factors collectively contribute to market fluctuations and vulnerabilities.

Secondly, our study considers the effect of climate indices on multiple markets, namely, commodities and financial equity markets. By simultaneously examining the impacts of climate change on diverse markets, including commodities and financial equities, we aim to unveil the intricate relationships and interdependencies within the global economic landscape.

Thirdly, our study focuses on analyzing the direct effect of climate on real markets, as well as indirect effects through natural disaster events. By exploring both direct and indirect effects, we aim to comprehend the multifaceted nature of climate change's impact on global markets.

Fourthly, we employ VAR models through the lens of networks to identify the causal impact of climate-related indexes on commodities and financial markets. This approach allows for a more nuanced analysis of the intricate relationship between climate dynamics and market performances, contributing to a more comprehensive understanding of the vulnerabilities and potential risk factors inherent in this complex interplay.

The empirical application aims to provide a comprehensive analysis to assess the impacts of climate factors on major global

commodity markets, including energy, agriculture, and metals, as well as the top ten global stock markets. The primary goal is to determine whether climate change has a significant direct and/or indirect impact on commodity prices and financial equity market returns.

Specifically, the research questions addressed in this study are as follows:

1. How is climate change impacting commodity and financial markets?
2. Which commodity and financial markets are most vulnerable to climate change, and which are considered the safest?
3. What is the influence of climate indices and climate-induced natural disasters on commodity and financial markets?

These research questions will guide the empirical analysis to provide insights into the complex interactions between climate change, commodity markets, and financial markets, contributing to a better understanding of the potential risks and vulnerabilities associated with climate-related factors.

This study endeavors to bridge the gap between existing research on climate dynamics and their economic impacts, with a specific focus on providing actionable insights for policymakers and stakeholders. Through a comprehensive examination of the literature on climate-related variables, their regional complexities, and the evolving landscape of climate indices, our research aims to provide a holistic framework for understanding the diverse implications of climate change on global economic systems.

The study serves as a critical foundation for fostering proactive measures to address the challenges posed by climate-related shocks and natural disaster events. By obtaining monthly data on financial market and commodity variables from the Bloomberg database, natural disaster variables from the Emergency Events Database (EM-DAT), and climate indices from the Physical Sciences Laboratory (PSL), we aim to provide robust empirical evidence regarding the interplay between climate dynamics and economic outcomes.

A notable aspect of our study is the consideration of multiple climate-related indices, which distinguishes it from previous research that often focused on a single factor, primarily the ENSO/SOI. This comprehensive approach allows us to capture a more nuanced understanding of the complex relationships between climate variability and economic performance.

Ultimately, our research endeavors to empower policymakers and stakeholders with valuable insights to inform decision-making processes and the development of effective policy interventions aimed at promoting sustainable economic growth and resilience in the face of climate-related challenges.

In our study, we employ Bayesian network vector autoregressive (BNVAR) models, as proposed by Ref. [2], to address the objectives outlined above. While several studies have focused on the predictive power of general macroeconomic variables in forecasting prices and indices, our model incorporates exogenous climate-related factors and natural disasters, thus extending the existing literature in this area.

Our analysis reveals evidence of the direct impact of climate-related events on global commodity markets, particularly in the agricultural and energy sectors, which is consistent with the findings of [18,38]. Additionally, we observe a direct impact of climate on financial stock market performances.

Over the past two decades, we identify the PNA Pattern as the climate index with the most significant impact on commodities, while the EPN index stands out as the most influential on financial markets. Our results also highlight the top three commodities most affected by climate indices, namely crude oil, cotton, and sugar, while the top three impacted financial market indexes are the Hong Kong Hang Seng, the Indian Sensex, and the Spain IBEX 35.

Furthermore, in relation to natural disasters, we find that the extreme temperature of South America (SAM.Et) has the most significant influence on commodities, while in the financial market, it is the extreme temperature of East and Southeast Asia (ESA.Et). The top three most affected commodities by natural disasters are wheat, coal, and sugar, whereas the top three most influential financial market indexes are the Indian Sensex, the Spain IBEX 35, and the Japanese Nikkei.

Moreover, our analysis demonstrates that our climate-natural-disaster augmented VAR model produces competitive forecasts against conventional Bayesian VAR models when predicting out-of-sample commodities and financial market returns. This underscores the efficacy of our approach in capturing the complex interactions between climate dynamics, natural disasters, and market performances.

Overall, the manuscript provides valuable insights into the complex interactions between climate dynamics, natural disasters, commodity markets, and financial markets, which can have significant implications for investment decisions, risk management practices, and policy development. By leveraging these insights, stakeholders can better navigate the challenges posed by climate change and build more resilient and sustainable economic systems.

The rest of the paper is organized as follows: Section 2 presents the methods that is an overview of the BNVAR methodology and extensively describes the data, Section 3 reports the results of our main findings, Section 4 presents the discussion and Section 5 presents the conclusion.

## 2. Methods/data

### 2.1. Bayesian network VAR model estimation

To address the study's objectives, we adopt the BNVAR models as our analytical framework. The BNVAR model, presented in this paper, addresses the challenge posed by a high number of variables in traditional vector autoregressive (VAR) models. By incorporating the statistical properties of variables as the prior distribution of parameters, the BNVAR model effectively mitigates the issue of dealing with an abundance of variables. In essence, the model utilizes Bayesian theory to preselect significant variables, thus

facilitating more manageable and accurate estimations focused on variables that genuinely impact the dependent variables, thereby overcoming the challenge of handling extensive data. In line with previous research, our approach incorporates exogenous climate-related variables and natural disaster data, and endogenous financial and commodity markets.

Let  $F_t \in \mathbb{R}^{n_1}$  denote a vector of returns of financial market variables composed of major stocks indices observed at time  $t$ ,  $C_t \in \mathbb{R}^{n_2}$  - a vector of commodities,  $D_t \in \mathbb{R}^{n_3}$  - a vector of natural disaster events, and  $X_t \in \mathbb{R}^{n_4}$  - a vector of climate indices. We denote with  $Y_t = (F_t, C_t) \in \mathbb{R}^{n_1+n_2}$  the vector of market variables. We model  $Y_t$  and  $D_t$  as a vector autoregressive (VAR) model augmented with exogenous variables, and each element in  $X_t$  as an autoregressive (AR) model. We approximate the model as follow:

$$Y_t = \alpha_y + B_{11}(L) Y_{t-1} + B_{12}(L) D_t + B_{13}(L) X_t + u_t \tag{1}$$

$$D_t = \alpha_n + B_{22}(L) D_{t-1} + B_{23}(L) X_t + \varepsilon_t$$

where 
$$\begin{bmatrix} u_t \\ \varepsilon_t \end{bmatrix} \sim \mathcal{N} \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \Sigma_u & 0 \\ 0 & \Sigma_\varepsilon \end{bmatrix} \right) \tag{2}$$

and  $\alpha_y, \alpha_n$  and  $\alpha_c$  are constants;  $B = (B_{11}(L), \dots, B_{32}(L))$ , are lag operator polynomials of coefficients;  $u_t \in \mathbb{R}^{n_1+n_2}$  is a vector of market shocks; and  $\varepsilon_t \in \mathbb{R}^{n_3}$  is a vector of natural disaster shocks.

Equation (1) represents the dynamics of the market variables  $Y_t$  incorporating the effects of past market variables  $Y_{t-1}$ , natural disaster events  $D_t$ , and climate indices  $X_t$ . Similarly, Equation (2) models the dynamics of natural disaster events  $D_t$ , considering the influence of their past values  $D_{t-1}$  and the current climate indices  $X_t$ .

The assumptions underlying this model ensure that elements of climate events  $X_t$  do not influence each other, and are not influenced by natural disasters  $D_t$  or market events  $Y_t$ . Thus, we assume  $X_t$  are exogenous, affecting  $D_t$  and  $Y_t$  both temporally and contemporaneously, but not vice versa. Furthermore, we assume elements of  $D_t$  can influence each other temporally and affect  $Y_t$  temporally and contemporaneously, but not vice versa. Additionally, the model assumes that the shocks to climate events, natural disasters, and market events are uncorrelated and follow a multivariate Gaussian distribution.

The application of Bayesian graphical (network) models to analyze VAR proposed by is based on viewing VAR's as a network model with the coefficients encoding the weights of the conditional (in-)dependent relationships among the variables. We represent the relationships between variables of VAR with a network model defined by  $\mathcal{M} = \{V, G_{0:p}, A_{0:p}, W\}$ , where  $V = (V_1, \dots, V_m) \equiv (Y, D, X)$  is a set of vertices which represents the variables of the model. Each  $G_k(A_k), k = 0, 1, \dots, p$ , is an  $m \times m$  binary (weight) matrix that depicts the connectivity between variables at different times points such that the  $(i, j)$ -th entry of  $G_k(A_k)$  is given by

$$G_{k,ij} = \begin{cases} 1 & \implies V_{j,t-k} \rightarrow V_{i,t} \\ 0 & \implies V_{j,t-k} \not\rightarrow V_{i,t} \end{cases}, \quad A_{k,ij} = \begin{cases} B_{k,ij} \in \mathbb{R} & \text{if } G_{k,ij} = 1 \\ 0 & \text{if } G_{k,ij} = 0 \end{cases} \tag{3}$$

In (3),  $G_{k,ij} = 1$  implies the existence of a directed link from  $V_j$  to  $V_i$  at lag  $k$ ,  $V_{j,t-k} \rightarrow V_{i,t}$ , which means  $V_{j,t-k}$  is a parent (predictor) of  $V_{i,t}$ . The relationship between  $B$  and  $A$  depends on  $G$  such that, if  $G_{k,ij} = 1$  then the effect of  $V_{j,t-k}$  on  $V_{i,t}$  is measured by  $A_{k,ij} = B_{k,ij}$ . Otherwise,  $G_{k,ij} = 0$ , which means  $V_{j,t-k}$  has no influence on  $V_{i,t}$ , and  $A_{k,ij} = 0$ .

Finally,  $W$  is an  $m \times m$  weighted matrix that specifies the weights of the relationship between pairs of variables. These weights are obtained as a sum of the estimated contemporaneous and lagged coefficients, as shown in (4):

$$W_{ij} = \begin{cases} \sum_{k=0}^p A_{k,ij} & \text{if } V_j \rightarrow V_i \\ 0 & \text{if } V_j \not\rightarrow V_i \end{cases} \tag{4}$$

where  $W_{ij} \neq 0$  implies the existence of a contemporaneous or temporal influence of  $V_j$  on  $V_i$ , and  $W_{ij} = 0$  means  $V_j$  does not influence  $V_i$ .

To facilitate the easy implementation of Bayesian graphical (network) VAR model in practice, we follow the estimation approach of [2,3] which involve prior specification and posterior approximations.

Let  $Z_t = (Y_t', \dots, Y_{t-p}', D_t', \dots, D_{t-p}', X_t', \dots, X_{t-p}')'$  be  $m$ -dimensional vector of contemporaneous and lagged observations, where  $m = (n_1 + n_2 + n_3 + n_4)(p + 1)$ . Denote with  $Z = (Z_1', \dots, Z_N')'$  be  $N \times m$  matrix collection of  $Z_t$ . Under the assumption that  $Z \sim \mathcal{N}(0, \Sigma)$ , the likelihood function is given by (5):

$$P(Z|\Omega, G) = (2\pi)^{-\frac{mN}{2}} |\Omega|^{-\frac{N}{2}} \exp \left\{ -\frac{1}{2} \langle \Omega, \hat{S} \rangle \right\} \tag{5}$$

where  $\langle A, B \rangle = \text{tr}(A'B)$  denotes the trace inner product and  $\hat{S} = ZZ'$ .

Prior on  $G$  and  $\Omega$ .

We consider the inclusion of a link in  $G$  as a Bernoulli trial,  $G_{ij} \sim \text{Ber}(\gamma_{ij})$ , with density

$$P(G) = \prod_{i \neq j} \gamma_{ij}^{G_{ij}} (1 - \gamma_{ij})^{(1-G_{ij})} \tag{6}$$

In (6),  $\gamma_{ij} \in (0, 1)$  is the probability of a directed link from nodes  $j$  to  $i$ . We assign to each variable inclusion a prior probability,  $\gamma_{ij} = 1/2, \forall i, j$ , which is equivalent to assigning equal prior probability to all network structures, i.e,  $P(G) \propto 1$ .

Following [27], we assume the unconstrained  $\Omega$  given a complete network graph, is Wishart distributed  $\Omega|G \sim \mathcal{W}(S_0^{-1}, \nu)$ , with density as (7):

$$P\left(\Omega|G = \frac{1}{K_m(\nu, S_0)} |\Omega|^{\frac{(\nu-m-1)}{2}} \exp\left\{-\frac{1}{2}\langle \Omega, S_0 \rangle\right\}\right) \tag{7}$$

where  $S_0$  is the prior scale matrix,  $\nu > m + 1$  is the degree of freedom parameter, and  $K_m(\nu, S_0)$  is the normalizing constant.

### 2.1.1. Posterior inference of $G$

Under the Bayesian framework of [27],  $\Omega$  can be integrated out analytically to obtain a marginal likelihood function with a close-form local expression expression given by [1,2]

$$P(Z_{y_i} | Z_{x_i}) = \frac{\pi^{-\frac{1}{2}N} \nu^{\frac{1}{2}\nu}}{(\nu + N)^{\frac{1}{2}(\nu + N)}} \frac{\Gamma\left(\frac{\nu + N - n_f}{2}\right)}{\Gamma\left(\frac{\nu - n_f}{2}\right)} \left(\frac{|Z_{x_i}' Z_{x_i} + \nu I_{n_x}|}{|Z_{f_i}' Z_{f_i} + \nu I_{n_f}|}\right)^{\frac{1}{2}(\nu + N)} \tag{8}$$

In (8),  $Z_{y_i}$  is the  $i$ -th dependent variable,  $Z_{x_i}$  is a set of predictor variables of  $Z_{y_i}$ ,  $Z_{f_i} = (Z_{y_i}, Z_{x_i})$ ,  $n_x$  is the number of nodes in  $Z_{x_i}$ , and  $n_f = n_x + 1$  is the number of nodes in  $Z_{f_i}$ .

Given the data,  $Z$ , the prior distributions on  $G$ , and the marginal likelihood, we are particularly interested in the posterior inference of  $G$  in Ref. [3]. This is achieved by sampling  $G$  from the marginal posterior distribution,  $G \sim P(G|Z) \propto P(Z|G)$ . Following [4], we sample  $G$  from  $P(Z|G)$  via hybrid search algorithm that initializes the network graph with a conditional Granger-causality-like structure and advances to perform local network updates via a Metropolis-within-Gibbs scheme with random walk proposal.

#### Posterior Inference of $A$ .

Given the data,  $Z$ , and  $G$ , we proceed to estimate the parameters in  $A$ . We follow the conventional maximum-likelihood estimation for a seemingly unrelated regression (SUR). Conditional on  $G$ , the selected predictors for each equation of [1] may differ. Thus,  $\hat{A}$  is computed for one equation at a time as shown in (9):

$$\hat{A}_{y_i, x_i} = (Z_{x_i}' Z_{x_i})^{-1} Z_{x_i}' Z_{y_i} \tag{9}$$

## 2.2. Network centrality

Various centrality measures have been proposed in the networks literature. Given that our BNVAR model naturally provides a network representation of the dependence among time series, we focus on the in-degree, out-degree, authority, and hubs [10,12,40].

Let  $A$  denote the  $n \times n$  zero-diagonal unweighted adjacency matrix, and  $W$  denote the weighted adjacency matrix of the interconnections among the  $n$  variables. The unweighted in-degree of node  $i$ , denoted  $\overleftarrow{D}_i^U$ , and the unweighted out-degree of node  $j$ , denoted  $\overrightarrow{D}_j^U$ , can be defined as (10):

$$\overleftarrow{D}_i^U = \sum_j A_{ij} \quad \overrightarrow{D}_j^U = \sum_i A_{ij} \tag{10}$$

where  $\overleftarrow{D}_i^U$  counts the number of links directed towards node- $i$ , while  $\overrightarrow{D}_j^U$  is the number of links going out of node- $j$ . The weighted in-degree of node- $i$ ,  $\overleftarrow{D}_i^W$ , and the weighted out-degree of node- $j$ ,  $\overrightarrow{D}_j^W$ , can be defined by (11):

$$\overleftarrow{D}_i^W = \sum_j W_{ij} \quad \overrightarrow{D}_j^W = \sum_i W_{ij} \tag{11}$$

where  $\overleftarrow{D}_i^W$  and  $\overrightarrow{D}_i^W$  are the row and column sums of  $W$  respectively.

We compute centrality measures that consider the significance of the neighborhood of a node in a network graph. Hub and authority centrality assign a score to nodes in the network proportional to the importance of their neighbors. For a weighted adjacency network represented by  $W$ , the hub and authority scores are determined by solving (12):

$$(W'W) h_w = \lambda_h h_w \quad (WW) a_w = \lambda_a a_w \tag{12}$$

In this context,  $h_w$  and  $a_w$  represent the hub score and authority score eigenvectors, respectively. They correspond to  $\lambda_h$  and  $\lambda_a$ , which

are the largest eigenvalues of  $W'W$  and  $WW'$ , respectively. A hub node typically exhibits a large out-degree, while an authority node has a large in-degree. From a network perspective, nodes with high authority scores or in-degrees are strongly influenced by others, whereas nodes with high hub scores or out-degrees are influential or act as propagators within the network.

### 2.3. Data description

Based on the studies conducted on climate change, it is evident that climate variables significantly impact the economy. However, it is crucial to acknowledge that these variables are often analyzed within the context of particular regions or markets due to the diverse nature of global climate patterns. As a result, relying solely on a single numerical representation for each climate variable may overlook the intricate complexities of the global climate system. Given these limitations, a more holistic approach is necessary to understand global market dynamics. This necessitated a thorough review of extensive literature across various categories to select climate-related proxies and markets for our studies. The dataset for our study comprises four categories of variables: financial market indicators, commodities, natural disaster occurrences, and climate indices (see Table 1). Table 2 provides an overview of the variables considered, while Table A.7 outlines their detailed descriptions. Monthly observations on these variables were collected from January 2000 to August 2022.

Fig. 1 illustrates the distribution of natural disaster events across different regions. In this representation, natural disaster events are quantified by the number of occurrences in a given month. The figure highlights that the most significant incidence of drought was documented between 2014 and 2016, reaching its peak in late 2015 to early 2016, which appears to align with the 2015-16 El Niño-induced drought crisis in Southern Africa. Additionally, the highest occurrence of epidemics was observed between 2006 and 2007, coinciding with outbreaks of the H5N1 virus infection in poultry reported in over 38 countries from late 2003 through early 2007.

Fig. 2 presents the full-sample correlations among the climate indices. The correlation coefficients are color-coded, with light (deep) blue cells indicating weak (strong) positive correlations at the 5% significance level, and light (deep) red cells indicating weak (strong) negative correlations. Notably, a strong negative correlation is observed between BES–SOI, while strong positive correlations are found among the following pairs: NN3–N34, N34–NN4, N34–NOI, NN3–NOI, MEI–NOI, MEI–N34, BES–N34, and BES–NOI. These observations are not surprising as these indices measure similar climate variability patterns but at different latitudes and longitudes, covering various regions.

Given that our methodology involves variable selection, the Bayesian search and score scheme samples the set of predictors with conditional dependent relationships with the de-pendent variables and improves their prediction. Thus, we are able to overcome the issue of high collinearity among the climate indices and spurious correlations that lack predictive power.

## 3. Results

This section presents the findings of our empirical study on modeling the impact of climate on commodities and financial markets. We examine how climate-related factors can serve as significant risk factors in these markets. To achieve this, we analyze the effect of selected climate indices on commodity and financial markets.

In our approach, we model the selected commodity and financial market variables as de-pendent outcomes in first log differences, while the climate indices and natural disaster events are considered in levels. Recognizing the importance of climate lag in modeling and policy-making related to climate change, we determined the lag number using the Bayes Information Criterion (BIC), which indicated three as the optimal lag value.

We incorporate dynamic interactions through a rolling window of 120 months (equivalent to a 10-year period). This setup allows

**Table 1**  
Details of categories of variables.

Category	Selected Indices	Source
Financial Market Indicators	Top 10 equity indices chosen based on their market capitalization. These include the United States S&P-500, Canadian SPTSX, Hong Kong Hang Seng, Indian Sensex, Japanese Nikkei, German DAX-30, Switzerland SMI, Spain IBEX-35, France CAC-40, and UK FTSE-100.	Bloomberg database.
Commodities Market	Comprises three primary groups: Energy (Brent Crude Oil, Natural Gas, Coal), Agricultural products (Wheat, Corn, Cotton, Soybean, Sugar), and Metals (Gold, Aluminum).	Bloomberg database.
Natural Disaster Events	Include Droughts, Earthquakes, Epidemics, Extreme temperatures, Floods, and Storms. These events are grouped according to eight regions: East and Southeast Asia (ESA), West and South Asia (WSA), South America (SAm), Europe (EU), Australia and Oceania (AuO), Africa (AF), Central America and Caribbean (CAC), and North America (NAm).	Emergency Events Database (EM-DAT).
Climate Indices	24 Indices, several of which have been utilized in previous empirical studies.	Physical Sciences Laboratory (PSL)

Note: the Emergency Events Database (EM-DAT: <https://www.emdat.be/>), which is curated by the Centre for Research on the Epidemiology of Disasters (CRED), and Physical Sciences Laboratory (PSL: <https://psl.noaa.gov/data/climateindices/list/>).

**Table 2**  
Variable description and classification.

No.	Name	Idn	Code	No.	Name	Idn	Code
<b>Financial Markets</b>				<b>Natural Disasters (Cont.)</b>			
1	United States S&P-500	1	US	47	Epidemic	27	AuO.Ep
2	Canadian SPTSX	2	CN	48	Extreme temperature	28	AuO.Et
3	Hong Kong Hang Seng	3	HK	49	Flood	29	AuO.Fl
4	Indian Sensex	4	IN	50	Storm	30	AuO.St
5	Japanese Nikkei	5	JP	51	Drought	31	AF.Dr
6	German DAX-30	6	DE	52	Earthquake	32	AF.Er
7	Switzerland SMI	7	CH	53	Epidemic	33	AF.Ep
8	Spain IBEX-35	8	SP	54	Extreme temperature	34	AF.Et
9	France CAC-40	9	FR	55	Flood	35	AF.Fl
10	UK FTSE-100	10	UK	56	Storm	36	AF.St
				57	Drought	37	CAC.Dr
<b>Commodities Markets</b>				<b>Climate Indices</b>			
11	Brent Crude Oil	1	OIL	58	Earthquake	38	CAC.Er
12	Natural Gas	2	GAS	59	Epidemic	39	CAC.Ep
13	Coal	3	COL	60	Extreme temperature	40	CAC.Et
14	Wheat	4	WHT	61	Flood	41	CAC.Fl
15	Corn	5	CON	62	Storm	42	CAC.St
16	Cotton	6	CTN	63	Drought	43	NAm.Dr
17	Soybean	7	SYB	64	Earthquake	44	NAm.Er
18	Sugar	8	SUG	65	Epidemic	45	NAm.Ep
19	Gold	9	GLD	66	Extreme temperature	46	NAm.Et
20	Aluminium	10	ALM	67	Flood	47	NAm.Fl
				68	Storm	48	NAm.St
21	Drought	1	ESA.Dr	69	Atlantic Meridional Mode	1	AMM
22	Earthquake	2	ESA.Er	70	Atlantic Multidecadal Oscillation	2	AMO
23	Epidemic	3	ESA.Ep	71	Arctic Oscillation	3	AO
24	Extreme temperature	4	ESA.Et	72	Bivariate ENSO Index	4	BES
25	Flood	5	ESA.Fl	73	East Pacific.North Pacific Osculation	5	ENP
26	Storm	6	ESA.St	74	ENSO Precipitation Index	6	ESP
27	Drought	7	WSA.Dr	75	Global Mean Land.Ocean Temperature	7	GMS
28	Earthquake	8	WSA.Er	76	Multivariate ENSO Index	8	MEI
29	Epidemic	9	WSA.Ep	77	North Atlantic Oscillation	9	NAO
30	Extreme temperature	10	WSA.Et	78	Niño 1 + 2 SST Index	10	NN1
31	Flood	11	WSA.Fl	79	Niño 3 SST Index	11	NN3
32	Storm	12	WSA.St	80	Niño 3.4 SST Index	12	N34
33	Drought	13	SAm.Dr	81	Niño 4 SST Index	13	NN4
34	Earthquake	14	SAm.Er	82	Northern Oscillation Index	14	NOI
35	Epidemic	15	SAm.Ep	83	Pacific Decadal Oscillation	15	PDO
36	Extreme temperature	16	SAm.Et	84	Pacific North American Index	16	PNA
37	Flood	17	SAm.Fl	85	Quasi-Biennial Oscillation	17	QBO
38	Storm	18	SAm.St	86	Southern Oscillation Index	18	SOI
39	Drought	19	EU.Dr	87	Solar Flux Unit	19	SFU
40	Earthquake	20	EU.Er	88	Tropical Northern Atlantic Index	20	TNA
41	Epidemic	21	EU.Ep	89	Trans-Niño Index	21	TNI
42	Extreme temperature	22	EU.Et	90	Tropical Southern Atlantic Index	22	TSA
43	Flood	23	EU.Fl	91	Western Hemisphere Warm Pool	23	WH
44	Storm	24	EU.St	92	Western Pacific Index	24	WP
45	Drought	25	AuO.Dr				
46	Earthquake	26	AuO.Er				

Note: East and Southeast Asia (ESA), West and South Asia (WSA), South America (SAm), Europe (EU), Australia and Oceania (AuO), Africa (AF), Central America and Caribbean (CAC), North America (NAm).value.

for structural and coefficient changes in the interaction among the model variables. Monitoring monthly changes in dynamic relationships, we shift the rolling window by one month. Consequently, the first window spans from February 2000 to January 2010, followed by March 2000 to February 2010, and so forth, with the final window covering September 2012 to August 2022. In total, we consider 152 rolling windows.

For each window, we generate an out-of-sample one-month ahead forecast, covering the period from February 2010 to August 2022. We also explored alternative window quantities, including 100 and 180. However, our analysis determined that employing 120 windows offers a superior representation, facilitating a more comprehensive evaluation of the effects under consideration.

In Section 3.1, we present the results of the Direct and Indirect Effect of Climate on Com-mo-dity Markets. Section 3.2 outlines the Direct and Indirect Effect of Climate on Financial Markets. Section 3.3 provides the Centrality Analysis of Climate-to-Commodity Interconnec-tivity. Section 3.4 offers the Centrality Analysis of Climate-to-Financial Market Interconnec-tivity. Section 3.5reports the findings on the Centrality Analysis of Natural Disasters and Commodity Markets. Lastly, Section 3.7presents the Model Comparison of our model.

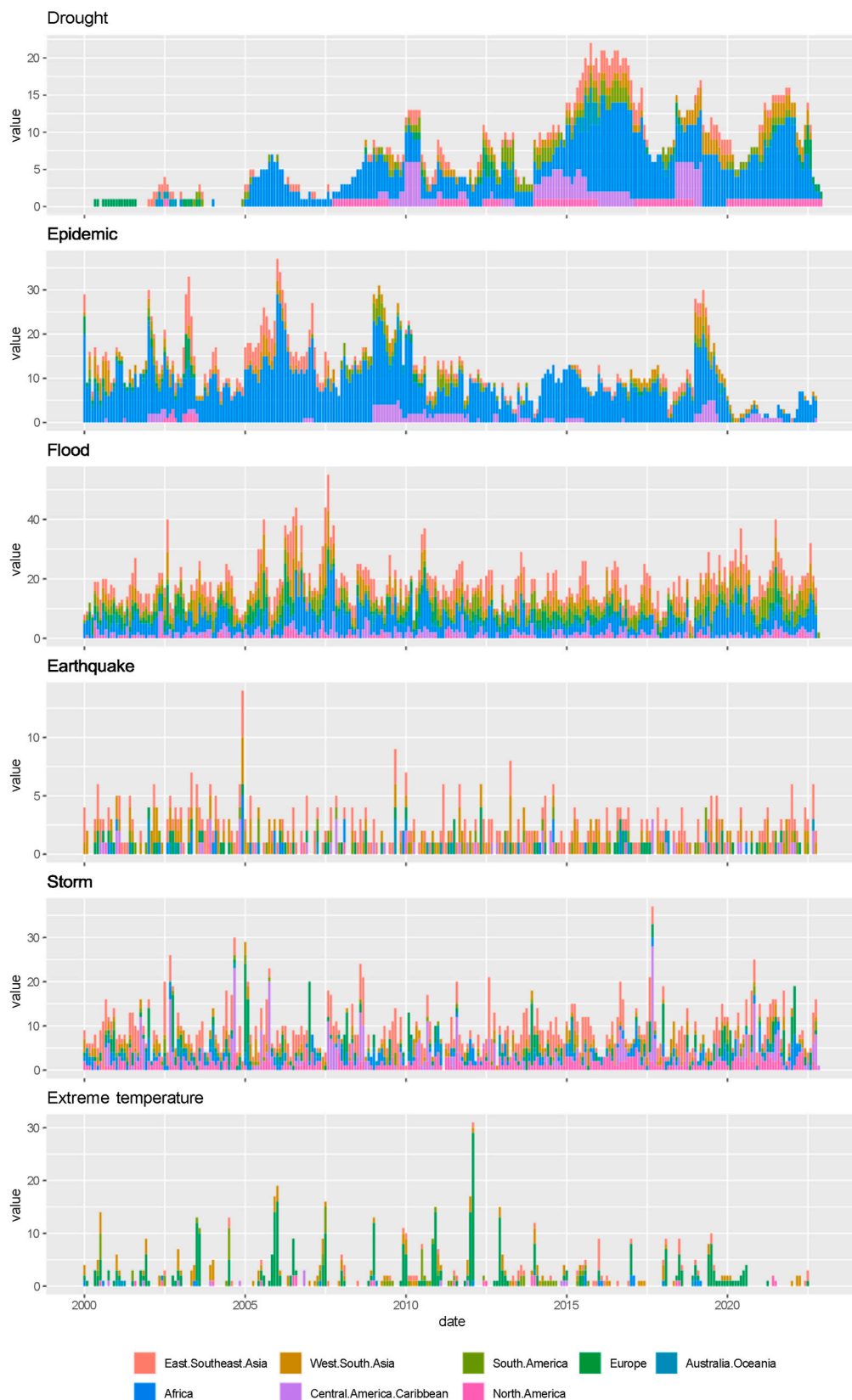


Fig. 1. Distribution of each natural disasters in different regions.

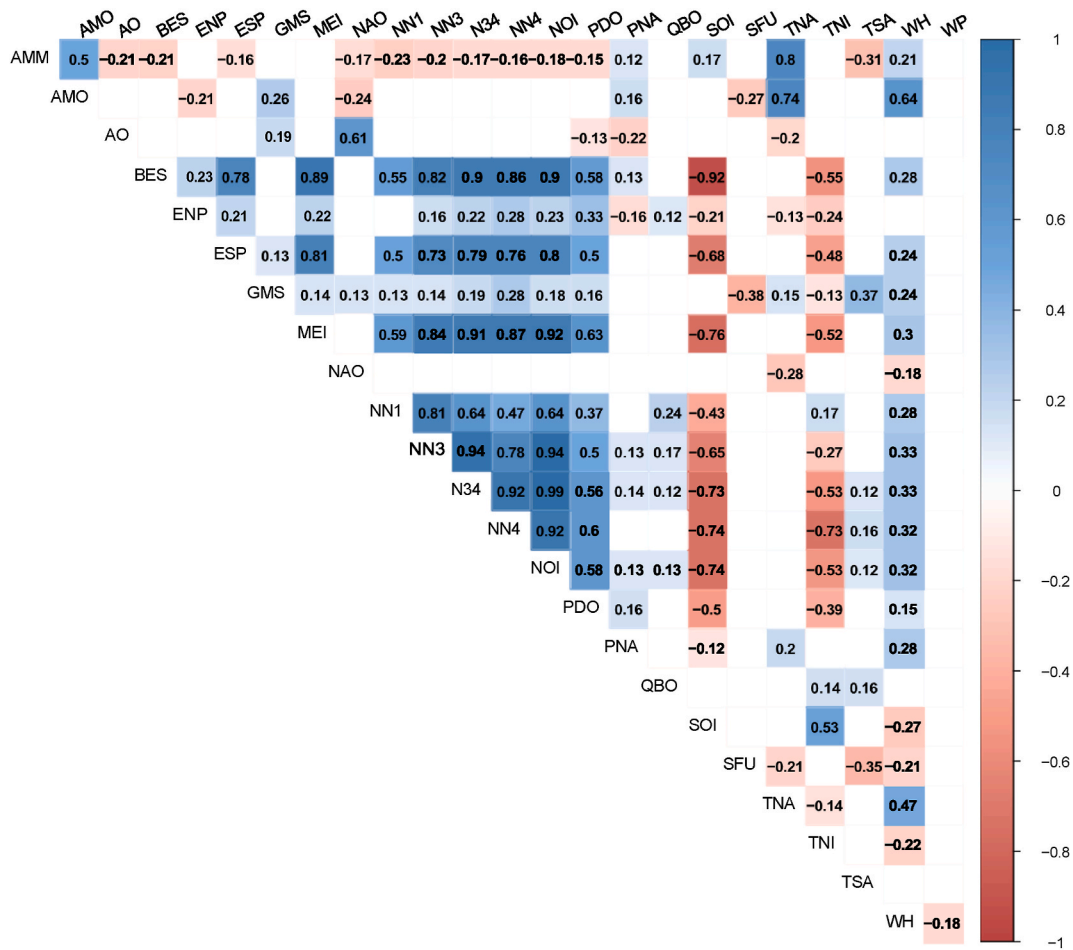


Fig. 2. The Correlation between Climate Indices. The light (deep) blue color cells indicates weak (strong) positive correlations, and light (deep) red color cells indicates weak (strong) negative correlations.

### 3.1. Direct and Indirect Effect of Climate on Commodity markets

In the previous section, we discussed that some studies have demonstrated the economic losses caused by climate indices and natural disasters. However, there remains uncertainty in the existing literature regarding their impact on commodity and financial markets.

We examined the direct and indirect impact of climate indices on commodity markets. Additionally, we considered the direct effect of natural disasters. Thus, we analyzed how climate indices influence natural disasters and how natural disasters, in turn, affect markets—illustrating both the indirect effect of climate indices and the direct effect of natural disasters.

Through Figs. 3 and 5, we observed the impact of climate indices and natural disasters on commodity markets. These findings demonstrate that climate indices and natural disasters have varied effects on commodity markets, which differ across commodities depending on their types and intensity.

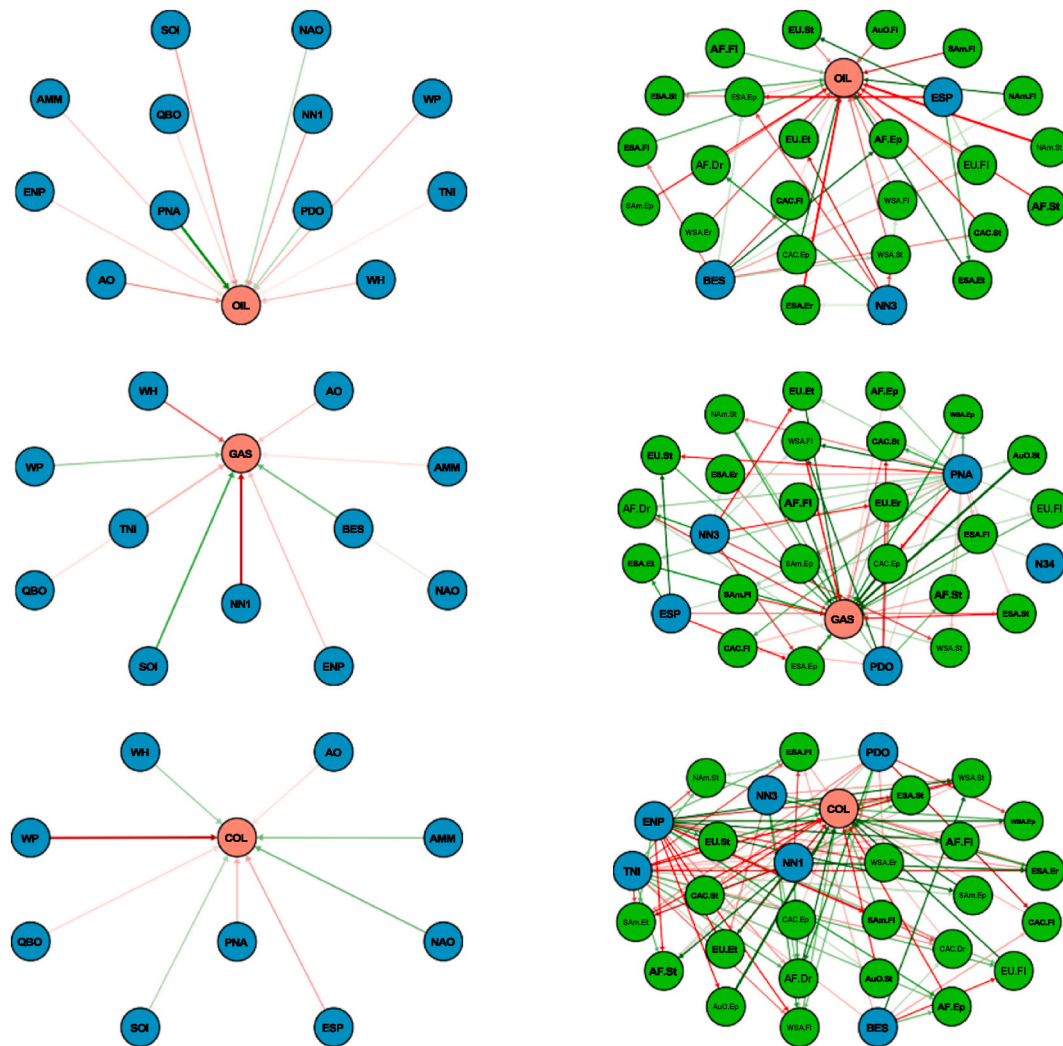
#### 3.1.1. Climate impact on energy commodities

Fig. B.10 presents the plots of the coefficients associated with the pure direct effect of climate indices on commodities over the rolling window estimation. The colors represent different climate indices, while each plot illustrates the impact on individual commodity prices. Notably, it is observed that the various climate indices have differing effects on the selected commodities.

Considering the most effective indices identified in Fig. 3 and their patterns, it is evident that the effects of these indices follow their respective patterns. For instance, in the case of Natural Gas, NN1, which is most effective during its negative phase, predominantly exhibited a negative phase between 2012 and 2020.

In general, throughout the remainder of the paper, we can infer that the effect of the indices on commodity prices is correlated with their patterns or phases. Specifically, a green line indicates that a positive phase of the climate index positively impacts the price, whereas a red line signifies that a negative phase of the climate index negatively impacts the price.

Fig. 3 presents a summary of the average effect of climate factors on energy commodities.



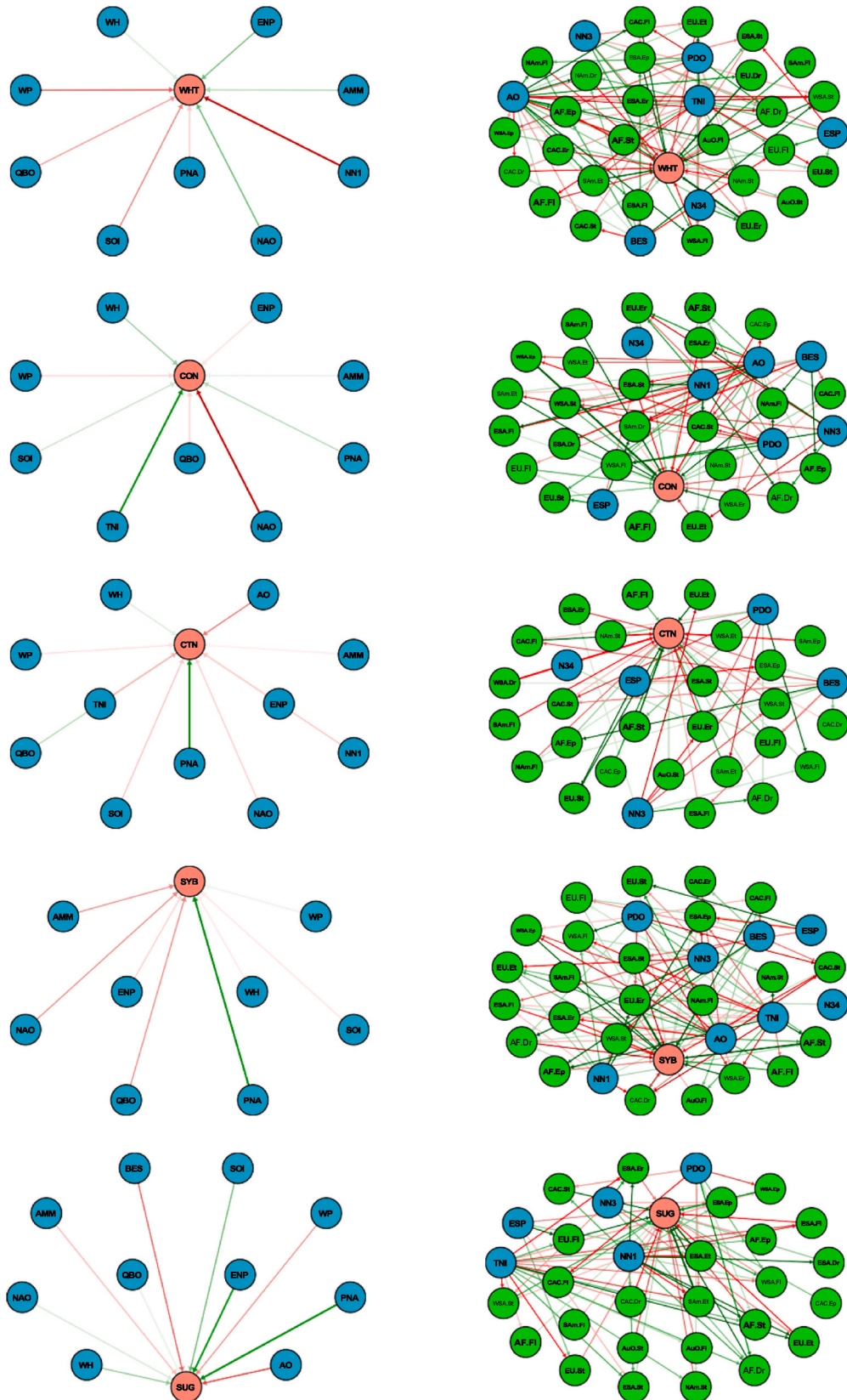
**Fig. 3.** Averaged Direct and Indirect Effect of Climate on Energy Commodities. Light (deep) green links indicate a weak (strong) effect that comes from the positive phase of indices, and light (deep) red links indicate a weak (strong) effect that comes from the negative phase of them. Red nodes denote energy commodities, blue for climate indices, and green for natural disasters.

The left panel of the figure reports the direct effect of climate on crude oil, natural gas, and coal. The right panel reports the climate-induced natural disaster effect on crude oil, natural gas, and coal. Again with the knowledge of having tow-phase for climate indices, it should be noted the green links show an effect on crude oil from a positive phase of the indices, and the red shows an effect on crude oil from a negative phase of the climate indices. Blue colored nodes represent climate indices, red nodes denote energy commodities, and green nodes represent natural disasters. The figure shows that on average, the PNA index has a significant direct effect on Crude Oil when it is in the positive phase, an indirect effect on Natural Gas, and a direct mild effect on Coal when is in the negative phase. AO has a direct effect on Crude Oil, Natural Gas, and Coal in the negative phase. The result also shows that the SOI has a direct effect on Crude Oil in the negative phase and affect Natural Gas and Coal in the positive phase. This finding is confirmed by Ref. [13] about the significant effect of ENSO (in this case SOI) on Oil and its power to predict the price of Oil. We also find evidence of Niño indices (NN1, NN3, N34) recording in some cases direct and indirect effects on Crude Oil, Natural Gas, and Coal. This corroborates the findings of [43] who documented an influence of El Niño in its negative phase on Oil prices.

### 3.1.2. Climate impact on Agricultural Commodities

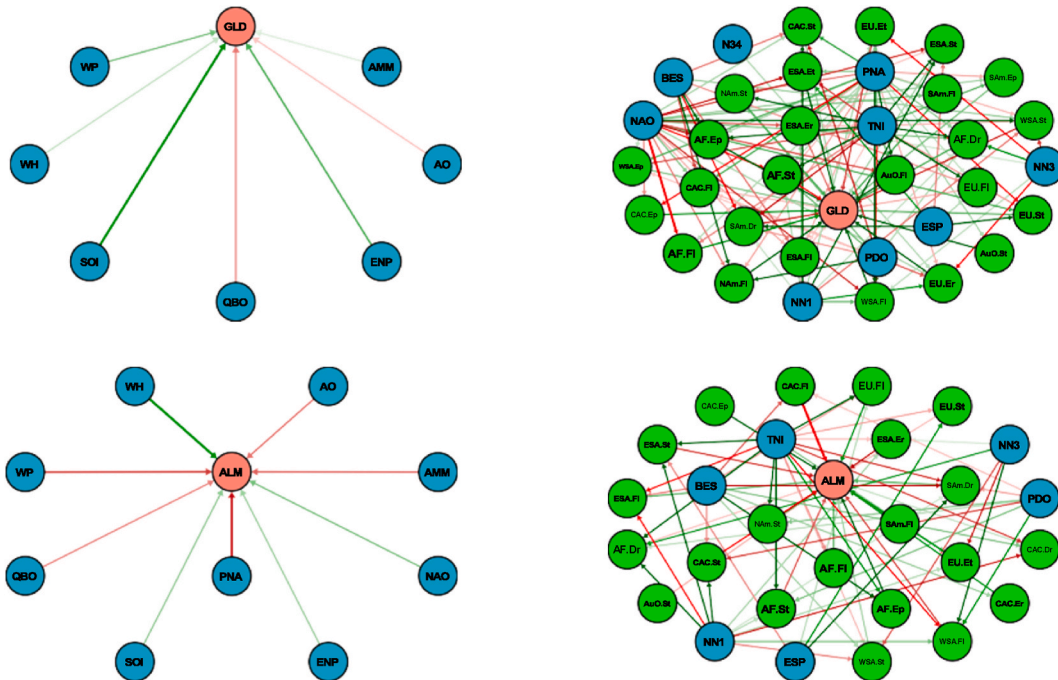
It is well-known that any anomaly in climate or extreme natural events, such as floods, droughts and extreme temperature, can harm crops and reduce yields.

Fig. 4 presents a summary of the average effect of climate factors on agricultural commodities. Again, the left panel of the figure reports the direct effect of climate on Wheat, Corn, Cotton, Soybean, and Sugar and the right panel reports the climate-induced natural disaster effect on them. The green links show the effect comes from the positive phase of climate indices, and the red shows impact comes from the negative phase of them. Blue-colored nodes represent climate indices, red nodes denote agricultural commodities, and



(caption on next page)

**Fig. 4.** Averaged Direct and Indirect Effect of Climate on Agricultural Commodity. Light (deep) green links indicate a weak (strong) effect that comes from the positive phase of indices, and light (deep) red links indicate a weak (strong) effect that comes from the negative phase of them. Red nodes denote energy commodities, blue for climate indices, and green for natural disasters.



**Fig. 5.** Averaged Direct and Indirect Effect of Climate on Metal Commodity. Light (deep) green links indicate a weak (strong) effect that comes from the positive phase of indices, and light (deep) red links indicate a weak (strong) effect that comes from the negative phase of them. Red nodes denote energy commodities, blue for climate indices, and green for natural disasters.

green nodes represent natural disasters.

The figure shows that the NN1 index has a significantly strong direct effect on Wheat and, a mild impact on Cotton when is in the negative phase, with an indirect effect on Corn, Soybean, and Sugar. NAO has a direct effect on Corn, Cotton, and Soybean in its negative phase, and an impact on Wheat and Sugar when is in the positive phase. PNA Index has a strong direct effect on Cotton, Soybean, and Sugar, a mild impact on Corn in its positive phase, and an effect on Wheat in its negative phase. The result also shows that the SOI has a direct effect on Wheat, Cotton, and Soybean when is in the negative phase and a direct impact on Corn and Sugar in its positive phase. TNI has a significant direct effect on Corn in its positive phase and an impact on Cotton when is in the negative phase, and an indirect effect on Wheat, Soybean, and Sugar. This finding is confirmed by Ref. [38] about the significant effect of ENSO on commodity markets, especially Corn and Soybeans. We also find evidence of ENSO on wheat. The findings of [50] showed that after La Nina events wheat prices tend to increase, and the price decrease after El Nino events.

### 3.1.3. Climate impact on Metal Commodities

Fig. 5 presents a summary of the average effect of climate indices on metal commodities. The figure shows the SOI has a significant strong direct effect on Gold and a light impact on Aluminium when is in positive phase. This confirmed the findings of [45] that showed the asymmetric effects of the two phases of the ENSO (here SOI) cycle on the gold market. PNA Index has a direct effect on Aluminium in its negative phase and an indirect effect on Gold.

WP has a direct effect on Gold in the positive phase and a direct impact on Aluminium in its negative phase.

## 3.2. Direct and Indirect Effect of Climate on Financial Markets

Figure B.11 reports the coefficients associated with the pure direct effect of climate indices on financial markets over the rolling window estimation. Again, the colors denote the different climate indices and each plot denote the impact on each financial equity price. We see that the different climate indices affect the selected financial equity differently. Also, climate indices and stock prices relationship is not always the same at every given window.

### 3.2.1. Climate impact on American financial markets

Fig. 6 presents a summary of the average effect of climate indices on American financial equity. The left panel of the figure reports the direct effect of climate indices on the US S&P500 Index and Canadian SPTSX. The right panel reports the climate-induced natural disaster effect on US S&P500 Index and Canadian SPTSX. The green links show the effect which comes from the positive phase of indices and the red shows the impact that comes from the negative phase of them. Blue-colored nodes represent climate indices, yellow nodes denote American financial equity, and green nodes represent natural disasters. The figure shows that on average, the SOI and NN1 has a significant direct effect on both US S&P500 Index and Canadian SPTSX when they are in their negative part. ENP has a significant direct impact on Canadian SPTSX in its positive phase and an indirect effect on US S&P500 Index. The climate indices affect US mainly in their negative phase. The average impacts also show WH is the one which is impacted more from indices in the positive phase, which is obvious from the first figure that the power of the positive phase impacts through the.

windows is bigger compared to negative phase impacts. Considering all figures, we notice that the average impact of WH on all affected stocks comes from the positive phase.

### 3.2.2. Climate impact on Asian Financial Markets

Fig. 7 presents a summary of the average effect of climate indices on Asian financial equity. The left panel of the figure reports the direct effect of climate indices on Asian financial equity and the right panel reports the climate-induced natural disaster effect on them. The figure shows that on average, the NN1 has a significantly strong direct effect on Hong Kong Hang Seng, Indian Sensex, and Japanese Nikkei when is in its negative phase. ENP has a significant direct impact on Hong Kong Hang Seng, and Indian Sensex when is in the positive phase, and an effect on the Japanese Nikkei in its negative phase. ESP has a direct effect on the Japanese Nikkei in its negative phase and an indirect effect on Indian Sensex, and the Japanese Nikkei.

### 3.2.3. Climate impact on european financial markets

Fig. 8 presents a summary of the average effect of climate indices on European financial equity. The left panel of the figure reports the direct effect of climate on European financial equity and the right panel reports the climate-induced natural disaster effect on them. The figure shows that the ENP index has a significant direct effect on the German DAX 30, Switzerland SMI, Spain IBEX 35, France CAC 40, and UK FTSE 100 when is in its positive phase. PNA Index has a direct effect on Switzerland SMI, Spain IBEX 35, France CAC 40, and UK FTSE 100 in its negative part and a direct effect on the German DAX 30 in its positive part. TNI has an impact on Spain IBEX 35, German DAX 30, and France CAC 40 when is in the negative phase, an effect on UK FTSE 100 when is in its positive phase, and

an indirect effect on Switzerland SMI. SOI has a direct effect on UK FTSE 100, and other European financial equity in its negative phase. BES has an indirect impact on all European financial equity. Closely related to our findings is the result of [54] who document the effect of ENSO (SOI, TNI, and BES) on the EU renewable energy market. In summary, by knowing the pattern of the climate indices it is possible to have a better prediction for the price.

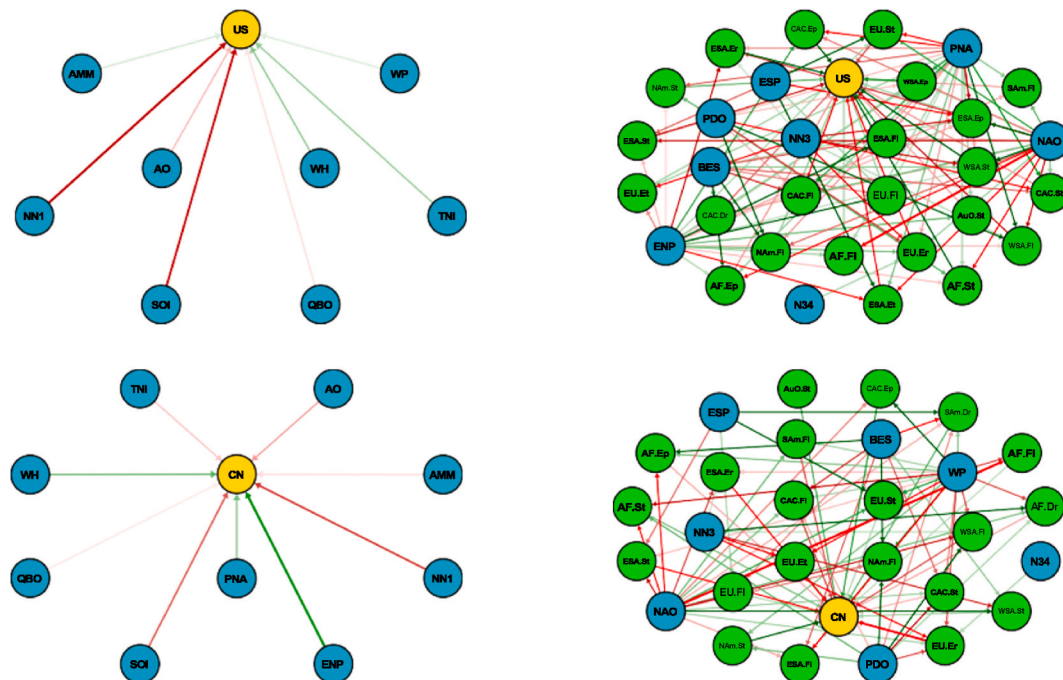


Fig. 6. Averaged Direct and Indirect Effect of Climate on American Financial Markets. Light (deep) green links indicate a weak (strong) effect that comes from the positive phase of indices, and light (deep) red links indicate a weak (strong) effect that comes from the negative phase of them. Yellow nodes denote energy commodities, blue for climate indices, and green for natural disasters.

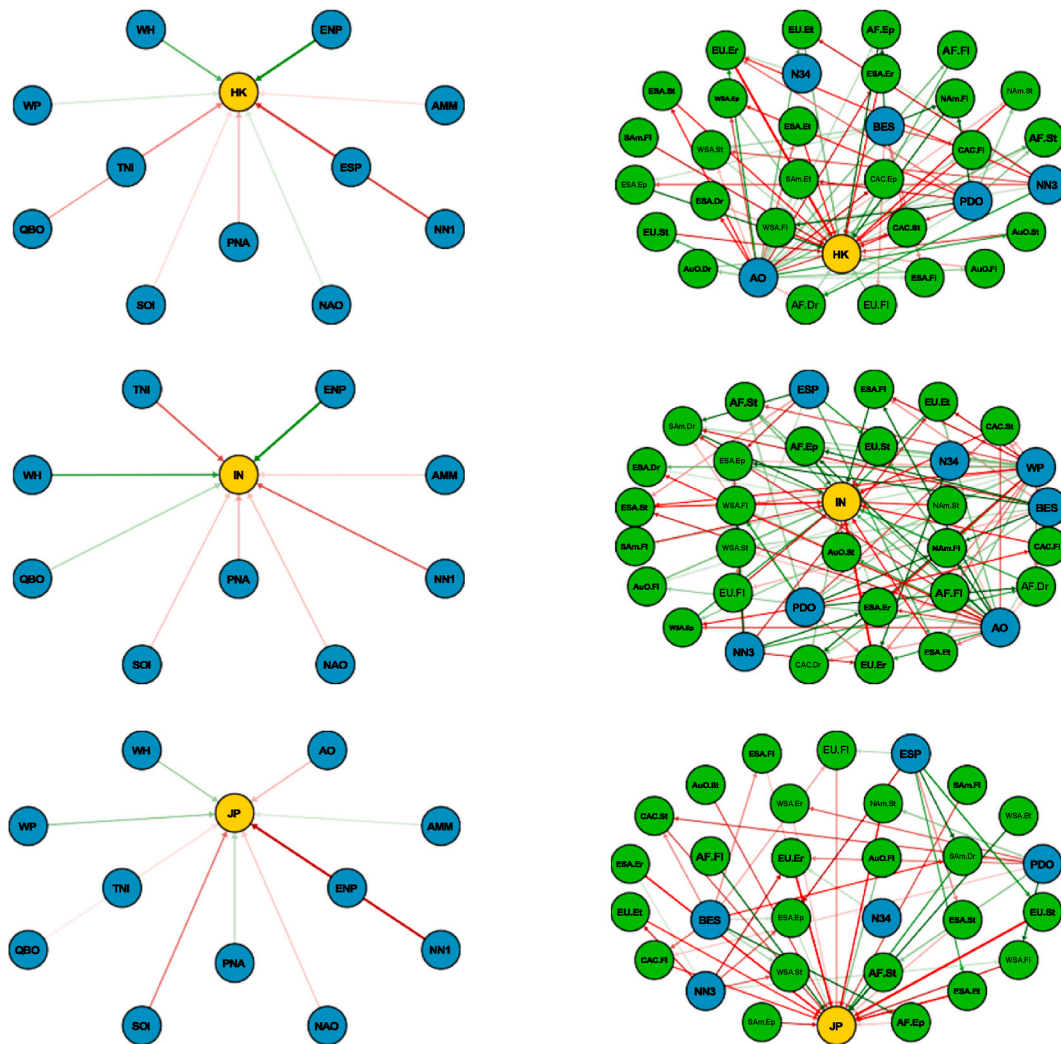


Fig. 7. Averaged Direct and Indirect Effect of Climate on Asian Financial Markets. Light (deep) green links indicate a weak (strong) effect that comes from the positive phase of indices, and light (deep) red links indicate a weak (strong) effect that comes from the negative phase of them. Yellow nodes denote energy commodities, blue for climate indices, and green for natural disasters.

### 3.3. Centrality Analysis of climate-to-commodity interconnectivity

We now turn our attention to identify the most central/influential players in the climate-to-commodity interconnections.

We summarize the results of the centrality of interconnectedness between climate indices, natural disasters and markets using the standard network measures described above.

Table 3 presents the results of the climate-to-commodities centrality. For convenience, report the rank of the variables according to the hub/authority measures. The top panel of the table ranks commodities according to authorities measure, while the bottom panel reports the rank of climate indices based on their hub score effect on commodities. The table shows that the top-three commodities highly influenced by climate are Crude Oil, Cotton.

and Sugar. The unweighted in-degree measure shows that Crude-oil is affected by 12 climate indices, Cotton by 10, and Sugar by 11. The weighted sum of the effects averaged over the sample period is 4.813 for climate-to-crude oil, 3.625 for climate-to-cotton, and 4.319 for climate-to-sugar. The fourth ranked commodity is Natural Gas affected by 11 climate indices with a weighted sum of 4.879. This suggests that although Crude-oil may be influenced by a higher number of climate indices, the aggregate effect of the impact on Natural Gas is relatively higher than the former. A careful study of the climate-commodities connectivity shows that Crude-oil, Cotton and Sugar are directly impacted by PNA while Natural-Gas is indirectly impacted through a natural disaster element.

The bottom panel of Table 3 reports the ranking of the influential commodity related climate indices based on hub scores. The result of the table shows that in terms of the unweighted out-degrees, the climate indices that impact more commodities are SOI, WH, WP, AMM, and QBO. However, the aggregate weighted effects of these indices seems to be much lower compared to the like of the PNA and



**Fig. 8.** Averaged Direct and Indirect Effect of Climate on European Markets. Light (deep) green links indicate a weak (strong) effect that comes from the positive phase of indices, and light (deep) red links indicate a weak (strong) effect that comes from the negative phase of them. Yellow nodes denote energy commodities, blue for climate indices, and green for natural disasters.

**Table 3**  
Climate-Commodity centrality.

	InDgU	OutDgU	InDgW	OutDgW	Auth	Hub
OIL	12	0	4.813	0	0.583	0
CTN	11	0	3.625	0	0.510	0
SUG	10	0	4.319	0	0.432	0
GAS	11	0	4.879	0	0.328	0
WHT	9	0	2.270	0	0.168	0
SYB	8	0	1.058	0	0.161	0
ALM	9	0	1.641	0	0.141	0
CON	9	0	2.024	0	0.115	0
COL	9	0	2.507	0	0.115	0
GLD	7	0	1.145	0	0.074	0
PNA	0	8	0	5.505	0	0.723
NN1	0	4	0	3.304	0	0.358
AO	0	7	0	2.284	0	0.296
ENP	0	9	0	2.412	0	0.260
SOI	0	10	0	2.809	0	0.232
WH	0	10	0	2.150	0	0.220
WP	0	10	0	2.740	0	0.187
NAO	0	9	0	2.339	0	0.155
AMM	0	10	0	1.351	0	0.096
PDO	0	1	0	0.530	0	0.092
BES	0	2	0	0.846	0	0.085
TNI	0	4	0	1.181	0	0.085
QBO	0	10	0	0.515	0	0.029
ESP	0	1	0	0.317	0	0.011

Note: unweighted in-degree (InDgU), unweighted outdegree (Out- DgU), weighted indegree (InDgW), weighted out-degree (OutDgW), hub (Hub), and authority (Auth).

**Table 4**  
Climate-Financial market centrality.

	InDgU	OutDgU	InDgW	OutDgW	Auth	Hub
HK	11	0	4.088	0	0.539	0
IN	9	0	2.938	0	0.436	0
SP	8	0	2.550	0	0.381	0
CN	9	0	2.153	0	0.322	0
FR	10	0	1.939	0	0.264	0
DE	9	0	1.863	0	0.251	0
JP	11	0	2.075	0	0.247	0
UK	9	0	1.555	0	0.201	0
US	8	0	1.471	0	0.171	0
CH	7	0	0.848	0	0.083	0
ENP	0	9	0	4.812	0	0.659
NN1	0	5	0	2.794	0	0.379
WH	0	10	0	2.792	0	0.378
SOI	0	10	0	3.039	0	0.300
PNA	0	9	0	1.955	0	0.257
TNI	0	9	0	1.620	0	0.249
AMM	0	10	0	1.360	0	0.144
ESP	0	1	0	0.635	0	0.130
WP	0	7	0	0.895	0	0.100
AO	0	6	0	0.978	0	0.095
NAO	0	5	0	0.408	0	0.058
QBO	0	10	0	0.190	0	0.024

Note: unweighted in-degree (InDgU), unweighted outdegree (OutDgU), weighted indegree (InDgW), weighted out-degree (OutDgW), hub (Hub), and authority (Auth).

NN1. According to the hub scores, the topmost influential commodity related climate indices are PNA, NN1 and AO. Again, we notice that the top three ranked commodity related climate indices all have direct impact on the top-three ranked commodities.

In summary, we find that Crude Oil is the topmost commodity whose return is likely to be affected highly by climate risk, followed by Cotton and Sugar. In other words, the highest commodity receivers climate risk are Crude oil, Cotton and Sugar. We also find evidence that the safest commodities - the least receiver of climate risk, is Gold. On the other hand, the climate indices most likely to transmit climate-related risk to commodities are PNA, NN1 and AO. In other words, climate risk that can impact commodities will likely be propagated by PNA, NN1 and AO.

### 3.3.1. Centrality Analysis of climate-to-financial market interconnectivity

We now focus centrality in climate-to-financial market interconnections.

Table 4 presents the results of the climate-to-financial market centrality. For convenience, report the rank of the variables according to the hub/authority measures. The top panel of the table ranks equities according to authorities' measure, while the bottom panel reports the rank of climate based on their hub score effect on equities. The table shows that the top-three equities highly influenced by climate are Hong Kong Hang Seng, Indian Sensex, and Spain IBEX 35. The unweighted in-degree measure shows that Hong Kong Hang Seng is affected by 11 climate indices, Indian Sensex by 9, and Spain IBEX 35 by 8. The weighted sum of the effects averaged over the sample period is 4.088 for climate-to-Hong Kong Hang Seng, 0.938 for climate-to-Indian Sensex, and 2.55 for

**Table 5**  
Centrality measures for natural disasters-to-commodities.

	InDgU	OutDgU	InDgW	OutDgW	Auth	Hub
WHT	27	0	11.639	0	0.602	0
COL	24	0	9.746	0	0.413	0
SUG	25	0	8.408	0	0.412	0
CON	25	0	6.627	0	0.279	0
CTN	26	0	6.562	0	0.246	0
SYB	24	0	5.601	0	0.207	0
GAS	23	0	5.819	0	0.198	0
OIL	23	0	5.677	0	0.179	0
GLD	25	0	4.456	0	0.157	0
ALM	21	0	4.407	0	0.140	0
SAm.Et	0	5	0	4.979	0	0.494
EU.Er	0	6	0	3.605	0	0.334
ESA.Er	0	10	0	3.557	0	0.228
SAm.Fl	0	10	0	3.151	0	0.219
EU.Dr	0	1	0	1.576	0	0.212
AuO.St	0	7	0	2.618	0	0.197
WSA.Ep	0	7	0	2.618	0	0.191
ESA.St	0	10	0	2.917	0	0.187
EU.Et	0	10	0	2.127	0	0.184
EU.St	0	10	0	2.440	0	0.172
AF.St	0	10	0	3.077	0	0.171
WSA.St	0	10	0	2.372	0	0.165
EU.Fl	0	10	0	2.170	0	0.164
NAm.St	0	10	0	2.806	0	0.162
AF.Ep	0	10	0	1.976	0	0.157
CAC.Fl	0	10	0	2.570	0	0.149
AuO.Ep	0	1	0	1.534	0	0.141
WSA.Fl	0	10	0	2.011	0	0.129
AF.Dr	0	10	0	1.673	0	0.129
NAm.Dr	0	1	0	0.914	0	0.123
SAm.Ep	0	5	0	2.015	0	0.122
CAC.Ep	0	8	0	2.264	0	0.116
ESA.Fl	0	10	0	1.790	0	0.114
WSA.Er	0	4	0	1.622	0	0.106
CAC.Er	0	3	0	1.006	0	0.095
NAm.Fl	0	6	0	1.835	0	0.094
AuO.Fl	0	5	0	1.055	0	0.089
CAC.St	0	10	0	1.088	0	0.080
AF.Fl	0	10	0	1.120	0	0.064
ESA.Ep	0	6	0	0.806	0	0.053
ESA.Et	0	4	0	1.182	0	0.052
CAC.Dr	0	6	0	0.706	0	0.052
ESA.Dr	0	2	0	0.565	0	0.044
WSA.Dr	0	1	0	0.535	0	0.029
SAm.Dr	0	3	0	0.530	0	0.018
WSA.Et	0	2	0	0.132	0	0.008

Note: unweighted in-degree (InDgU), unweighted outdegree (OutDgU), weighted indegree (InDgW), weighted out-degree (OutDgW), hub (Hub), and authority (Auth).

climate-to-Spain IBEX 35. The fifth and seventh-ranked equities are France CAC 40 and the Japanese Nikkei affected by 10 and 11 climate indices with a weighted sum of 1.939 and 2.075. This suggests that although a higher number of climate indices may influence these two equities, the aggregate effect of the impact on them is relatively higher than the former.

The bottom panel of Table 4 reports the ranking of the influential equities-related climate indices based on hub scores. The result of the table shows that in terms of the unweighted out-degrees, the climate indices that impact more equities are the WH, SOI, AMM, and QBO. However, the aggregate weighted effects of these indices seem to be lower compared to the like of the ENP. According to the hub scores, the topmost influential equities-related climate indices are ENP, NN1, and WH. Again, we notice that the top three ranked equities-related climate indices all have a direct impact on the top three ranked equities.

In summary, we find that Hong Kong Hang Seng is the topmost equity whose return is likely to be affected highly by climate risk, followed by Indian Sensex and Spain IBEX 35. We also find evidence that the safest equity - the least receiver of climate risk, is Switzerland SMI. On the other hand, the climate indices most likely to transmit climate-related risk to the financial market are ENP, NN1, and WH.

### 3.3.2. Centrality Analysis of Natural Disasters and Commodity Markets

We now focus on centrality in natural disaster-to-commodity market interconnections.

Table 5 indicate the calculated summary measures for Commodity Market. The top panel of the table ranks commodities according to authorities' measure, while the bottom panel reports the rank of natural disasters based on their hub score effect on commodities. The table shows that the top-three commodities highly influenced by natural disasters are Wheat, Coal, and Sugar. The unweighted in-degree measure shows that Wheat is affected by 27 natural disasters, Coal by 24, and Sugar by 25. The weighted sum of the effects averaged over the sample period is 11.639 for natural disaster-to-Wheat, 9.746 for natural disaster-to- Coal, and 8.408 for natural disaster-to-Sugar.

**Table 6**  
Centrality Measures for Natural Disasters-to-Financial Markets according to unweighted in-degree (InDgU), unweighted outdegree (OutDgU), weighted indegree (InDgW), weighted out-degree (OutDgW), hub (Hub), and authority (Auth).

	InDgU	OutDgU	InDgW	OutDgW	Auth	Hub
IN	26	0	7.059	0	0.426	0
SP	28	0	7.978	0	0.426	0
JP	24	0	7.111	0	0.415	0
HK	27	0	6.998	0	0.388	0
DE	24	0	5.380	0	0.273	0
FR	25	0	4.717	0	0.261	0
US	23	0	4.270	0	0.243	0
CN	21	0	3.571	0	0.209	0
UK	25	0	3.918	0	0.206	0
CH	22	0	2.994	0	0.159	0
ESA.Et	0	9	0	4.174	0	0.369
EU.Er	0	8	0	3.862	0	0.360
CAC.Fl	0	10	0	3.303	0	0.305
NAm.St	0	10	0	3.175	0	0.302
SAm.Fl	0	10	0	2.709	0	0.229
EU.St	0	10	0	2.389	0	0.227
CAC.St	0	10	0	2.561	0	0.215
WSA.Fl	0	10	0	2.436	0	0.212
SAm.Dr	0	7	0	2.094	0	0.203
CAC.Ep	0	8	0	2.869	0	0.202
AF.St	0	9	0	2.394	0	0.196
ESA.St	0	10	0	2.326	0	0.188
ESA.Er	0	10	0	2.050	0	0.184
AuO.Fl	0	7	0	1.707	0	0.167
AuO.St	0	10	0	1.951	0	0.152
EU.Et	0	10	0	1.719	0	0.142
WSA.Ep	0	7	0	1.423	0	0.136
ESA.Fl	0	10	0	1.576	0	0.124
AF.Fl	0	10	0	1.253	0	0.111
NAm.Fl	0	5	0	1.471	0	0.110
SAm.Et	0	2	0	0.779	0	0.084
SAm.Ep	0	2	0	0.875	0	0.076
ESA.Ep	0	9	0	0.673	0	0.063
EU.Fl	0	10	0	0.685	0	0.060
WSA.Er	0	5	0	0.617	0	0.057
WSA.St	0	9	0	0.576	0	0.054
AF.Ep	0	10	0	0.622	0	0.052
CAC.Dr	0	4	0	0.482	0	0.049
WSA.Et	0	1	0	0.382	0	0.042
AF.Dr	0	7	0	0.439	0	0.031
AuO.Dr	0	4	0	0.261	0	0.028
ESA.Dr	0	2	0	0.162	0	0.017

The bottom panel of Table 5 reports the ranking of the influential commodity-related natural disaster based on hub scores. The result of the table shows that in terms of the unweighted out-degrees, the natural disasters that impact more commodities are East and Southeast Asia Earthquake (ESA.Er), South America Flood (SAm.Fl), East and Southeast Asia Storm (ESA.St), Europe Extreme temperature (EU.Et), Europe Storm (EU.St), Africa Storm (AF.St), West and South Asia Storm (WSA.St), Europe Flood (EU.Fl), North America Storm (NAm.St), Africa Epidemic (AF.Ep), Central America and Caribbean Flood (CAC.Fl), West and South Asia Flood (WSA.Fl), Africa Drought (AF.Dr), East and Southeast Asia Flood(ESA.Fl), Central America and Caribbean Storm(CAC.St) and Africa Flood (AF.Fl). However, the aggregate weighted effects of some of them seem to be lower compared to the South America Extreme temperature (SAm.Et) and Europe Earthquake (EU.Er). According to the hub scores, the topmost influential commodity-related natural disasters are the South America Extreme temperature (SAm.Et), Europe Earthquake (EU.Er), and the East and Southeast Asia Earthquake (ESA.Er).

In summary, we find that Wheat is the topmost commodity whose return is likely to be affected highly by natural disaster, followed by Coal and Sugar. In other words, the highest commodity receivers of natural disasters risk are Wheat, Coal, and Sugar. We also find evidence that the safest commodity - the least receiver of natural disaster risk, is Aluminium. On the other hand, the natural disasters most likely to transmit natural disasters-related risk to commodities are SAm.Et, EU.Er and ESA.Er.

3.3.3. Centrality Analysis of natural disasters and financial markets

Here we focus on centrality in natural disaster-to-financial market interconnections.

Table 6 indicate the calculated summary measures for financial Market. The top panel of the table ranks equities according to authorities' measure, while the bottom panel reports the rank of natural disasters based on their hub score effect on equities. The table shows that the top-three equities highly influenced by natural disasters are the Indian Sensex, Spain IBEX-35, and the Japanese Nikkei. The unweighted in-degree measure shows that Indian Sensex is affected by 26 natural disasters, Spain IBEX-35 by 28, and the Japanese Nikkei by 24. The weighted sum of the effects averaged over the sample period is 7.059 for natural disaster-to-Indian Sensex, 7.978 for natural disaster-to-Spain IBEX-35, and 7.111 for natural disaster-to-Japanese Nikkei. The fourth-ranked equity is Hong Kong Hang Seng affected by 27 natural disasters with a weighted sum of 6.998. This suggests that although this equity is.

Influenced by a higher number of natural disasters, the aggregate effect of the impact on it is relatively lower than the former.

The bottom panel of Table 6 reports the ranking of the influential equity-related natural disaster based on hub scores. The result of the table shows that in terms of the unweighted out-degrees, the natural disasters that impact more equities are Central America and Caribbean Flood (CAC.Fl), North America Storm (NAm.St), South America Flood (SAm.Fl), Europe Storm (EU.St), Central America and Caribbean Storm(CAC.St), West and South Asia Flood (WSA.Fl), East and Southeast Asia Storm (ESA.St), East and Southeast Asia Earthquake (ESA.Er), Australia and Oceania (AuO.St), Europe Extreme temperature (EU.Et), East and Southeast Asia Flood (ESA.Fl), Africa Flood(AF.Fl), Europe Flood (EU.Fl), Africa Epidemic (AF.Ep). However, the aggregate weighted effects of some of them seem to be lower compared to the East and Southeast Asia Extreme temperature (ESA.Et), and Europe.

Earthquake (EU.Er). According to the hub scores, the topmost influential equity-related natural disasters are the East and Southeast Asia Extreme temperature (ESA.Et), Europe Earthquake (EU.Er), and Central America and Caribbean Flood (CAC.Fl).

In summary, we find that Indian Sensex is the topmost equity whose return is likely to be affected highly by a natural disaster, followed by Spain IBEX-35, and the Japanese Nikkei. We also find evidence that the safest equity-the least receiver of natural disaster risk, is Switzerland SMI. On the other hand, the natural disasters most likely to transmit natural disasters-related risk to equities are ESA.Et, EU.Er and CAC.Fl.

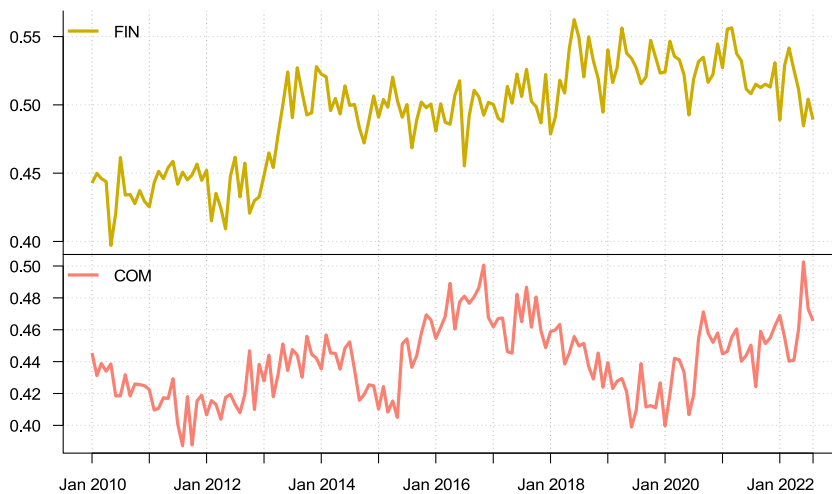


Fig. 9. Relative RMSE. Note that Relative RMSE is ratio of the BNVAR RMSE over BVAR RMSE. Values less than one show superior performance of BNVAR over BVAR.

### 3.4. Model Comparison

We conduct a comparison of the performance of our climate-induced model estimated by the BNVAR with the conventional Bayesian VAR (BVAR) on the financial and commodity variables only. We compare the models in terms of the relative root mean squared error (RRMSE). More precisely, we compute the ratio of the RMSE of the BNVAR to the BVAR. Thus, RRMSE greater than 1 favors the BVAR over the BNVAR, while RRMSE less than 1 favor the BNVAR. We report in Fig. 9 the relative performance of the models for financial and commodities. The figure shows superior efficiency of the BNVAR over the BVAR. This validates the impact of climate on commodities and financial market performances.

Our findings of the impact of climate on the performance of markets corroborates with the results of [51], who document the role of ENSO in commodity price movement and pre-dictability. Our findings in a way confirms the results of [39], who showed that climate risk could predict commodity returns. Finally, our results follows [30], who showed the power of climate-related factors in predicting oil prices and natural gas.

## 4. Discussion

Climate change is a global, multidimensional problem requiring consideration of scientific, economic, social, political, and moral questions. The risks coming from climate factors cannot be avoided entirely or mitigated, so governments, companies, civil society, and community organizations must make plans and take action to ensure they are better managed. In this paper, we developed a comprehensive approach to studying the impact of climate-related factors on commodity and financial markets. We applied a Bayesian network VAR model to examine the effect of climate risk on commodity prices and financial market returns. The dataset consisted of four classes of variables, namely, financial market variables, commodities, natural disasters, and climate indices. We find that Crude Oil, followed by Cotton and Sugar, are commodities whose return is affected highly by climate risk and Gold is the safest commodity. We also find that Hong Kong Hang Seng, Indian Sensex, and Spain IBEX 35 are the topmost equity whose return is likely to be affected highly by climate risk and Switzerland SMI is the safest. Regarding the climate indices, PNA, NN1, and AO are most likely to transmit climate-related risks to commodities, and ENP, NN1, and WH are the climate indices most likely to transmit climate-related risks to the financial market. The highest commodity receivers of natural disaster risk are Wheat, Coal, and Sugar. Aluminum is the safest commodity. Indian Sensex, Spain IBEX-35, and the Japanese Nikkei are the topmost equity whose return is likely to be affected highly by natural disasters and Switzerland SMI is the safest. Regarding natural disasters, the most likely to transmit natural disaster-related risk to commodities is SAm.Et, EU.Er and ESA.Er. and the natural disasters most likely to transmit natural disaster-related risk to equities are ESA.Et, EU.Er and CAC.Fl.

The comprehensive analysis of the effects of climate indices on various commodity markets elucidates the intricate interplay between climate dynamics and market fluctuations, underscoring the critical need for comprehensive climate risk management strategies across global commodity sectors. The differential impacts observed across energy, agricultural, and metal commodities emphasize the nuanced vulnerabilities and sensitivities of supply chains and market stability to climate-induced disruptions, highlighting the imperative for tailored risk assessment frameworks and adaptive strategies to ensure long-term market sustainability. The findings emphasize the necessity of a nuanced and comprehensive approach to understanding the diverse impacts of climate indices on commodity markets. The observed vulnerabilities in energy commodities underscore the need for resilient supply chain management strategies, while the implications for agricultural commodities stress the importance of ensuring food security amidst climate-related uncertainties. Furthermore, the insights into the long-term implications for metal commodities underscore the critical role of integrating climate considerations into policy frameworks to safeguard the economic prospects of metal-producing economies. Recognizing the intricate connections between climate dynamics and commodity market fluctuations, the analysis underscores the crucial role of proactive climate risk management and adaptive strategies in mitigating potential market vulnerabilities. By fostering a comprehensive understanding of global climate dynamics and their cascading impacts, stakeholders can effectively develop resilient supply chains and diversified market portfolios, ensuring market stability and sustainability in the face of evolving climate challenges.

The comprehensive analysis of the effects of climate indices on commodity markets serves as a call to action for global stakeholders, policymakers, and market participants to prioritize the integration of climate risk management strategies into commodity market frameworks. Emphasizing the interconnected nature of global climate dynamics and market fluctuations, this analysis underscores the critical importance of proactive adaptation and resilient practices to ensure the long-term stability and sustainability of global commodity markets amidst an increasingly dynamic and uncertain climate landscape. The comprehensive analysis of the effects of climate indices on global financial equity markets illuminates the intricate interdependencies between climatic dynamics and the performance of diverse financial indices across various regions. The differential impacts observed in American, Asian, and European markets underscore the varying vulnerabilities and sensitivities to climate-induced disruptions, emphasizing the critical need for region-specific adaptive strategies and robust climate risk management frameworks.

Our study comes from an economic point of view, which can affect the whole process of decision-making in the markets. It should be said, maybe a physical link between climate indices and economic/financial indicators cannot be established easily but following the award of 2018's Nobel Prize in Economics to William Nordhaus for his work on integrated assessment models [41], a new kind of literature called climate finance came up indicating that financial economists should assess the risks associated with climate change as a global externality [28,31,52]. It means an improved understanding of the physical impacts and formulation of better plans to prepare for and adapt to the risks that come from climate-related factors can result in more reliable decisions. Our results give a clear idea about the effecting time and phase of climate-related factors on the markets that can help policy-makers in the process of deciding about determining the price. Also, according to the model and the results by knowing the future pattern of the indices and understanding they

are impacting in which phase, investors can find out a better perception of the price to invest.

## 5. Conclusion

The findings of our study underscore the importance of comprehensively understanding the intricate connections between climate indices and market fluctuations to develop informed predictive models and adaptive strategies. By prioritizing the implementation of proactive climate risk management measures, financial markets can better withstand the challenges posed by evolving climate dynamics and foster long-term stability and sustainability. This analysis serves as a call to action for global financial institutions, policymakers, and stake-holders to collaboratively prioritize climate risk management as an integral component of sustainable financial market development and resilience in the face of increasingly complex climate challenges.

### Data availability

The data used in the paper is publicly available at the Physical Sciences Laboratory (PSL: <https://psl.noaa.gov/data/climateindices/list/>), and the Emergency Events Database (EM- DAT: <https://www.emdat.be/>), but can also be obtained from the authors upon request.

### CRedit authorship contribution statement

**Fatemeh Mojtahedi:** Writing – review & editing, Writing – original draft, Software, Project administration, Formal analysis, Data curation, Conceptualization. **Daniel Felix Ahelegbey:** Writing – review & editing, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Mario Martina:** Writing – review & editing, Supervision, Project administration.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Acknowledgement

This paper and related research have been conducted during and with the support of the Italian inter-university PhD course in sustainable development and climate change (link: [www.phd-sdc.it](http://www.phd-sdc.it)). This research has also received funding from the European Union's Horizon 2020 research and innovation program "PERISCOPE: Pan European Response to the ImpactS of COVID-19 and future Pandemics and Epidemics", under the Grant Agreement No. 101016233, H2020-SC1-PHE-CORONAVIRUS-2020-2-RTD.

## A. Details of Data Variables

Table A.7 lists the detailed description and definition of the variables used in our empirical study. The table segments the variables according to financial markets, commodities, natural disasters, and climate indices.

**Table A.7**

Description of financial markets, commodities, natural disasters, and climate indices.

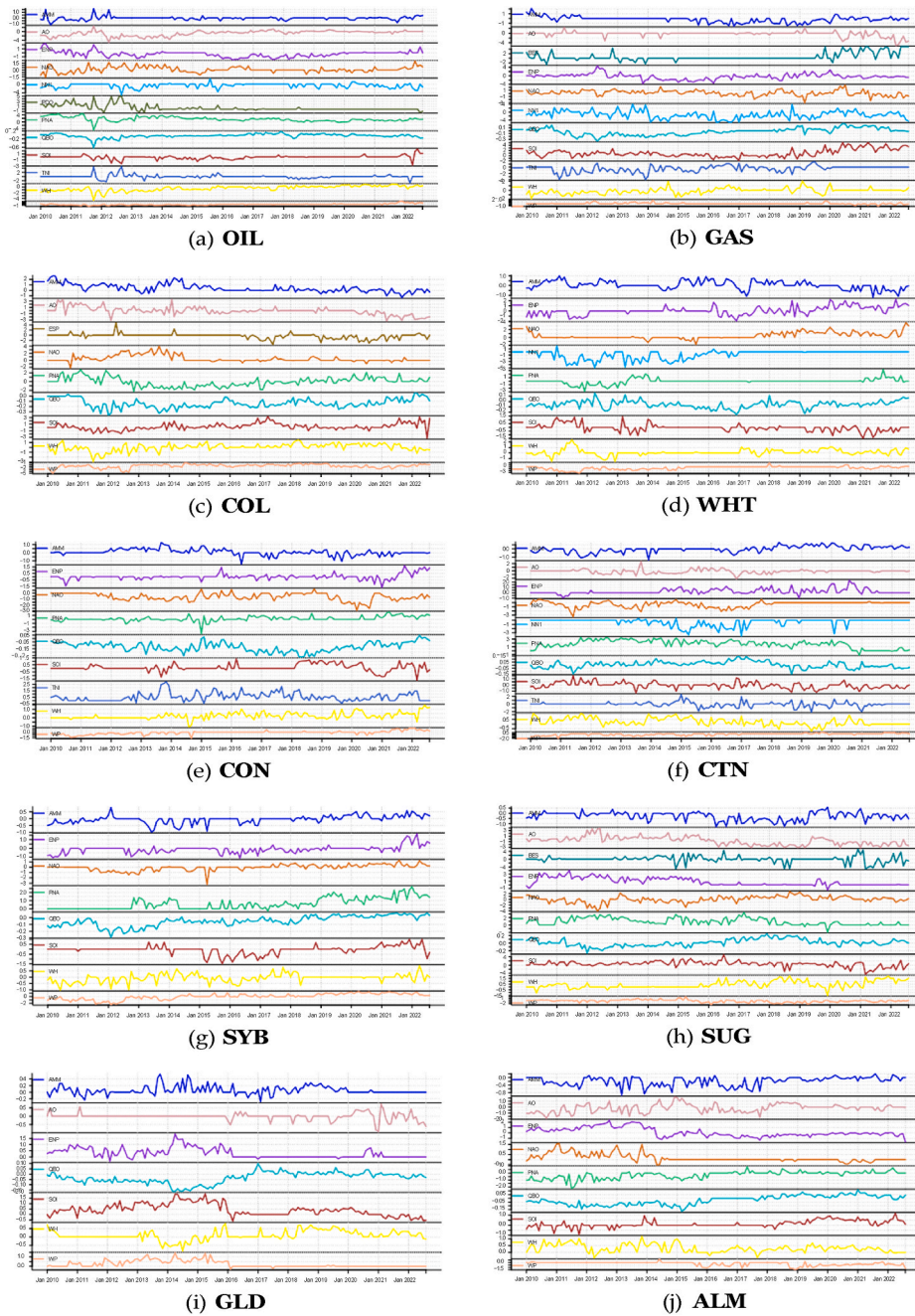
Name	Description
<i>Financial Market Indicators</i>	
US S&P500	Index of 500 large companies listed on stock exchanges in the US
Canadian SPTSX	Index of the largest companies listed on Canada's primary stock exchange
Hong Kong Hang Seng	Index of the largest companies listed on Hong Kong stock exchange
Indian Sensex	Index of 30 well-established companies listed on the Bombay Stock Exchange
Japanese Nikkei	Index of Japan's top 225 companies traded on the Tokyo Stock Exchange
German DAX 30	Index of the 30 major German companies on the Frankfurt Stock Exchange
Switzerland SMI	Index of the 20 largest and most liquid Swiss Performance Index stocks
Spain IBEX 35	Index of the Bolsa de Madrid, Spain's principal stock exchange
France CAC 40	Index for the 40 largest companies traded on Euronext Paris
UK FTSE 100	Index of the 100 largest companies traded on the London Stock Exchange
<i>Commodities Market</i>	
Brent Crude Oil	Crude oil (Europe), UK Brent 38' API
Natural Gas	Natural Gas (US), spot price at Henry Hub, Louisiana
Coal	Coal (Australia), FOB Newcastle, 6000 kcal/kg spot price.
Wheat	Wheat (US), No.1 Hard Red Winter, Ordinary Protein, FOB Gulf of Mexico
Corn	Corn (US), no. 2, yellow, f.o.b. US Gulf ports

(continued on next page)

Table A.7 (continued)

Name	Description
Cotton	Cotton (US), Memphis/Eastern, middling 1–3/32 inch.
Soybean	Soybean (US), Gulf Yellow, CIF Rotterdam
Sugar	Sugar (World), ISA daily price, raw, FOB and stowed at greater Caribbean Ports
Gold	Gold (UK), 99.5 % fine, London afternoon fixing, average of daily rates
Aluminium	Aluminium (UK), 99.5 % minimum purity, LME spot price, CIF UK ports
<i>Natural Disaster Events</i>	
Drought	Climatological: Drought
Earthquake	Geophysical: Ground movement, Tsunami
Epidemic	Biological: Viral disease, Bacterial disease, Parasitic disease
Extreme temperature	Meteorological: Cold wave, Heat wave
Flood	Hydrological: Coastal flood, Riverine flood, Flash flood
Storm	Meteorological: Convective storm, Tropical cyclone, Extra-tropical storm
<i>Climate Indices</i>	
Atlantic Meridional Mode (AMM)	This Index is one of the “meridional modes” that appear as variability innate to the tropical coupled ocean-atmosphere system. These meridional modes have positive feedback between surface winds, evaporation, and SST.
Atlantic Multidecadal Oscillation (AMO)	This Index has been identified as a long-term fluctuation of oscillatory changes in North Atlantic SST. It is indicated, the AMO has derived from Atlantic thermohaline circulation variations and associated ocean heat transport fluctuations.
Arctic Oscillation (AO)	This Index is known as an annular mode of atmospheric circulation in the Northern Hemisphere and happens in cold and warm seasons.
Bivariate ENSO Index (BES)	The Niño 3.4 SST and SOI are normalized and combined. SST is from the HadISST1.1. SOI is from NOAA/CPC. Produced at NOAA PSL. Note: El Niño Southern Oscillation (ENSO).
East Pacific North Pacific Oscillation (ENP)	A major mode in the inter-annual atmospheric variability is the North Pacific Oscillation (NPO), which indicates the pattern of the sea-level pressure variability between high and low latitudes in the North Pacific.
Name	Description
ENSO Precipitation Index (ESP)	The index is based on rainfall anomalies in two rectangular areas, one in the eastern tropical Pacific (10°S–10°N, 160°E–100°W) and the other over the Maritime Continent (10°S–10°N, 90°E–150°E). The ESPI index is normalized to have zero mean and unit standard deviation. Calculated at UMD.
Global Mean Land Ocean Temperature (GMS)	The constant ratio of mean of this anomalies is one of the observed climates phenomena. Estimate differences in Earth’s climate, global land–ocean temperature indices combining 2m surface air temperature over land with SSTs over oceans are used.
Multivariate ENSO Index (MEI)	A multi-variate index of ENSO which uses SST, winds, SLP, and OLR. It is calculated using the JRA55 reanalysis dataset and the NCEI OLR. Produced at NOAA PSL.
North Atlantic Oscillation (NAO)	This index describes irregular fluctuation of atmospheric pressure over the North Atlantic Ocean. It is derived from air-pressure readings taken at sea level at stations in Iceland and the Azores Islands.
Niño 1 + 2 SST Index (NN1)	SST anomalies averaged over the NINO1 and NINO2 regions 0–10° South; 90° West– 80° West (eastern most of the Niña indices). Total SSTs also available for this region. Calculated from the Monthly ERSST V5 (at NOAA/CPC).
Niño 3 SST Index (NN3)	SST anomalies averaged over the NINO3 region 5° North–5° South; 150° West–90° West. Total SSTs also available for this region. Calculated from the Monthly NOAA ERSST V5 (at NOAA/CPC).
Niño 3.4 SST Index (N34)	SST anomalies averaged over the NINO34 region 5° North–5° South; 170–120° West. Total SSTs also available for this region. Correlates well with teleconnections to North America. Calculated from the Monthly NOAA ERSST V5 (at NOAA/CPC).
Niño 4 SST Index (NN4)	SST anomalies averaged over the NINO4 region 5° North–5° South; 160° East–150° West (western most of Niño indices). Total SSTs also available for this region. Calculated from the Monthly NOAA ERSST V5 (at NOAA/CPC).
Northern Oscillation Index (NOI)	This index is based on the difference in sea level pressure anomalies in the north-east Pacific and near Darwin, Australia. NOI holds information about some climate variations, including EN/LN events, Madden Julian oscillations, and intra-seasonal to decadal variations of the Asian–Australian monsoon system.
Pacific Decadal Oscillation (PDO)	It is the leading principal component of monthly SST anomalies in the North Pacific Ocean, poleward of 20N (global SST mean removed). Calculated from the NOAA ERAATV5, COBE SST, and HadISST1.1 (PSL/ESRL/NOAA).
Pacific North American Index (PNA)	This is one of the most prominent modes of extratropical variability in the northern Hemisphere. This version is calculated at NOAA/CPC. It is based on EOF’s calculated from monthly anomalies of 500 mb height from the NCEP Reanalysis.
Quasi-Biennial Oscillation (QBO)	QBO is one of the main modes of variability influencing atmospheric circulation at altitudes and latitudes in tropical atmosphere.
Southern Oscillation Index (SOI)	Difference between standardized Darwin and standardized Tahiti surface pressure values. It represents the atmospheric component of the ENSO. The sign is opposite that of the Niño indices and it is noisier than those indices. From NOAA/CPC
Solar Flux Unit (SFU)	This solar index is measured by detecting the level of radio noise emitted at a frequency of 2800 MHz (10.7 cms). The index is quoted in terms of Solar Flux Units.
Tropical Northern Atlantic Index (TNA)	TNA sea surface temperature is one of the boreal summer climate regulators over the western North Pacific and also an indicator of the surface temperatures in the eastern tropical North Atlantic Ocean.
Trans-Niño Index (TNI)	Standardized Niño 1 + 2 minus the Niño 4 with a 5 month running mean applied (restandardized). It represents the gradient of the SST in the ENSO region of the tropical Pacific. Calculated from the Monthly HadISST1.1 dataset.
Name	Description
Tropical Southern Atlantic Index (TSA)	TSA sea surface temperature indicates the surface temperatures in the Gulf of Guinea, the eastern tropical South Atlantic Ocean.
Western Hemisphere Warm Pool (WH)	WH is a region of SST warmer than 28.5 °C extends from the eastern North Pacific to the Gulf of Mexico and the Caribbean with a large seasonal cycle.
Western Pacific Index (WP)	The primary mode of low-frequency variability over the North Pacific is the WP. Strong positive or negative phases of this pattern reflect pronounced zonal and meridional variations in the location and intensity of the Pacific jet stream entrance region

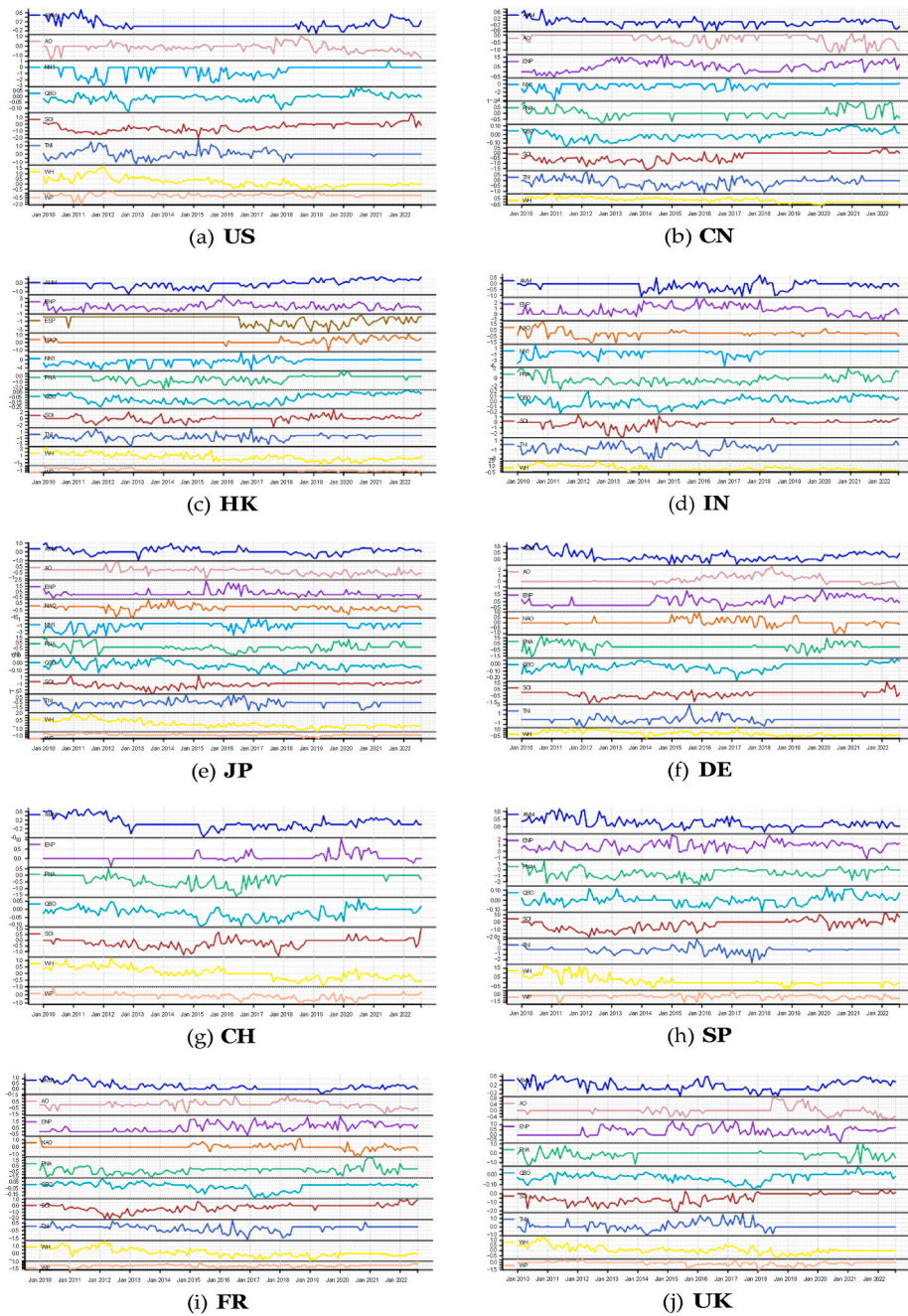
## B. Rolling Coefficients



**Fig. B.10.** Rolling Window Coefficients of the Effect of Climate Indices on Commodity. The colors denote the different climate indexes on each commodity price.

**Fig. B.11**

Rolling Window Coefficients of the Effect of Climate Indices on Financial Market. The colors denote the different climate indexes on each financial market.



## References

- [1] Daniel Felix Ahelegbey, Monica Billio, Roberto Casarin, Sparse graphical vector autoregression: a bayesian approach, *Annals of Economics and Statistics* 123/124 (2016) 333–361.
- [2] Daniel Felix Ahelegbey, Monica Billio, Roberto Casarin, Bayesian graphical models for structural vector autoregressive processes, *J. Appl. Econom.* 31 (2) (2016) 357–386.
- [3] Daniel Felix Ahelegbey, Paolo Giudici, Shatha Qamhie Hashem, Network VAR models to measure financial contagion, *N. Am. J. Econ. Finance* 55 (2021) 101318.
- [4] Daniel Felix Ahelegbey, Paola Cerchiello, Roberta Scaramozzino, Network Based Evidence of the Financial Impact of Covid-19 Pandemic, 2022.
- [5] Mahdi Akbari, Hamed Najafi Alamdarlo, Seyed Habibollah Mosavi, The effects of climate change and groundwater salinity on farmers' income risk, *Ecol. Indic.* 110 (2020) 105893.
- [6] Spyros Alogoskoufis, Sante Carbone, Wouter Coussens, Stephan Fahr, Margherita Giuzio, Friderike Kuik, Laura Parisi, Dilyara Salakhova, Martina Spaggiari, et al., Climate-related risks to financial stability, *Financ. Stabil. Rev.* 1 (2021) 1.
- [7] Nahomy Alvarez, Alessandro Cocco, Ketan B. Patel, A new framework for assessing climate change risk in financial markets, *Chicago Fed Letter* 448 (1) (2020) 1–8.
- [8] Financial Stability Board. Recommendations of the task force on climate-related financial disclosures, Technical report, Task Force on Climate-Related Financial Disclosures, 2017, pp. 35–39.
- [9] Patrick Bolton, Morgan Després, L. Pereira da Silva, Frédéric Samama, Romain Svartzman, 'green swans': central banks in the age of climate-related risks, *Banque de France Bulletin* 229 (8) (2020) 1–15.
- [10] Phillip Bonacich, Technique for analyzing overlapping memberships, *Socio. Methodol.* 4 (1972) 176–185.
- [11] Dario Bonciani, Martino Ricci, The international effects of global financial uncertainty shocks, *J. Int. Money Finance* 109 (2020) 102236.
- [12] Stephen P. Borgatti, Martin G. Everett, A graph-theoretic perspective on centrality, *Soc. Network.* 28 (4) (2006) 466–484.
- [13] Elie Bouri, Rangan Gupta, Christian Pierdzioch, Afees A. Salisu, El niño and forecastability of oil-price realized volatility, *Theor. Appl. Climatol.* 144 (3) (2021) 1173–1180.
- [14] D Brunner Allan, El nino and world primary commodity prices: warm water or hot air? *Rev. Econ. Stat.* 84 (1) (2002) 176–183.
- [15] Xiaojing Cai, Ryuta Sakemoto, El niño and commodity prices: new findings from partial wavelet coherence analysis, *Front. Environ. Sci.* 10 (1) (2022) 893879.
- [16] Emanuele Campiglio, Louis Daumas, Pierre Monnin, Adrian von Jagow, Climate-related risks in financial assets, *J. Econ. Surv.* 1 (1) (2022) 1–43.
- [17] Mark Carney, Breaking the tragedy of the horizon—climate change and financial stability, Speech given at Lloyd's of London 29 (2015) 220–230.
- [18] Cashin Paul, Kamiar Mohaddes, Mehdi Raissi, Fair weather or foul? the macroeconomic effects of el niño, *J. Int. Econ.* 106 (2017) 37–54.
- [19] Ambrogio Cesa-Bianchi, Andrej Sokol, Financial shocks, credit spreads, and the international credit channel, *J. Int. Econ.* 135 (2022) 103543.
- [20] IPCC Climate Change, Impacts, Adaptation and Vulnerability: Regional Aspects, Intergovernmental panel on climate change, 2014.
- [21] Tim Cholibois, Electrifying the 'eighth continent': exploring the role of climate finance and its impact on energy justice and equality in Madagascar's planned energy transition, *Climatic Change* 161 (2) (2020) 345–364.
- [22] J. Chou, W. Dong, X. Yan, The impact of climate change on the socioeconomic system: a mechanistic analysis, *Chin. J. Atmos. Sci.* 40 (1) (2016) 194–203.
- [23] Sarath Delpachitra, Keqiang Hou, Simon Cottrell, The impact of oil price shocks in the canadian economy: a structural investigation on an oil-exporting economy, *Energy Econ.* 91 (2020) 104846.
- [24] Oleksandr Faryna, Heli Simola, The transmission of international shocks to cis economies: a global var approach, *Econ. Syst.* 45 (2) (2021) 100769.
- [25] Andrea Flori, Fabio Pammolli, Alessandro Spelta, Commodity prices co-movements and financial stability: a multidimensional visibility nexus with climate conditions, *J. Financ. Stabil.* 54 (2021) 100876.
- [26] Gaffney Owen, Will Steffen, The anthropocene equation, *The Anthropocene Review* 4 (1) (2017) 53–61.
- [27] Dan Geiger, David Heckerman, Parameter priors for directed acyclic graphical models and the characterization of several probability distributions, *Ann. Stat.* 30 (5) (2002) 1412–1440.
- [28] Stefano Giglio, Bryan Kelly, Johannes Stroebel, Climate finance, *Annual Review of Financial Economics* 13 (2021) 15–36.
- [29] Daniel Gros, Philip R. Lane, Sam Langfield, Sini Matikainen, Marco Pagano, Dirk Schoenmaker, Javier Suarez, Too late, too sudden: transition to a low-carbon economy and systemic risk, Technical Report 6, European Systemic Risk Board (ESRB), European System of Financial Supervision, in: 6, 2016, pp. 1–23.
- [30] Rangan Gupta, Christian Pierdzioch, Climate risks and the realized volatility oil and gas prices: results of an out-of-sample forecasting experiment, *Energies* 14 (23) (2021) 8085.
- [31] Hong Harrison, G Andrew Karolyi, José A. Scheinkman, Climate finance, *Rev. Financ. Stud.* 33 (3) (2020) 1011–1023.
- [32] Mohammad Shakhawat Hossain, Muhammad Arshad, Lu Qian, Harald Kächele, Imran Khan, Md Din Il Islam, M Golam Mahboob, Climate change impacts on farmland value in Bangladesh, *Ecol. Indic.* 112 (2020) 106181.
- [33] Vassili Kitsios, Lurion De Mello, Richard Matear, Forecasting commodity returns by exploiting climate model forecasts of the el niño southern oscillation, *Environmental Data Science* 1 (2022) 1–16.
- [34] Philip Liu, Haroon Mumtaz, Angeliki Theophilopoulou, The transmission of international shocks to the UK. estimates based on a time-varying factor augmented var, *J. Int. Money Finance* 46 (2014) 1–15.
- [35] Parag Mahajan, Dean Yang, Taken by storm: hurricanes, migrant networks, and us immigration, *Am. Econ. J. Appl. Econ.* 12 (2) (2020) 250–277.
- [36] Haroon Mumtaz, Paolo Surico, The transmission of international shocks: a factor-augmented var approach, *J. Money Credit Bank.* 41 (2009) 71–100.
- [37] Haroon Mumtaz, Francesco Zanetti, The impact of the volatility of monetary policy shocks, *J. Money Credit Bank.* 45 (4) (2013) 535–558.
- [38] Kyungsik Nam, Investigating the effect of climate uncertainty on global commodity markets, *Energy Econ.* 96 (2021) 105123.
- [39] Jacobus Nel, Rangan Gupta, Mark Wohar, Christian Pierdzioch, Climate Risks and Predictability of Commodity Returns and Volatility: Evidence from over 750 Years of Data, Department of Economics, University of Pretoria, Pretoria, South Africa, 2022. Technical report.
- [40] Mark Newman, *Networks: an Introduction*, Oxford University Press, 2010.
- [41] William D. Nordhaus, Economic growth and climate: the carbon dioxide problem, *Am. Econ. Rev.* 67 (1) (1977) 341–346.
- [42] Paolo Pagnottoni, Alessandro Spelta, Andrea Flori, Fabio Pammolli, Climate change and financial stability: natural disaster impacts on global stock markets, *Phys. Stat. Mech. Appl.* 599 (2022) 127514.
- [43] Men Qui, Lian-Hong Qui, Muhammad Umar, Chi-Wei Su, Wen Jiao, The inevitable role of el niño: a fresh insight into the oil market, *Economic Research-Ekonomiska istraživanja* 33 (1) (2020) 1943–1962.
- [44] D.R. Reidmiller, C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, B.C. Stewart, Fourth National Climate Assessment. *Volume II: Impacts, Risks, and Adaptation In the United States, Report-In-Brief*, vol. 440, 2019, pp. 1–21.
- [45] Afees A. Salisu, Rangan Gupta, Jacobus Nel, Elie Bouri, The (asymmetric) effect of el niño and la niña on gold and silver prices in a gvar model, *Resour. Pol.* 78 (2022) 102897.
- [46] Ishuwar Seetharam, Environmental Disasters and Stock Market Performance, Stanford University Working paper, 2017.
- [47] Minchul Shin, Molin Zhong, A new approach to identifying the real effects of uncertainty shocks, *J. Bus. Econ. Stat.* 38 (2) (2020) 367–379.
- [48] Ruishi Si, Noshaba Aziz, Mingyue Liu, Qian Lu, Natural disaster shock, risk aversion and corn farmers' adoption of degradable mulch film: evidence from zhangye, China, *International Journal of Climate Change Strategies and Management* 13 (1) (2021) 60–77.
- [49] Mark Skidmore, Hideki Toya, Do natural disasters promote long-run growth? *Econ. Inq.* 40 (4) (2002) 664–687.
- [50] David Ubilava, The enso effect and asymmetries in wheat price dynamics, *World Dev.* 96 (2017) 490–502.
- [51] David Ubilava, The role of el niño southern oscillation in commodity price movement and predictability, *Am. J. Agric. Econ.* 100 (1) (2018) 239–263.
- [52] Alessio Venturini, Climate change, risk factors and stock returns: a review of the literature, *Int. Rev. Financ. Anal.* 79 (2022) 101934.

- [53] Y.M. Wei, X.C. Yuan, G. Wu, L.X. Yang, Climate change risk assessment: a bibliometric analysis based on web of science, *Bulletin of National Natural Science Foundation of China* 28 (5) (2014) 347–356.
- [54] Yu Wei, Jiahao Zhang, Yongfei Chen, Yizhi Wang, The impacts of el niño-southern oscillation on renewable energy stock markets: evidence from quantile perspective, *Energy* 260 (2022) 124949.
- [55] Xianhua Wu, Ji Guo, Disaster probability, optimal government expenditure for disaster prevention and mitigation, and expected economic growth, in: *Economic Impacts and Emergency Management of Disasters in China*, Springer, 2021, pp. 3–44.
- [56] Caixia Zhang, Xunming Wang, Jinchang Li, Ting Hua, Identifying the effect of climate change on desertification in northern China via trend analysis of potential evapotranspiration and precipitation, *Ecol. Indicat.* 112 (2020) 106141.