Renewable and Sustainable Energy Reviews 191 (2024) 114182

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Determinants of renewable stock returns: The role of global supply chain pressure

Guoheng Hu [a,g], Giray Gozgor [b,c,h,*], Zhou Lu [d,**], Mantu Kumar Mahalik [e], Shreya Pal [e,f]

[a] School of Business, Henan Normal University, Xinxiang, China
[b] School of Management, University of Bradford, Bradford, United Kingdom
[c] Adnan Kassar School of Business, Lebanese American University, Beirut, Lebanon
[d] School of Management, Qingdao City University, Qingdao, China
[e] Department of Humanities and Social Sciences, Indian Institute of Technology Kharagpur, West Bengal, India
[f] School of Business and Management, Christ University (Deemed to be University), Bangaluru, Karnataka-560029, India
[g] School of Digital Commerce, Zhejiang Yuexiu University, Shaoxing, China
[h] Faculty of Political Sciences, Istanbul Medeniyet University, Istanbul, Turkiye

ARTICLE INFO

Keywords:
renewable energy stocks
Global supply chain pressure
Global economic activity
Climate policy uncertainty
crude oil prices

ABSTRACT

This study investigates the determinants of the global renewable stocks index returns from November 2003 to August 2022. The explanatory variables include global supply chain pressure measures, climate policy uncertainty, global economic activity, and crude oil prices. The long-run panel dynamic Autoregressive Distributed Lag estimations show that the global supply chain pressure, climate policy uncertainty, and global economic activity redound renewable stock returns. These results are robust enough to utilise different long-run estimation techniques. Potential policy implications are also discussed.

1. Introduction

What drives the rise of renewable energy? Since renewable energy is regarded as sustainable, there is a rise in demand for renewable energy [1]. Potential determinants of renewable energy demand are essential due to several issues, such as climate change and energy sustainability. Rising renewable energy consumption can help decrease greenhouse gas emissions and slow global warming. This issue will be a practical policy implication for combating the climate change crisis [2].

A significant transformation has been made from fossil fuel to renewable energy since the 1990s. Therefore, renewable energy companies have flourished, and various companies have traded in the stock markets. Given this backdrop, this study investigates the determinants of the global renewable stocks index returns from November 2003 to August 2022. The explanatory variables include traditional measures (global economic activity and crude oil prices) and new measures (global supply chain pressures and climate policy uncertainty).

Several factors can affect the stock prices of renewable energy companies. The first channel is government policies and subsidies. Government policies play a crucial role in determining the growth of renewable energy. Government policies, such as tax credits and renewable portfolio standards, can determine investment and the development of renewable energy companies. In addition, government policies and subsidies can significantly affect renewable energy stocks since they can affect the investment costs of the renewable energy sector [3,4].

Secondly, technological advances have greatly improved the efficiency of renewable energy production, making it more cost-effective and competitive with traditional energy sources [5–7]. Therefore, improving renewable energy technology is also critical in determining renewable energy companies' stock prices. For instance, energy storage solutions and grid integration are essential for the success of the renewable energy sector [8]. Improved energy storage solutions increase the reliability and versatility of renewable energy. At the same time, grid integration allows for greater integration of renewable energy into the existing energy grid [9]. These factors can positively impact renewable energy companies' growth and stock prices.

Thirdly, natural disasters such as hurricanes, droughts, and wildfires can disrupt the energy market and cause fluctuations in renewable energy stock prices. In addition, climate change also affects the renewable energy sector, as the increasing frequency of natural disasters can

* Corresponding author. School of Management, University of Bradford, Bradford, United Kingdom.
** Corresponding author.
E-mail addresses: g.gozgor@bradford.ac.uk (G. Gozgor), luzhou59@tjcu.edu.cn (Z. Lu).

https://doi.org/10.1016/j.rser.2023.114182
Received 29 April 2023; Received in revised form 22 November 2023; Accepted 7 December 2023
Available online 16 December 2023
1364-0321/

Nomenclature

Abbreviations

ADF	Augmented Dickey-Fuller
ARCH	Autoregressive Conditional Heteroskedasticity
ARDL	Autoregressive Distributed Lag
CCR	Canonical Cointegrating Regression
CPU	Climate Policy Uncertainty
CUSUM	Cumulative Sum
CUSUMSQ	Cumulative Sum of Squares
DOLS	Dynamic Least Squares
ECT	Error-Correction Term
FMOLS	Fully Modified Least Squares
G7	Groups of Seven
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GSCPI	Global Supply Chain Pressure Index
JB	Jarque-Bera
LM	Lagrange Multiplier
PP	Phillips-Perron
RENIXX	Renewable Energy Industrial Index
WTI	West Texas Intermediate

Symbols and units

Δ =	First Difference
ε_t =	Error Term
γ	Short-run coefficients
θ_1 to θ_5	Long-run coefficients
t-1	Optimal lag
H0	Null hypotheses
H1	Alternate hypotheses
α_i	Short-run coefficients
β_0	Intercept
ρ_0	Intercept
τ_0	Coefficient Matrix
φ_1	Long-run coefficient
ϑ_1	Short-run coefficient
ε_t	Eroor term
χ^2	Chi-Square
p	Probability value
C	Constant term
F	F-Stat
Dt	Dummy year

damage energy infrastructure, reducing energy production and affecting renewable energy stock prices [10–12].

Fourthly, renewable energy companies are capital-intensive, and access to funding is crucial to their growth. Economic conditions, such as recessions and slowdowns, can affect the availability of funding and the cost of capital, impacting renewable energy companies' growth and stock prices. In addition, political and economic events, such as trade conflicts and currency fluctuations, can affect the sector and individual company stock prices. Interest rates also play a role in determining the cost of capital, as higher interest rates make it more expensive for companies to raise funds. As the renewable energy sector grows, competition between companies increases, leading to market saturation and reduced profitability for some companies. This issue can hurt the stock prices of renewable energy companies.

Finally, the availability and cost of traditional energy sources, such as fossil fuels, can significantly impact the renewable energy sector. For example, suppose traditional energy sources become more plentiful or cheaper. In that case, the competitiveness of renewable energy may be reduced, leading to decreased demand for renewable energy stocks [13,14].

This work suggests two drivers of the renewable energy sector, i.e., the index of Climate Policy Uncertainty (CPU) introduced by Ref. [15] and the Global Supply Chain Pressure Index (GSCPI) downloaded from Ref. [16]. The CPU index uses the methodology of [17] and models the uncertainty policies on environmental topics, such as environmental regulations. Policy changes in ecological principles increase policy uncertainty, decreasing renewable energy consumption and delaying renewable energy investments; thus, the CPU can significantly affect renewable energy stocks. Renewable energy stocks are highly dependent on government policies, as these policies determine the level of investment in renewable energy and the incentives that support it. Favourable climate change policies, such as increased government investment in renewable energy and incentives like tax credits or subsidies, can increase the demand for renewable energy stocks. This increased demand can drive up the stock prices of renewable energy companies, leading to higher returns for investors. However, harmful climate change policies, such as reduced investment in renewable energy or removing incentives, can decrease the demand for renewable energy stocks. This reduced demand can lead to lower stock prices and concentrated investor returns [18].

Furthermore, the GSCPI can affect renewable energy stocks in several ways. First, supply chain disruptions can cause delays in producing and delivering renewable energy components, leading to increased costs and reduced revenues for renewable energy companies. This can, in turn, lead to lower stock prices. Secondly, global supply chain pressures can affect the availability and cost of raw materials that produce renewable energy components. For example, suppose the price of a critical raw material used in solar panels increases due to supply chain pressures. In that case, the cost of producing solar panels may increase, leading to lower stock prices for renewable energy companies. Thirdly, supply chain pressures can also affect the demand for renewable energy products. For example, if a critical market for renewable energy products experiences supply chain disruptions, this can reduce the need for renewable energy products, leading to lower stock prices for renewable energy companies [19].

Several studies in the empirical works examine the determinants of global renewable energy stocks. However, these works neglect the effects of the CPU index and the GSCPI on renewable energy stocks. This study is the first research in the empirical literature to use the CPU index of [15] and the GSCPI of [16] as the determinants of renewable energy stocks for the global market. Therefore, this study offers two new determinants of global renewable energy stock to the empirical literature. Furthermore, the Panel Dynamic Autoregressive Distributed Lag (ARDL) estimations from November 2003 to August 2022 show that the global supply chain pressure, climate policy uncertainty, and global economic activity redound international renewable stock returns in the long run. These results are robust enough to utilise different long-run estimation techniques.

The remainder of the study is organised as follows. Section 2 provides the literature review on the determinants of renewable energy. Section 3 explains the details of the data, the empirical model, and the econometric methodology. Section 4 discusses the empirical findings with potential implications. Finally, section 5 concludes by providing limitations and suggestions for future research.

2. Previous empirical studies

Several studies in the empirical literature examine the determinants of renewable energy stocks. The study by Ref. [20] is among the first research on the determinants of renewable energy stocks. The authors found that technology stock prices significantly impact renewable (alternative) energy stock prices more than crude oil prices. Similarly

[21], implemented four multivariate Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models and found that clean energy companies' stock prices correlate more with technology stocks than oil prices [22]. also observed that oil and technology prices significantly affect clean energy stock prices. However, carbon prices have an insignificant impact on clean energy stock prices.

In addition [23], provided evidence that renewable energy companies in Germany had a positive sentiment for their stock prices despite the significant price bubbles during the mid-2000s [24]. analysed the dependence structure between oil and renewable energy markets using copula models. The results indicated a time-varying and symmetric tail dependence between oil returns and global renewable energy stocks. In a further study [25], investigated co-movement and causality between oil and renewable energy stock prices. The authors used wavelet approaches and linear and nonlinear Granger causality tests in the time-frequency domain from 2006 to 2015. The results stated that dependence between oil and renewable energy returns is weak in the short run but strengthened in the long run. However, causality tests indicated mixed evidence of causality between oil and renewable energy prices at different time horizons.

In addition [26], analysed the spillover between crude oil prices and stock prices of technology and clean energy companies with the daily data from May 2005 to April 2015. The empirical findings indicated that technology stocks significantly affect the return and volatility spillover between renewable energy stocks and crude oil prices [27]. examined the time and frequency connectedness between the United States stock prices of clean energy companies and crude oil prices. According to the findings, most of the return and the volatility connectedness are valid in the concise term (up to five days), and the long-run connectedness is insignificant. A significant pairwise connectedness exists between clean energy and technology stock prices in the short term [28]. employed a quantile-based regression approach to examine the dependence between crude oil prices and clean energy stock indices. The authors indicated significant evidence for reducing the reliance between clean energy stock returns and crude oil returns [29]. also provided evidence for the dynamic impact of oil price changes on European clean energy companies' stock returns. Crude oil prices and clean energy stock returns are significantly connected. There is also a significant leverage effect, implying that the impact of bad news on connectedness is higher than good news.

Several works have focused on the effects of uncertainty measures on renewable energy stocks. For instance Ref. [30], examined the impact of Twitter sentiment on returns, volatility, and trading volumes of renewable energy stocks with the daily time series. The authors concluded Twitter sentiment has an insignificant effect on returns, volatility, or trading volumes of renewable energy stocks [31]. used the daily return data for renewable and fossil fuel energy stocks in different regions, such as the United States, Europe, and Asia, from March 24, 2000 to May 29, 2020. The authors found that investors were more sensitive to asset losses after the Global Financial Crisis of 2007–9, meaning there was a significant herding behaviour in the renewable stock market [32]. analysed the effects of pandemic uncertainty and economic policy uncertainty on the renewable energy stock indices with the daily data from January 3, 2005 to June 30, 2020. The findings from the quantile regression indicated that pandemic uncertainty has a significant positive impact on renewable energy stocks. However, the effect of economic policy uncertainty on renewable energy stocks is negative [33]. used nonparametric causality-in-quantiles to analyse the causality between the returns and the price volatility of crude oil prices and clean energy stock indices from October 13, 2010 to September 8, 2020. According to their findings, crude oil returns caused renewable stock returns in normal market conditions. The results are valid for the pre-COVID-19 pandemic era and the entire sample. However, during the COVID-19 pandemic, there has been an insignificant causality between crude oil prices and renewable energy stocks regarding returns and price volatility.

Table 1
Summary statistics and pairwise correlations.

Variable	*RENIXX*	*WTI*	*Killian*	*GSCPI*	*CPU*
Mean	699.5	65.46	11.17	0.118	118.9
Median	509.4	61.28	−2.541	−0.166	102.3
Maximum	2175	132.9	190.4	4.311	403.2
Minimum	151.8	15.27	−136.6	−1.485	33.39
Std. Dev.	447.1	24.91	72.42	1.046	63.71
Skewness	1.284	0.285	0.402	1.906	1.491
Kurtosis	3.698	2.284	2.465	6.565	5.413
Jarque-Bera	73.25	8.641	9.641	281.5	152.1
Probability	0.000	0.013	0.008	0.000	0.000
Obs.	248	248	248	248	248
RENIXX	1.000				
WTI	0.144	1.000			
Killian	0.482	0.194	1.000		
GSCPI	0.550	0.111	0.086	1.000	
CPU	0.397	0.014	−0.162	0.623	1.000

Source: The authors' estimations.

Table 2
Results of traditional unit root tests.

Variable	ADF		PP		Decision
	Level	Δ	Level	Δ	
lnRENIXX	−1.290	−10.76***	−1.408	−10.73***	I (1)
lnWTI	0.307	−11.74***	−2.888	−11.24***	I (1)
Killian	−3.126	−8.067***	−2.394	−11.82***	I (1)
GSCPI	−3.554**		−2.846*		I (0)
lnCPU	−4.163***		−6.218***		I (0)

Note: ***$p < 0.01$ and **$p < 0.05$. Source: The authors' estimations.

[34] examined the spillover between news-based economic uncertainty caused by the COVID-19 pandemic and renewable energy stock indices in Europe, the United States, and the World. The authors found that the effects of economic uncertainty caused by the COVID-19 pandemic on renewable energy stock returns and volatilities are statistically significant and greater than the Global Financial Crisis of 2007–9 [35]. investigated the causal relations of oil and renewable energy stock markets with different time and frequency domains. The relationship between oil and renewable energy stock markets is mainly valid during extreme shocks in short-term horizons. During the COVID-19 pandemic, the causal relationship remained valid for the severe shocks, but the impact is weaker [36]. examined the connectedness network among clean-energy stocks and fossil fuels markets, including the Global Financial Crisis of 2007–2009 and the COVID-19 pandemic era. The authors found weak volatility connections between clean-energy stocks and fossil fuels in the long run. Finally [37], used the daily data from August 3, 2021 to March 30, 2022 to analyse the impact of the Russia-Ukraine War in 2022 on renewable and traditional energy markets. The authors observed higher pairwise return connectedness between conventional and renewable energy markets during the war in Ukraine.

Following previous studies, it is observed that there is no work in the literature on the effects of climate policy uncertainty and global supply chain pressure on renewable energy stocks. To the best of our knowledge, this study provides the first evidence in empirical literature using the CPU index of [15] and the GSCPI of [16] as the determinants of renewable energy stocks for the global market. Therefore, the paper offers two new global renewable energy stocks determinants to the empirical literature.

3. Data, empirical model, and econometric methodology

3.1. Data and empirical model

The paper estimates the following models for renewable energy stocks with the monthly frequency data from November 2003 to August 2022.

RENIXX = f (*Killian, GSCPI, CPU, WTI*).

The model assumes that four dimensions drive renewable stock returns: Demand factors, supply factors, price shocks, and policy uncertainty. Here, the Killian index captures business cycles (demand shocks), the GSCPI captures supply shocks, the WTI captures price shocks, and the CPU climate policy uncertainty shocks. The dependent variable is the Renewable Energy Industrial Index (RENIXX Global Top 30 Renewable Stocks Index), accessed from Reuters (Reuters Instrument Code: RENIXX). The data focuses on Austria, Canada, the Cayman Islands, China, Denmark, France, Germany, Spain, and the United States. For details, visit https://www.renewable-energy-industry.com/stocks.

Crude Oil Prices: West Texas Intermediate (WTI) is obtained from Ref. [38].

The Killian Index for Global Economic Activity: This measure is defined by Refs. [39,40], and [41]. The related data are downloaded from Ref. [16]. Refer also to Ref. [42]. For details, visit https://www.dallasfed.org/research/igrea.aspx.

The Global Supply Chain Pressure Index (GSCPI) is downloaded from Ref. [43]. For details, visit https://www.newyorkfed.org/research/policy/gscpi#/overview.

The Climate Policy Uncertainty (CPU) index is provided by Ref. [15], and it is downloaded the related data from the economic policy uncertainty website of [17]. For details, visit https://www.policyuncertainty.com/climate_uncertainty.html.

Since the paper uses monthly data series, which are high-frequency, the paper needs to check the seasonality of the variables. However, suppose the paper does not prevent the seasonality in the data series. In that case, using variables with seasonality will produce unreliable results. Therefore, the paper follows the Loess-driven seasonal and trend decomposition method to make a seasonally adjusted series [44] and found that all the variables follow the pattern of seasonality and hence made seasonally adjusted. Therefore, these seasonally adjusted variables are considered for the empirical analysis.

3.2. Econometric methodology

This study employs the ARDL Bounds test to cointegration approach to examine the effect of the crude oil prices, Killian index of global economic activity, global supply chain pressure, and climate policy uncertainty on global renewable stocks index returns in the long run, as this method is more appropriate in case of time-series data with all sort of integrations (I (0), I (1), or both). However, the ARDL Bounds test approach of [45] is represented as follows:

$$\Delta lnRENIXX_t=\gamma_0+\sum_{i=1}^{n}\gamma_{1i}\ \Delta lnRENIXX_{t-i}+\sum_{i=0}^{n}\gamma_{2i}\ \Delta lnWTI_{t-i}+\sum_{i=0}^{n}\gamma_{3i}\ \Delta Killian_{t-i}+\sum_{i=0}^{n}\gamma_{4i}\ \Delta GSCPI_{t-i}+\sum_{i=0}^{n}\gamma_{5i}\ \Delta lnCPU_{t-i}+\theta_1 lnRENIXX_{t-1}+\theta_2 lnWTI_{t-1}+\theta_3 Killian_{t-1}+\theta_4 GSCPI_{t-1}+\theta_5\ ln\ CPU_{t-1}+\varepsilon_t \quad (1)$$

where Δ is the first difference of the variables named lnRENIXX, lnWTI, Killian, GSCPI, and lnCPU and ε_t is the error term, following the property of Gaussian distribution. The subscript t-1 is the optimal lag provided by the Akaike information criterion (AIC). γ and θ_1 to θ_5 The coefficients assist in measuring the short and long-run linkages between the variables associated with this study. As per the thought of [46], the long-run associations across the variables in any estimated model scrutinise both the short and long-run relation. However, the null (H_0) and alternate (H_1) hypotheses provided by Ref. [45] are as follows:

H_0 (Null hypothesis) $= \theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = 0$

H_1 (Alternate hypothesis) $= \theta_1 \neq \theta_2 \neq \theta_3 \neq \theta_4 \neq \theta_5 \neq 0$

The calculated F-statistics from the ARDL Bounds test model choose the appropriate hypothesis from null (H0) and alternate (H1) hypotheses. As per the statement regarding F-statistics given by Ref. [45], if the calculated F-statistics is higher than the upper and lower bounds, it will be concluded that a long-run relationship exists. Otherwise, it might be inconclusive or have no linkage at all.

The error-correction model is also specified by using the format of [45], which is given as follows:

$$\Delta lnRENIXX_t=\beta_0+\sum_{i=1}^{q}\alpha_1\ \Delta lnRENIXX_{t-i}+\sum_{i=1}^{q}\alpha_2\ \Delta lnWTI_{t-i}+\sum_{i=1}^{q}\alpha_3\ \Delta Killian_{t-i}+\sum_{i=1}^{q}\alpha_4\ \Delta \mathrm{GSCPI}_{t-i}+\sum_{i=1}^{q}\alpha_5\ \Delta \mathrm{lnCPU}_{t-i}+\mathrm{ECT}_{t-i}+\varepsilon_t \quad (2)$$

where α_i is the short-run coefficients of the stated variables, and the ECT term is the error-correction term, which calculates the speed of adjustment towards achieving the long-run equilibrium of the global renewable stock. Generally, this term spans from −1 to 0. However, the ARDL Bounds test also considers the post-estimation analysis, like the Breusch-Godfrey Lagrange Multiplier (LM) test for serial correlation, Jarque-Bera test for normality checking, Autoregressive Conditional Heteroskedasticity (ARCH) test for heteroscedasticity, and Ramsey-Reset for model specification test. At last, it checks the ARDL model stability by using the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) proposed by Ref. [47].

The complications regarding the parameters of the long- and short-run estimations in the basic ARDL model by Refs. [45,48] constructed a new reliable model that can estimate, stimulate, and predict the real variables change instantly in the short and long-run. Therefore, this method can be the appropriate approach for this study because it can predict and stimulate and also plot the changes in the dependent variable due to the changes in one exogenous variable immediately by keeping other variables unchanged. However, the error correction of this approach follows the equation for the estimation of the specified model:

$$\Delta lnRENIXX_t = \rho_0 + \tau_0 lnRENIXX_{t-1} + \vartheta_1 \Delta lnWTI_t + \varphi_1 lnWTI_{t-1} + \vartheta_2 \Delta Killian_t + \varphi_2 Killian_{t-1} + \vartheta_3 \Delta GSCPI_t + \varphi_3 GSCPI_{t-1} + \vartheta_4 \Delta ln\ CPU_t + \varphi_4\ ln\ CPU_{t-1} + \varepsilon_t \quad (3)$$

4. Empirical findings

4.1. Preliminary tests

This study examines the descriptive statistics of the respective variables in Table 1 to know their characteristics and patterns. Table 1 consisted of each variable's mean, median, standard deviation, maximum, minimum, Kurtosis, Skewness, and Jarque-Bera. The mean value of global renewable stocks index returns (699.5) is high, which is followed by climate policy uncertainty (118.9), crude oil prices (65.46), global economic activity (11.17), and global supply chain pressure (0.118). The standard deviation is also high in global renewable stocks index returns (447.1). It is followed by global economic activity (72.42), climate policy uncertainty (63.71), crude oil prices (24.91), and global supply chain pressure (1.046). This high standard deviation forces us to take the natural logarithm of some of the selected variables, like global renewable stocks index returns, crude oil prices, and global supply chain pressure. Since the remaining variables contain negative values, they do not apply to the imposition of the logarithm. The Jarque-Bera (JB) statistics claim that the data series are normally distributed or follow the Gaussian distribution.

Table 1 further signifies that all the variables are in a positive trend. The correlation matrix in Table 1 also represents that global renewable stocks index returns have a positive relationship with the other exogenous variables. A negative relation between climate policy uncertainty and global economic activity can be observed, interpreting that the variables are moving in an opposite direction. However, this pre-estimation analysis validates that all the variables are in the proper pattern and well-fitted for further empirical investigation.

Moreover, time-series estimation always requires knowing about stationarity. Otherwise, the estimation will be spurious. In this regard, this study employs the two standard unit-root tests, like the Augmented Dickey-Fuller (ADF) unit root test of [49] and the Phillips-Perron (PP) unit root tests proposed by Ref. [50]. The outcome from the unit-root tests in Table 2 signifies that variables are in a mixed order of integration. Except for GSCPI and lnCPU, all the variables are stationary at first difference. Unfortunately, these basic standard unit-root tests can produce biased and unreliable results if the structural break is not accommodated in estimating time-series data. In this context, the paper further checks the single structural break unit-root test proposed by Ref. [50].

The unit root test results of [51] in Table 3 are again consistent with the standard unit root test result, which implies that variables are in a mixed order of integration. Therefore, these unit-root results favour employing the dynamic ARDL simulation model for this study.

4.2. ARDL bounds test for cointegration

Finally, this study has applied the ARDL Bounds test to learn about long-run linkages. The result of Table 4 calculates the F-statistics, which is the only factor of concern as it can determine whether variables are significantly cointegrating.

From the estimated F-statistics result, the paper finds that the value of F is 3.729, which is higher than the upper (3.53) and lower (2.68) bound tabulated values of F-statistics at a 10 % level of significance given by Ref. [52]. This outcome rejects the null hypothesis, which signifies those variables significantly cointegrate with each other in the long run.

4.3. Dynamic ARDL results

The study has applied the pioneering time-series dynamic ARDL simulation method for the long- and short-run analysis. The results in Table 5 reveal that the coefficient of crude oil price is negative but significant in both the long and short run. This evidence indicates that the change in crude oil prices reduces the global renewable energy stock index. Similar findings were also evidenced from the study of [13] for G7 countries and [53] for net oil-importing South Asian countries. However, these results justify the findings for global analysis, which signifies that the increase in crude oil prices reduces renewable stocks globally.

The Killian Index for Global Economic Activity positively affects the renewable energy stock index globally. This evidence implies that a 1 % increase in global economic activity enhances the renewable energy stock index in the long (2 %) and short-run (5 %). Moreover, the supply chain pressure index coefficient is positive and significant in the long and short run. It implies that a 1 % increase in the global supply chain pressure index is accompanied by a rise in the renewable stock index in the long (8.2 %) and short (16.3 %) run. The enhanced supply chain pressure leads to a growth in the renewable energy stock index, which means the advancement of supply change improves the stock of green energy due to advanced technology and modern infrastructure as many of the countries follow the United Nations framework convention goals and the Paris Agreement, which primarily accelerates the idea of more generation and utilisation of renewable energy in developed and developing economies. This issue can further help in making a low-carbonised economy worldwide. At this stage, the supply chain becomes a vital factor, which can enhance the use of renewable sources to mitigate long-term environment-friendly goals. However, this result signifies that most countries are concerned about this environmental issue. Therefore, they primarily focus on renewable sources rather than non-renewable ones, ultimately enhancing the global renewable energy stock index.

Furthermore, the coefficient of climate policy uncertainty is positive and significant in the long (19 %) and short (40 %) run. Therefore, it implies that the climate policy uncertainty enhances the renewable energy stock globally, meaning climate change mitigating policies imposed by the respective countries are effective in the case of renewable energy consumption. However, suppose the policymakers wish to reduce climate uncertainty more. In that case, they should give more importance to renewable energy sources by providing financial assistance and lowering taxes on renewable products. This way, clean energy sources promote natural health and reduce biodiversity loss.

However, these long results are robust enough to utilise different long-run estimation techniques, like Canonical Cointegrating Regression (CCR) of [54], Fully Modified Least Squares (FMOLS) of [55], and Dynamic Least Squares (DOLS) of [56]. Table 6 indicates that the results from the panel ARDL model are consistent with the stated panel models, which brings the accuracy of the results. Diagnostics tests like serial correlation, heteroskedasticity, and Jarque-Bera determine that the models are appropriate for knowing the determinants of the renewable energy stock index and its respective policies.

In addition, Fig. 1 represents the impulse response graph of this study. Fig. 1a and b imply the crude oil prices and renewable stock index have a positive relationship with each other in case of a 10 % increase and a 10 % decrease in the long and short run.

CUSUM and CUSUMsq in Fig. 2 show that the estimated ARDL model is stable and reliable. The error correction term (ECT) is negative and significant, meaning the model's accuracy. However, the dynamic ARDL simulation method plotted the impulse response graph to know the

Table 3
Results of second-generation unit root test [51].

Variable	Level		Δ		Decision
	t-Statistic	Break	t-Statistic	Break	
lnRENIXX	−2.594	February 2018	−7.391***	May 2005	I (1)
LnWTI	−3.383	August 2007	−10.97***	January 2015	I (1)
Killian	−4.123	December 2015	−8.697***	November 2008	I (1)
GSCPI	−5.126**	July 2019			I (0)
LnCPU	−6.228***	April 2015			I (0)

Note: ***p < 0.01 and **p < 0.05. Source: The authors' estimations.

Table 4
Results of the ARDL bounds cointegration test.

Estimated Model	Structural Break Date	Optimal Lag Length	F-Statistics	χ^2 Normal	χ^2 ARCH	χ^2 Ramsey	χ^2 Serial
lnRENIXX = f (lnWTI, Killian, G0SCPI, lnCPU)	May 2005	(1, 1, 0, 1, 0)	3.729*	0.086	0.791 [1]	0.065 [1]	20.61 [1]
Significance of Critical Value		Lower Bound I (0)			Upper Bound I (1)		
	10 %	2.68			3.53		
	2.5 %	3.40			4.36		
	1 %	3.81			4.92		

Notes: The lower and upper bounds values of [52] are used while comparing the estimated F-statistic values of the ARDL models. *p < 0.10. Source: The authors' estimations.

actual effect of the variables on the renewable energy stock index.

Notes: The impulse response plot for crude oil prices and renewable energy stocks. It shows a 10 % increase (a) and a decrease (b) in crude oil prices and its influence on renewable energy stocks where dots specify average prediction value, whereas the dark blue to light blue line specifies 75 %, 90 %, and 95 % confidence intervals, respectively. Source: The authors' estimations.

4.4. Policy implications

The findings of the study bear essential policy implications. The results suggest that climate policymakers at the global level must prioritise global supply chain pressure, climate policy uncertainty, and global economic activity because of their beneficial impacts on renewable stocks. In light of this, one can argue that countries importing fossil fuels worldwide while grappling with geopolitical risks and threats, need to multiply renewable stocks. This evidence becomes possible when fossil fuel-importing countries could enhance their economic activity and income level. Moreover, more significant fossil fuel supply uncertainty and environmental regulation uncertainty could motivate governments to import fossil fuels to stimulate renewable stocks.

In contrast, the study finds that crude oil prices hamper renewable stocks at the global level. Therefore, it could be an essential variable in climate change mitigating policy. This finding also benefits oil exporting countries worldwide when oil prices started increasing. In such a situation, one could hypothesise that the higher the crude oil prices, the lower the renewable stocks will be, which is evidence of the study. This issue implies that rising crude oil prices will enable oil-exporting countries to gain higher export revenue when more oil exports are traded. Eventually, oil exporting countries will further consider extracting more crude resources to generate more oil export revenue. At the same time, these economies will have less incentive for renewable stocks, which appear to be expensive in the international energy market.

Table 5
The dynamic ARDL estimations.

Dependent Variable: *lnRENIXX*			
Variable	Coefficient	Std. Error	t-value
C	6.123***	0.592	10.34
D_lnWTI	−0.451*	0.256	−1.761
L1_lnWTI	−0.205**	0.078	−2.612
D_Killian	0.002**	0.001	2.163
L1_Killian	0.005***	0.000	13.34
D_GSCPI	0.082*	0.048	1.712
L1_GSCPI	0.163***	0.032	4.974
D_lnCPU	0.186**	0.076	2.442
L1_lnCPU	0.396***	0.079	4.991
D_Dt (May 2005)	−0.463	0.390	−1.193
L1_Dt (May 2005)	−0.763	0.562	−1.362
ECMt (-1)	−0.133**	0.058	−2.271
Adjusted R-squared	0.601		
F (12, 212)	28.89		
Simulation	5000		
Root Mean Square Error	0.381		
Prob > F	0.000		

Notes: ***p < 0.01, **p < 0.05 and *p < 0.10. Source: The authors' estimations.

5. Conclusion

This study investigates the factors determining the global renewable stocks index returns using the monthly data from November 2003 to August 2022. The independent variables include the measures for crude oil prices, global supply chain pressure, climate policy uncertainty, and global economic activity. The long-run dynamic ARDL estimations show that the global supply chain pressure, climate policy uncertainty, and economic activity enhance international renewable stock returns. Moreover, crude oil prices are detrimental to renewable stocks at the global level. These results are robust enough to utilise different long-run estimation techniques, like the CCR, DOLS, and FMOLS.

Table 6
The CCR, FMOLS, and the DOLS long run estimations.

Dependent Variable: *lnRENIXX*			
Variable	Canonical Cointegrating Regression (CCR)	Fully Modified Least Squares (FMOLS)	Dynamic Least Squares (DOLS)
	Coefficient (Std. Error)		
C	0.090 (0.077)	0.090** (0.039)	0.150*** (0.012)
lnWTI	−0.151 (0.390)	−0.209*** (0.016)	−0.210*** (0.005)
Killian	0.009*** (0.002)	0.002** (0.001)	0.009*** (0.003)
GSCPI	0.991*** (0.232)	0.014*** (0.004)	0.020*** (0.002)
lnCPU	0.660*** (0.165)	0.024*** (0.005)	0.022*** (0.001)
Dt (May 2005)	0.044 (0.069)	0.048* (0.027)	0.046*** (0.002)
Adjusted R-squared	0.416	0.979	0.979

Notes: ***p < 0.01, **p < 0.05 and *p < 0.10. Source: The authors' estimations.

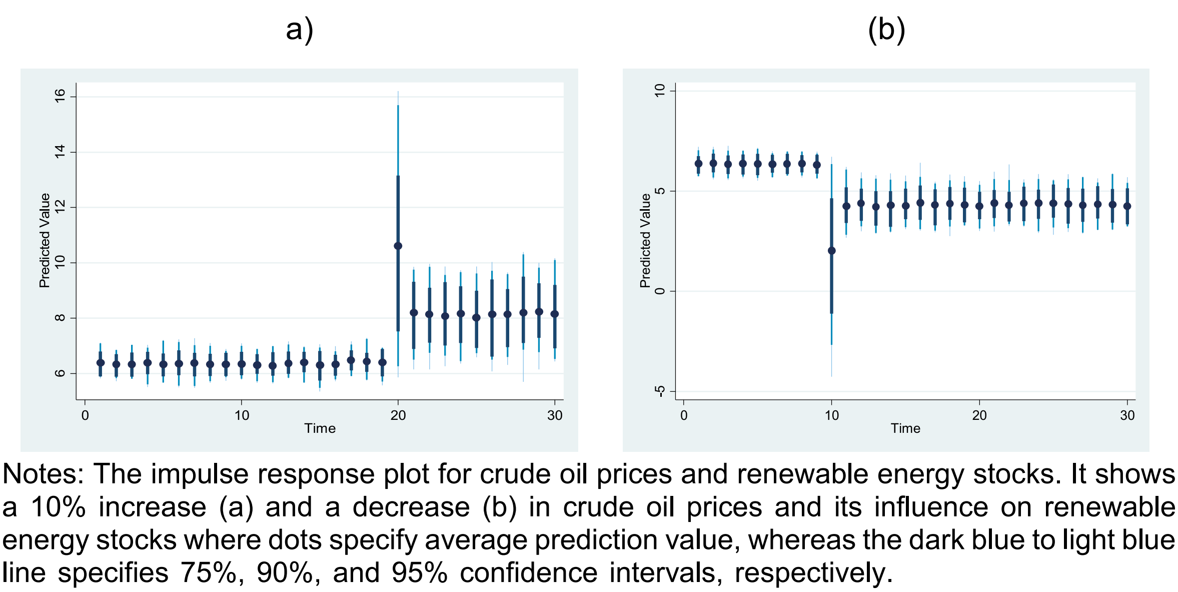

Fig. 1. The Impulse Response Plot
Source: The authors' estimations.

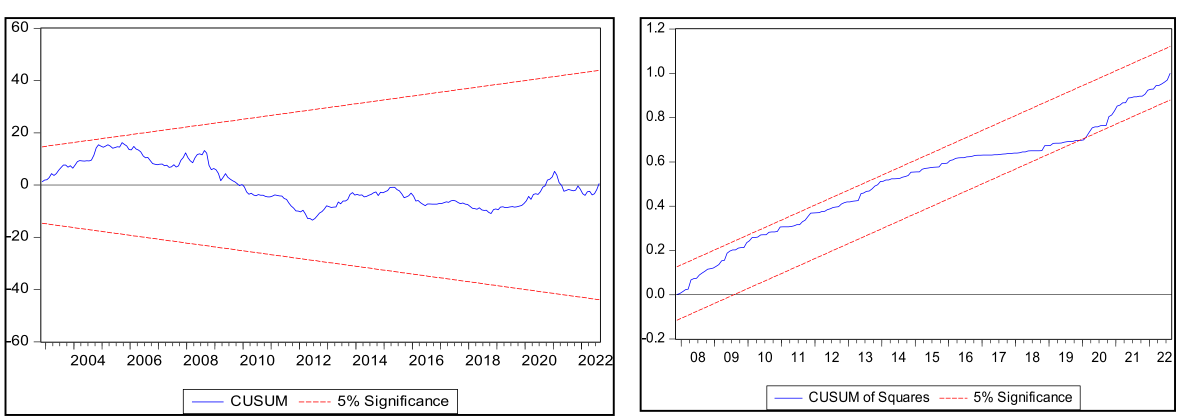

Fig. 2. The CUSUM and the CUSUM of Squares.

CRediT authorship contribution statement

Guoheng Hu: Data curation, Writing–original draft. **Giray Gozgor:** Conceptualization, Writing–original draft. **Zhou Lu:** Funding acquisition, Writing–review & editing. **Mantu Kumar Mahalik:** Validation, Writing–original draft. **Shreya Pal:** Investigation, Writing–original draft.

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.

Data availability

Data will be made available on request.

Acknowledgement

We acknowledge the grant from the National Social Science Fund of China (No. 21BJY084). We thank the Chief Editor, the Special Issue Editors, and four anonymous reviewers for their valuable comments and suggestions, which have enhanced the quality of the manuscript.

References

[1] Omri A, Nguyen DK. On the determinants of renewable energy consumption: international evidence. Energy Aug. 2014;72:554–60. https://doi.org/10.1016/j.energy.2014.05.081.
[2] Usman M, Balsalobre-Lorente D, Jahanger A, Ahmad P. Pollution concern during globalization mode in financially resource-rich countries: do financial development, natural resources, and renewable energy consumption matter? Renew Energy Jan. 2022;183:90–102. https://doi.org/10.1016/j.renene.2021.10.067.
[3] Apergis N, Payne JE. Renewable and non-renewable energy consumption-growth nexus: evidence from a panel error correction model. Energy Econ 2012;34(3):733–8. https://doi.org/10.1016/j.eneco.2011.04.007.
[4] Inglesi-Lotz R, Dogan E. The role of renewable versus non-renewable energy to the level of CO2 emissions a panel analysis of sub-Saharan Africa's Big 10 electricity generators. Renew Energy Aug. 2018;123:36–43. https://doi.org/10.1016/j.renene.2018.02.041.
[5] Apergis N, Payne JE. Renewable energy consumption and economic growth: evidence from a panel of OECD countries. Energy Pol Jan. 2010;38(1):656–60. https://doi.org/10.1016/j.enpol.2009.09.002.
[6] Apergis N, Payne JE. Renewable energy consumption and growth in Eurasia. Energy Econ Nov. 2010;32(6):1392–7. https://doi.org/10.1016/j.eneco.2010.06.001.
[7] Inglesi-Lotz R. The impact of renewable energy consumption to economic growth: a panel data application. Energy Econ Jan. 2016;53:58–63. https://doi.org/10.1016/j.eneco.2015.01.003.
[8] Hosseini SS, Badri A, Parvania M. A survey on mobile energy storage systems (MESS): applications, challenges and solutions. Renew Sustain Energy Rev Dec. 2014;40:161–70. https://doi.org/10.1016/j.rser.2014.07.183.
[9] Richardson DB. Electric vehicles and the electric grid: a review of modeling approaches, Impacts, and renewable energy integration. Renew Sustain Energy Rev Mar. 2013;19:247–54. https://doi.org/10.1016/j.rser.2012.11.042.
[10] Ajmi AN, Inglesi-Lotz R. Biomass energy consumption and economic growth nexus in OECD countries: a panel analysis. Renew Energy Oct. 2020;162:1649–54. https://doi.org/10.1016/j.renene.2020.10.002.
[11] Aydin M. Renewable and non-renewable electricity consumption–economic growth nexus: evidence from OECD countries. Renew Energy Jun. 2019;136:599–606. https://doi.org/10.1016/j.renene.2019.01.008.
[12] Payne JE. On the dynamics of energy consumption and output in the US. Appl Energy Apr. 2009;86(4):575–7. https://doi.org/10.1016/j.apenergy.2008.07.003.
[13] Sadorsky P. Renewable energy consumption, CO2 emissions and oil prices in the G7 countries. Energy Econ May 2009;31(3):456–62. https://doi.org/10.1016/j.eneco.2008.12.010.
[14] Sadorsky P. Renewable energy consumption and income in emerging economies. Energy Pol Oct. 2009;37(10):4021–8. https://doi.org/10.1016/j.enpol.2009.05.003.
[15] Gavriilidis K. "Measuring climate policy uncertainty," *Available at SSRN*, No. 3847388. 2021.
[16] Federal Reserve Bank of Dallas, "Index of global real economic activity. Dallas, TX: the Federal Reserve Bank of Dallas; 2023.
[17] Baker SR, Bloom N, Davis SJ. Measuring economic policy uncertainty. Q J Econ Jul. 2016;131(4):1593–636.
[18] Shang Y, Han D, Gozgor G, Mahalik MK, Sahoo BK. The impact of climate policy uncertainty on renewable and non-renewable energy demand in the United States. Renew Energy Sep. 2022;197:654–67. https://doi.org/10.1016/j.renene.2022.07.159.
[19] Gozgor G, Khalfaoui R, Yarovaya L. Global supply chain pressure and commodity markets: evidence from multiple wavelet and quantile connectedness analyses. Finance Res Lett Jun. 2023;54:103791. https://doi.org/10.1016/j.frl.2023.103791.
[20] Henriques I, Sadorsky P. Oil prices and the stock prices of alternative energy companies. Energy Econ May 2008;30(3):998–1010. https://doi.org/10.1016/j.eneco.2007.11.001.
[21] Sadorsky P. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ Jan. 2012;34(1):248–55. https://doi.org/10.1016/j.eneco.2011.03.006.
[22] Kumar S, Managi S, Matsuda A. Stock prices of clean energy firms, oil and carbon markets: a vector autoregressive analysis. Energy Econ Jan. 2012;34(1):215–26. https://doi.org/10.1016/j.eneco.2011.03.002.
[23] Bohl MT, Kaufmann P, Stephan PM. From hero to zero: evidence of performance reversal and speculative bubbles in German renewable energy stocks. Energy Econ May 2013;37:40–51. https://doi.org/10.1016/j.eneco.2013.01.006.
[24] Reboredo JC. Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Econ Mar. 2015;48:32–45. https://doi.org/10.1016/j.eneco.2014.12.009.
[25] Reboredo JC, Rivera-Castro MA, Ugolini A. Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. Energy Econ Jan. 2017;61:241–52. https://doi.org/10.1016/j.eneco.2016.10.015.
[26] Ahmad W. On the dynamic dependence and investment performance of crude oil and clean energy stocks. Res Int Bus Finance Dec. 2017;42:376–89. https://doi.org/10.1016/j.ribaf.2017.07.140.
[27] Ferrer R, Shahzad SJH, López R, Jareño F. Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. Energy Econ Oct. 2018;76:1–20. https://doi.org/10.1016/j.eneco.2018.09.022.
[28] Dawar I, Dutta A, Bouri E, Saeed T. Crude oil prices and clean energy stock indices: lagged and asymmetric effects with quantile regression. Renew Energy Jan. 2021;163:288–99. https://doi.org/10.1016/j.renene.2020.08.162.
[29] Geng J-B, Liu C, Ji Q, Zhang D. Do oil price changes really matter for clean energy returns? Renew Sustain Energy Rev Oct. 2021;150:111429. https://doi.org/10.1016/j.rser.2021.111429.
[30] Reboredo JC, Ugolini A. The impact of Twitter sentiment on renewable energy stocks. Energy Econ Oct. 2018;76:153–69. https://doi.org/10.1016/j.eneco.2018.10.014.
[31] Chang C-L, McAleer M, Wang Y-A. Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19. Renew Sustain Energy Rev Dec. 2020;134:110349. https://doi.org/10.1016/j.rser.2020.110349.
[32] Hemrit W, Benlagha N. Does renewable energy index respond to the pandemic uncertainty? Renew Energy Nov. 2021;177:336–47. https://doi.org/10.1016/j.renene.2021.05.130.
[33] Hammoudeh S, Mokni K, Ben-Salha O, Ajmi AN. Distributional predictability between oil prices and renewable energy stocks: is there a role for the COVID-19 pandemic? Energy Econ Nov. 2021;103:105512. https://doi.org/10.1016/j.eneco.2021.105512.
[34] Liu T, Nakajima T, Hamori S. The impact of economic uncertainty caused by COVID-19 on renewable energy stocks. Empir Econ Jun. 2021;62:1495–515. https://doi.org/10.1007/s00181-021-02087-3.
[35] Xi Y, Zeng Q, Lu X, Huynh TLD. Oil and renewable energy stock markets: unique role of extreme shocks. Energy Econ May 2022;109:105995. https://doi.org/10.1016/j.eneco.2022.105995.
[36] Umar M, Farid S, Naeem MA. Time-frequency connectedness among clean-energy stocks and fossil fuel markets: comparison between financial, oil and pandemic crisis. Energy Feb. 2022;240:122702. https://doi.org/10.1016/j.energy.2021.122702.
[37] Mohammed KS, Usman M, Ahmad P, Bulgamaa U. Do all renewable energy stocks react to the war in Ukraine? Russo-Ukrainian conflict perspective. Environ Sci Pollut Control Ser Dec. 2022;30:36782–93. https://doi.org/10.1007/s11356-022-24833-5.
[38] U.S. Energy Information Administration. "Crude oil prices: west Texas intermediate (WTI) - cushing, Oklahoma,". Washington DC: U.S. Energy Information Administration; 2023.
[39] Kilian L. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. Am Econ Rev May 2009;99(3):1053–69. https://doi.org/10.1257/aer.99.3.1053.
[40] Kilian L. Measuring global real economic activity: do recent critiques hold up to scrutiny? Econ Lett May 2019;178:106–10. https://doi.org/10.1016/j.econlet.2019.03.001.
[41] Kilian L, Zhou X. Modeling fluctuations in the global demand for commodities. J Int Money Finance 2018;88:54–78. https://doi.org/10.1016/j.jimonfin.2018.07.001.
[42] Hamilton JD. Measuring global economic activity. J Appl Econom Nov. 2019;36(3):293–303. https://doi.org/10.1002/jae.2740.
[43] Federal Reserve Bank of New York. Global supply chain pressure index (GSCPI)". New York, NY: The Federal Reserve Bank of New York; 2023.
[44] Cleveland RB, Cleveland WS, McRae JE, J E, Terpenning I. STL: a seasonal-trend decomposition. J Off Stat Mar. 1990;6:3–73.
[45] Pesaran MH, Shin Y, Smith RJ. Bounds testing approaches to the analysis of level relationships. J Appl Econom 2001;16(3):289–326. https://www.jstor.org/stable/2678547.
[46] Johansen S. Statistical analysis of cointegration vectors. J Econ Dynam Control Jun. 1988;12(2–3):231–54.

[47] Brown RL, Durbin J, Evans JM. Techniques for testing the constancy of regression relationships over time. J Roy Stat Soc B 1975;37(2):149–92. https://www.jstor.org/stable/2984889.
[48] Jordan S, Philips AQ. Cointegration testing and dynamic simulations of autoregressive distributed lag models. STATA J: Promoting Communications on Statistics and Stata Dec. 2018;18(4):902–23. https://doi.org/10.1177/1536867x1801800409.
[49] Dickey DA, Fuller WA. Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc Jun. 1979;74(366):427–31. https://doi.org/10.2307/2286348.
[50] Phillips PCB, Perron P. Testing for a unit root in time series regression. Biometrika 1988;75(2):335–46. https://doi.org/10.2307/2336182.
[51] Zivot E, Andrews DWK. Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. J Bus Econ Stat Jul. 1992;10(3):251–70. https://doi.org/10.2307/1391541.
[52] Narayan PK. The saving and investment nexus for China: evidence from cointegration tests. Appl Econ 2005;37(17):1979–90. https://doi.org/10.1080/00036840500278103.
[53] Murshed M, Tanha MM. Oil price shocks and renewable energy transition: empirical evidence from net oil-importing South Asian economies. Energy, Ecology and Environment May 2020;6:183–203. https://doi.org/10.1007/s40974-020-00168-0.
[54] Park JY. Canonical cointegrating regressions. Econometrica Jan. 1992;60(1):119–43. https://doi.org/10.2307/2951679.
[55] Phillips PCB, Hansen BE. Statistical inference in instrumental variables regression with I(1) processes. Rev Econ Stud Jan. 1990;57(1):99–125. https://doi.org/10.2307/2297545.
[56] Stock JH, Watson MW. A simple estimator of cointegrating vectors in higher order integrated systems. Econometrica Jul. 1993;61(4):783–820. https://doi.org/10.2307/2951763.