Science of the Total Environment 736 (2020) 139602

Contents lists available at ScienceDirect

Science of the Total Environment

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

Causal effect of environmental factors, economic indicators and domestic material consumption using frequency domain causality test

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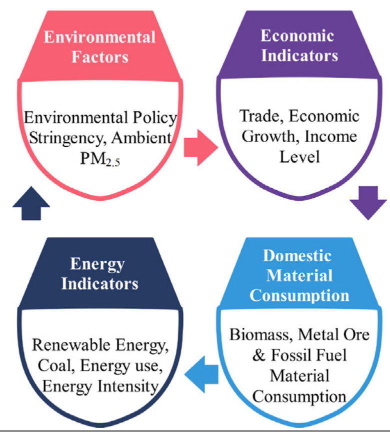
HIGHLIGHTS

- We assess the environmental, social and economic dimensions of natural resource extraction
- We utilize the novel Breitung-Candelon spectral Granger-causality test for 96 models
- We find strong evidence to support metal consumption-led ambient air pollution
- We confirm a coal-driven energy-based economic structure with limited green inputs
- We find strong evidence between metal ore consumption and wealth

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 2 April 2020
Received in revised form 17 May 2020
Accepted 19 May 2020
Available online 27 May 2020

Editor: Damia Barcelo

Keywords:
Spectral granger-causality test
Frequency domain causality test
Particulate matter
Material footprint
Air pollution

ABSTRACT

Economic growth-induced climate change is multifaceted with different dimensions, hence, requires scientific scrutiny. Herein, an assessment of the causal effect of environmental factors, economic assessment and domestic material consumption is presented. We utilized the novel Breitung-Candelon spectral Granger-causality aka frequency domain causality and parameter stability tests to account for the direction of causality. These tests, a resemblance to machine learning algorithm were required to examine the sequential shock of unobserved features of series not reported in traditional Granger-causality tests. The empirical results found a short-run relationship between renewables and economic growth, suggesting a strong effect of wealth on renewable energy consumption. We confirmed a strong and long-term metallurgical coal-controlled metal footprint through steelmaking, and coal-driven energy-based economic structure. The feedback hypothesis was validated between biomass consumption and economic growth. There was evidence that metal ore consumption predicts economic growth, income level and renewable energy consumption while it causes ambient air pollution. From a policy perspective, the study demonstrates that the diversification of the energy mix with renewable energy sources will reduce fossil fuel footprint.

1. Introduction

The trilemma between environmental, social and economic achievements underscores the difficulty in attaining a sustainable environment. In this study, we examine the causal effect between environmental, social and economic dimensions of domestic material consumption. Contrary to previous attempts, we develop conceptual tools using a comprehensive framework based on a battery of novel estimation techniques. This study contributes to the limited literature on material flow in environmental economics using a multidisciplinary approach.

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https://doi.org/10.1016/j.scitotenv.2020.139602

Natural resources extraction, in the form of domestic material consumption, underpins the economic structure (Havranek et al., 2016; Gilberthorpe and Hilson, 2016). While the dependence on agricultural, forestry and land use determines the agrarian economy, energy resources, metal and non-metal extraction are often raw materials for the industrial-based economy. However, either of these forms of natural resource extraction has environmental, social and economic dimensions of impact (Wu et al., 2017; Bergstrom and Randall, 2016). The environmental dimension entails drivers that hamper environmental performance and factors that mitigate environmental deterioration. Domestic material consumption namely biomass, fossil fuels (coal, oil and natural gas), non-metal and metal ores; energy intensity (energy use and economic growth); greenhouse gas emission intensity and population dynamics affect environmental performance (Wiedmann et al., 2015; Martinico-Perez et al., 2018). The resultant environmental deterioration and dimension effects include air, water and land pollution.

The economic dimension involves production and consumption, leading to export and import of goods and services through international trade (Schaffartzik et al., 2019). This means that the economic structure determines the extent of natural resource depletion. Thus, the economic structure determines the socio-political pressures on the management of natural resources that include technology, innovation, research and development, and environmental policies and regulations (Speirs et al., 2015; Martínez Arranz, 2017). Natural resource extraction is often a characteristic of agrarian-based economies that depend mostly on the exportation of raw materials due to limited innovation and technologies to transform raw materials into finished goods (Perrings, 1989). The exported raw materials often land in industrialized economies with carbon and energy-intensive manufacturing processes. The finished products that are often carbon-embedded are exported to higher-income countries with a huge service sector. Thus, the chain of operations from agrarian to industry and services underline

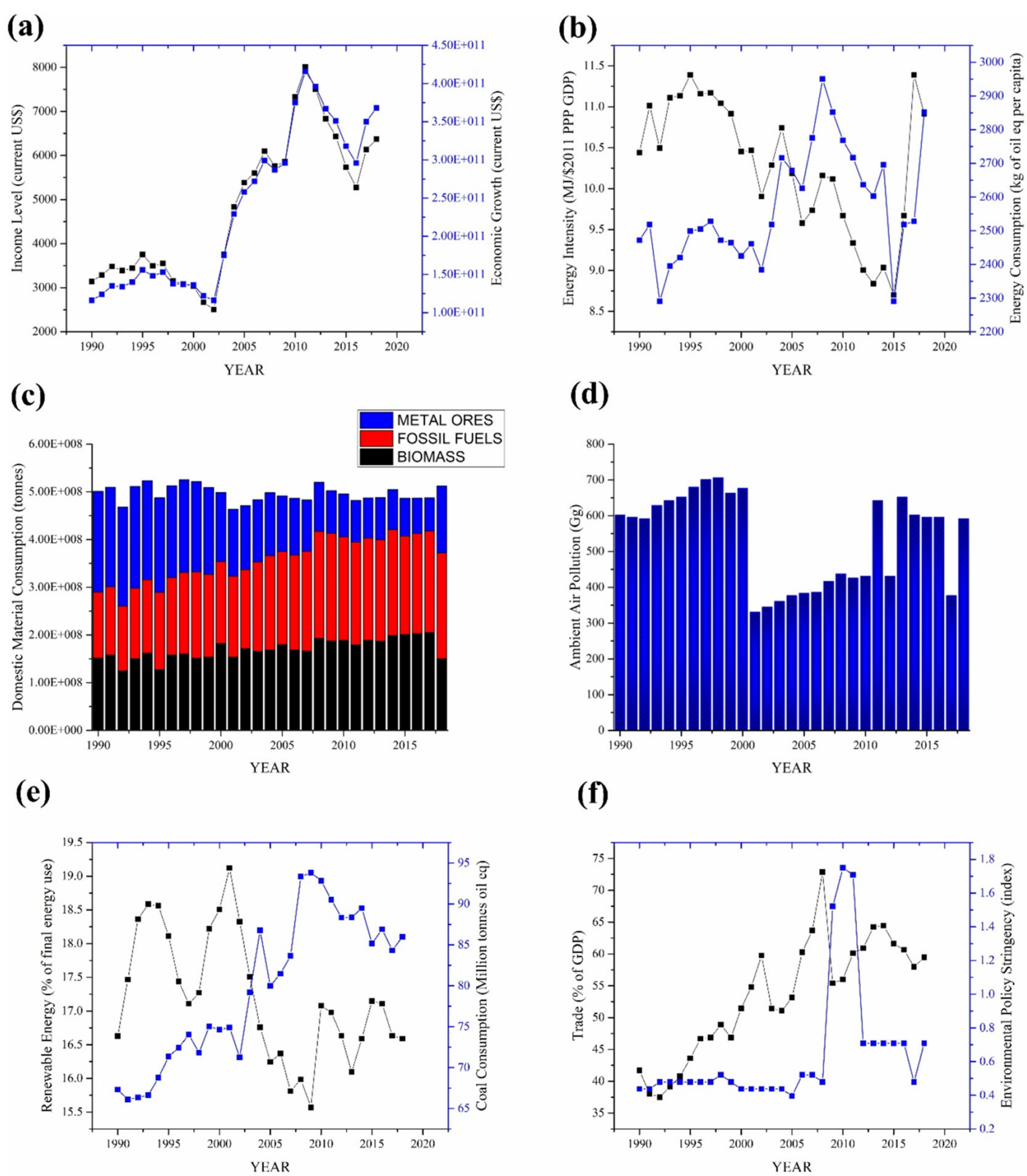

Fig. 1. Overview of sampled data series (a) Income level & Economic growth (b) Energy intensity & Energy consumption (c) Domestic material consumption (d) Ambient air pollution (e) Renewable energy & Coal consumption (f) Trade & Environmental policy stringency.

Table 1
Descriptive statistical analysis of data series.

Statistics	BIOMASS	COAL	ENEINT	ENERGY	ENVPS	FOSSILFUELS	GDP	METALORES	PGDP	PM25	RENCONS	TRADE
Mean	1.70E+08	79.6806	10.2774	2570.9870	0.6401	1.88E+08	2.35E+11	1.39E+08	4788.9150	535.2407	17.2006	53.4224
Median	1.69E+08	79.9883	10.4388	2518.3330	0.4792	1.95E+08	2.29E+11	1.32E+08	4833.6270	595.9343	17.1072	54.8016
Maximum	2.05E+08	93.8237	11.3896	2950.1540	1.7500	2.25E+08	4.16E+11	2.14E+08	8007.4130	706.5101	19.1214	72.8654
Minimum	1.25E+08	66.1009	8.6993	2290.6670	0.3958	1.36E+08	1.16E+11	6.95E+07	2502.2770	330.8114	15.5703	37.4875
Std. Dev.	2.12E+07	9.0590	0.8040	168.1999	0.3684	2.86E+07	1.03E+11	5.03E+07	1642.5720	128.3463	0.9405	9.1678
Skewness	−0.1700	−0.0185	−0.4133	0.4327	2.2950	−0.3205	0.2796	0.2385	0.3057	−0.2778	0.2918	−0.1222
Kurtosis	2.3988	1.6412	2.0595	2.4845	6.9182	1.7550	1.5092	1.5423	1.7619	1.4317	2.1397	2.2133
Jarque-Bera	0.5764	2.2325	1.8945	1.2261	44.0076	2.3692	3.0634	2.8425	2.3039	3.3449	1.3058	0.8200
Probability	*0.7496*	*0.3275*	*0.3878*	*0.5417*	*0.0000*	*0.3059*	*0.2162*	*0.2414*	*0.3160*	*0.1878*	*0.5205*	*0.6637*
Zero Mean ADF	−0.0302	1.0212	0.1071	0.4673	−1.4516	1.9968	1.7764	−0.5399	1.0485	−0.1095	−0.0442	0.7330
Single Mean ADF	−2.7789	−1.3899	−1.6463	−2.1815	−2.0872	−1.5269	−0.8208	−1.4597	−0.9439	−2.5566	−1.7156	−1.5094
Trend ADF	−5.5903	−1.9013	−1.7533	−2.7669	−2.4060	−1.8887	−1.5378	−1.0734	−1.5334	−2.5148	−2.6800	−2.4008
Fisher's Kappa	7.2677	10.8209	8.8568	6.4294	5.9944	9.4013	11.1084	10.6615	11.2282	6.2916	7.6342	9.0011
Prob > Kappa	*0.0010*	*0.0000*	*0.0000*	*0.0047*	*0.0098*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0060*	*0.0005*	*0.0000*
Bartlett's Kolmogorov-Smirnov	0.5797	0.7729	0.6517	0.4880	0.5701	0.6995	0.7935	0.7974	0.8020	0.6081	0.6558	0.6902

the complexity and trade-off between environment and economic development.

The social dimension of natural resource extraction involves livelihood, health and wellbeing (Panel and Consumption U N E P S and Branch P, 2011). Aside from natural resource consumption driving livelihood (income level), livelihood pressures, on the contrary, affect resources availability through excessive production and consumption patterns (Sarkodie and Owusu, 2020). This highlights the environmental framework that posits that livelihood pressures determine the level of environmental deterioration (Panayotou, 1993; Panayotou, 1997). Several studies (Panel and Consumption U N E P S and Branch P, 2011; Dixon et al., 2013) have thus far examined the environmental effect of natural resource extraction, however, very few or no studies widen the scope to include economic and social effects. Thus, a careful assessment of this trilemma has policy implications and useful to the global debate on environmental sustainability.

The sustainable development goals (SDGs) underscore the need for clean energy utilization (SDG 7), sustained economic development (SDG 8), responsible production and consumption (SDG 12), and clean environment via climate change mitigation (SDG 13) (United Nations, 2015). The interlink between these indicators of sustainable development goals is critical to understanding linear and circular economic growth (Sauvé et al., 2016).

Unlike renewable energy sources which are infinite, fossil energy sources such as coal, oil and natural gas are finite. In the same way, environmental factors and socioeconomic variables that exhibit volatility and response immediately to external shocks are time-bound. Hence, the application of a causal-effect estimation technique that postulates an infinite time horizon will produce erroneous results. In contrast, to develop the conceptual framework, we use the novel spectral causality test in the frequency domain to examine the possible direction of causality. We test the hypothesis of no causal relationship between domestic material consumption, environmental, energy, and economic indicators. The study develops 96 validated models with coal consumption, ambient air pollution, environmental policy stringency, energy intensity, energy use, economic growth, income level, trade, renewable energy, biomass, fossil fuels, and metal ores consumption.

2. Materials & method

Data for this study consist of twelve variables spanning 1990–2018 in South Africa (Fig. 1). The selection of the data variables was grounded on the various indicators outlined in the United Nations guidelines for Sustainable Development (United Nations, 2015; DiSano, 2002). Coal Consumption [COAL, measured in *Million tonnes oil equivalent*], Particulate matter 2.5 [PM2.5, *Gg*], and Environmental Policy Stringency [ENVPS, *index*] were sourced from British Petroleum (BP, 2020), Emission Database for Global Atmospheric Research (EDGAR, 2020) and OECD (OECD, 2020), respectively. Domestic material consumption namely Biomass [BIOMASS, *tonnes*], Fossil Fuels [FOSSILFUELS, *tonnes*], and Metal Ores [METALORES, *tonnes*] were obtained from Materials Flow (Materials Flow, 2017). The energy intensity level of primary energy [ENEINT, *MJ/$2011 PPP GDP*], Energy use [ENERGY, *kg of oil equivalent* per capita], Economic growth [GDP, *current US$*], Income level - GDP per capita [PGDP, *current US$*], Trade [TRADE, *% of GDP*] and Renewable energy consumption [RENCONS, *% of total final energy consumption*] were collated from the World Bank database (World Bank, 2020).

Our model assessment begins by first, examining the diagnostics of the time series. Second, we test for unit root and cointegration properties of the model. Third, we select the optimal lag using lag selection criteria. Next, we examine the causal relationship using Breitung-Candelon Spectral Granger-causality test and validate the models using a cumulative test for parameter stability.

Contrary to the traditional Granger causality test, the estimation technique used in this study allows the prediction of target variables at specific time frequencies (Breitung and Candelon, 2006). Meaning that it is possible to identify historical changes where policy intervention can be introduced. However, the methodology is only limited to a finite time horizon, hence cannot predict infinite time models. The causality framework in a frequency domain utilized in this study follows the specifications outlined in Hosoya (Hosoya, 1991). First, we represent the time series with two-dimensional vector $[x_t, y_t]'$ with d_t at time $t = 1, \ldots, T$. d_t is assumed to exhibit a finite-order vector autoregression form $\theta(L)d_t = \varepsilon_t$, where $\theta(L) = I - \theta_1 L - \ldots - \theta_p L^p$ ($L^k d_{t-k}$, k is a lag polynomial), ε_t denotes the error term.

The representation via a Moving Average assumes a stationary process with Cholesky decomposition of the positive definite error term expressed as:

$$d_t = \begin{bmatrix} \psi_{11}(L) & \psi_{12}(L) \\ \psi_{21}(L) & \psi_{22}(L) \end{bmatrix} \left[\eta_{1t}\, \eta_{2t} \right] \tag{1}$$

where ψ denotes the matrix of coefficients and η represents the white noise. The expression of the spectral density of x_t is:

$$f_x(\omega) = \frac{1}{2\pi}\left\{ \left|\psi_{11}\left(e^{-i\omega}\right)\right|^2 + \left|\psi_{12}\left(e^{-i\omega}\right)\right|^2 \right\} \tag{2}$$

Thus, the estimation of causality proposed by Hosoya (Hosoya, 1991) is expressed as:

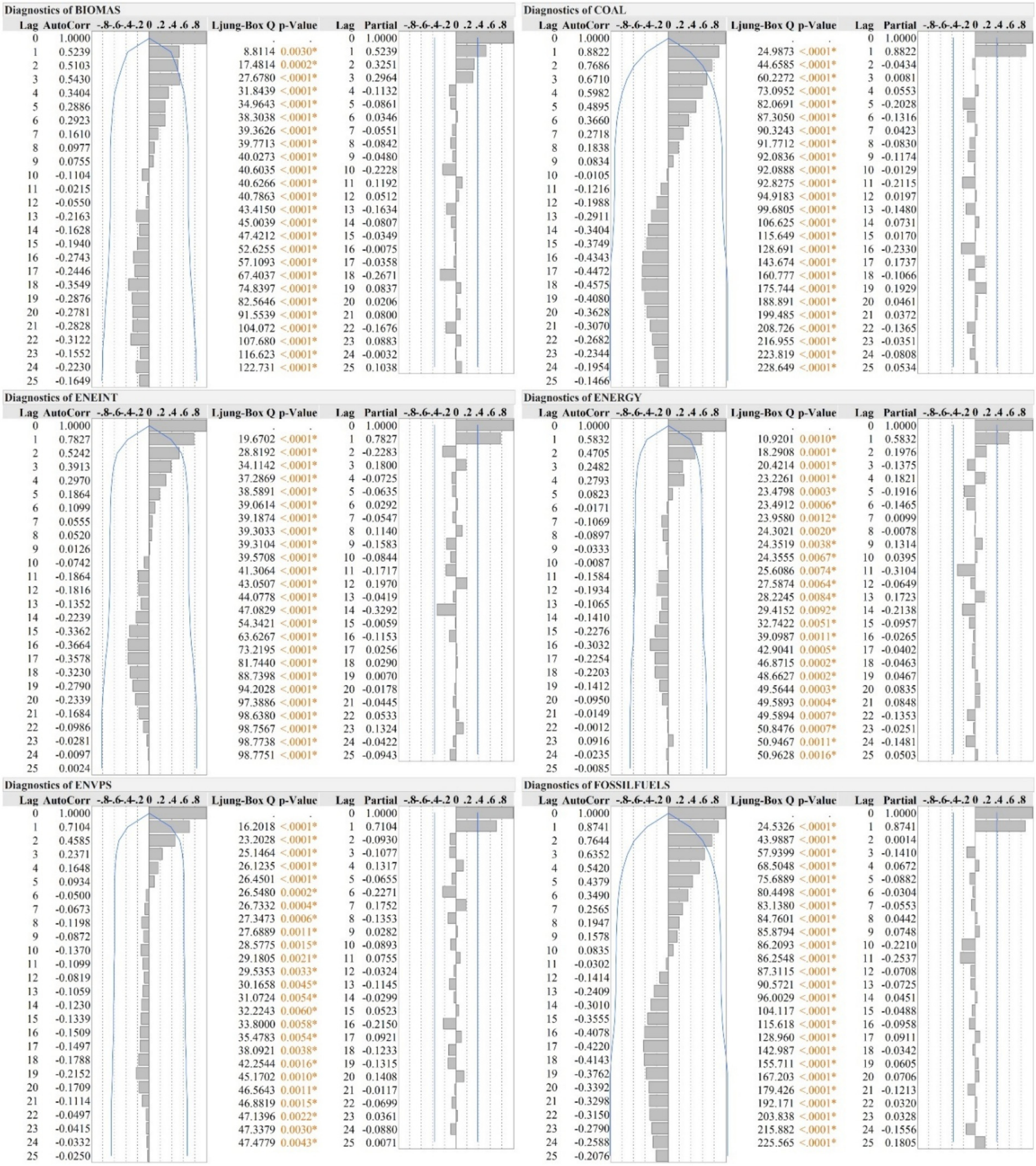

Fig. 2. Time series diagnostics of (a) BIOMAS (b) COAL (c) ENEINT (d) ENERGY (e) ENVPS (f) FOSSILFUELS. The blue line represents ±2 standard errors. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$M_{y\to x}(\omega) = \log\left[\frac{2\pi f_x(\omega)}{|\psi_{11}(e^{-i\omega})|^2}\right] = \log\left[1+\frac{|\psi_{12}(e^{-i\omega})|^2}{|\psi_{11}(e^{-i\omega})|^2}\right] \tag{3}$$

where ω is the frequency, y does not cause x ($y \to x$) at ω if $|\psi_{12}(e^{-i\omega})|$ is zero. If $d_t = [x_t, y_t]$ are cointegrated, the finite-order vector autoregression form $\theta(L)d_t = \varepsilon_t$ becomes:

$$\Delta d_t = (\theta_1 - I)d_{t-1} + \theta_2 d_{t-2} + \ldots + \theta_p d_{t-p} + \varepsilon_t = \tilde{\theta}(L)d_{t-1} + \varepsilon_t \tag{4}$$

The estimation of causality in a frequency domain for cointegrated elements ($[x_t, y_t]$) can be expressed as:

$$\Delta d_t = \tilde{\phi}(L)\varepsilon_t = \tilde{\xi}(L)\eta_t \tag{5}$$

where $\tilde{\phi}(L) = \tilde{\phi}(L)G^{-1}, \eta_t = G\varepsilon_t$, and the lower triangular matrix G has a corresponding $E(\eta_t \eta_t') = I$. Thus, the cointegration between the elements ($[x_t, y_t]$) is expressed as $\beta'\tilde{\phi}(1) = 0$, where the cointegration vector β is stationary $\beta' z_t$.

The estimation of causality of the stationary series still follows Hosoya (Hosoya, 1991) in Eq. (3) expressed as:

$$M_{y\to x}(\omega) = \log\left[1+\frac{|\psi_{12}(e^{-i\omega})|^2}{|\psi_{11}(e^{-i\omega})|^2}\right] \tag{6}$$

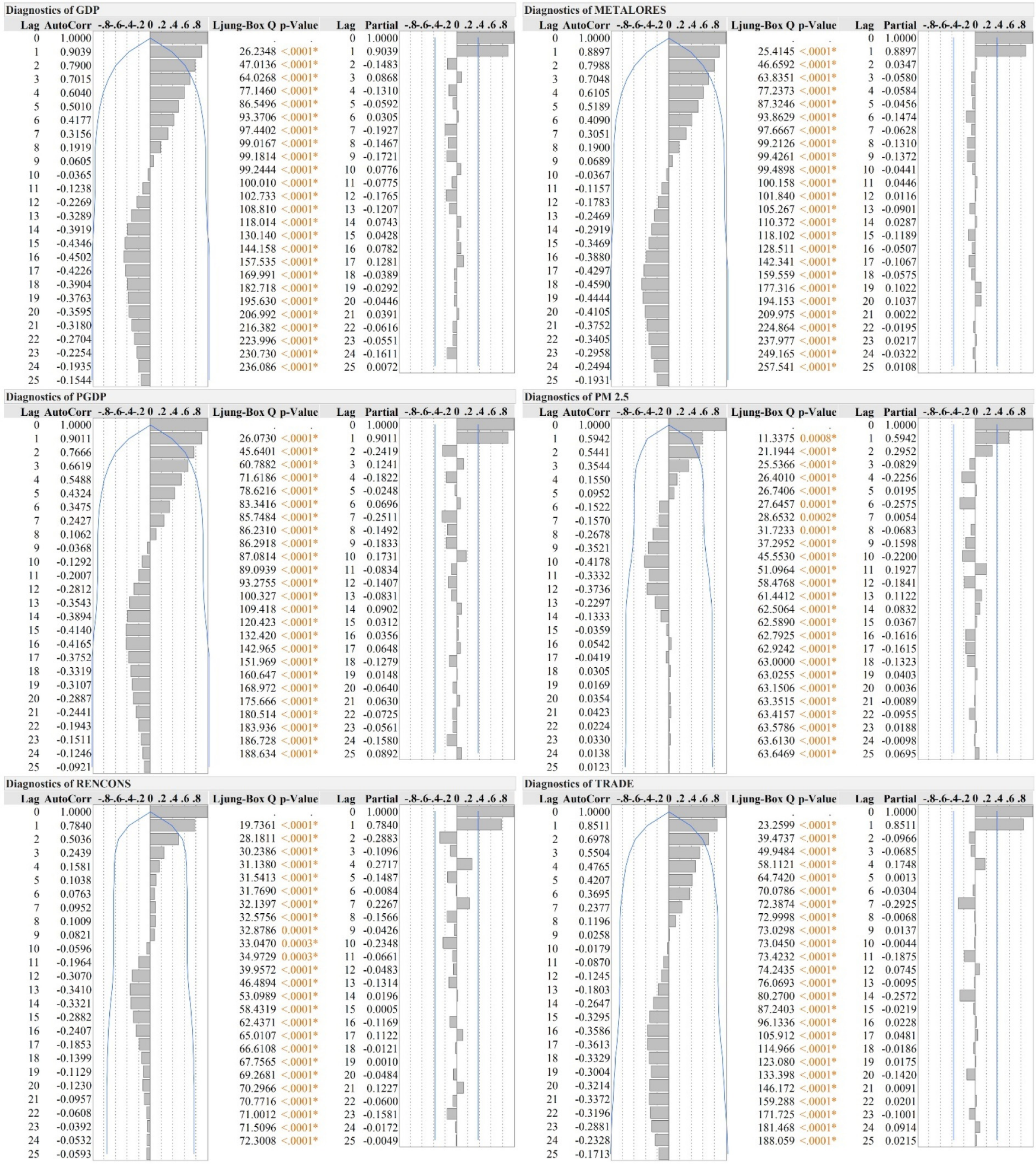

Fig. 3. Time series diagnostics of (a) GDP (b) PGDP (c) PM 2.5 (d) RECONS (e) TRADE (f) METALORES. The blue line represents ±2 standard errors. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Accordingly, the null hypothesis that y does not cause or predict x at a frequency (ω) in a bivariate framework estimation ($M_{y\to x}$) is expressed as:

$$M_{y\to x}(\omega) = 0 \tag{7}$$

For brevity, the null hypothesis of the cause-effect between two variables ($x_t|y_t$, both used as a target and predictor variable) can be estimated with an F-test statistic via a generic model specification. The equation for the VAR of x_t can be expressed as (Breitung and Candelon, 2006):

$$x_t = \alpha_1 x_{t-1} + \ldots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \varepsilon_{1t} \tag{8}$$

where the linear restriction in Eq. (8) is comparable to the null hypothesis $M_{y\to x}(\omega) = 0$.where α, and β are the estimated parameters in time t, lag p, and an error term ε_t.

3. Results & discussion

3.1. Descriptive statistics

Before the application of econometric techniques, the study examined the statistical features of the data series presented in Table 1 and the trend of variables depicted in Fig. 1. Biomass, fossil fuels and metal

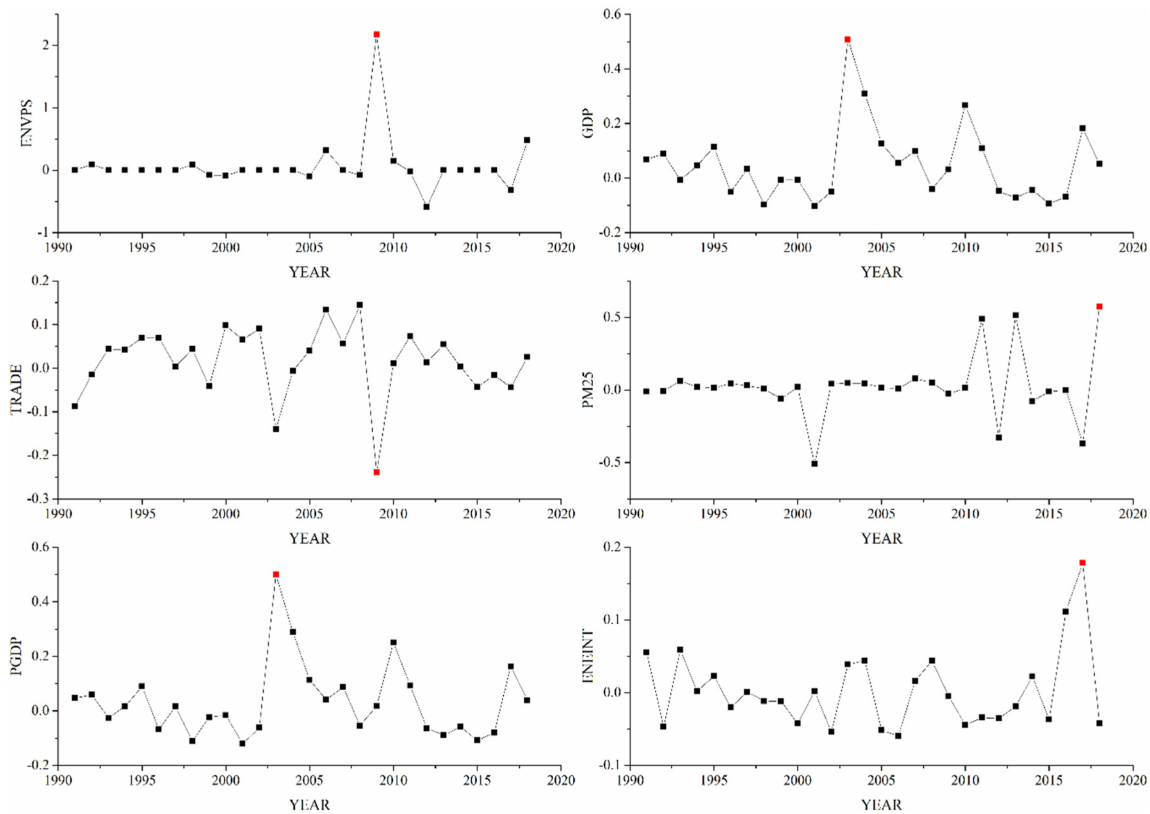

Fig. 4. Peak Analysis of % change in the annual rate. Legend: The *red* marker denotes the most prominent peak. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

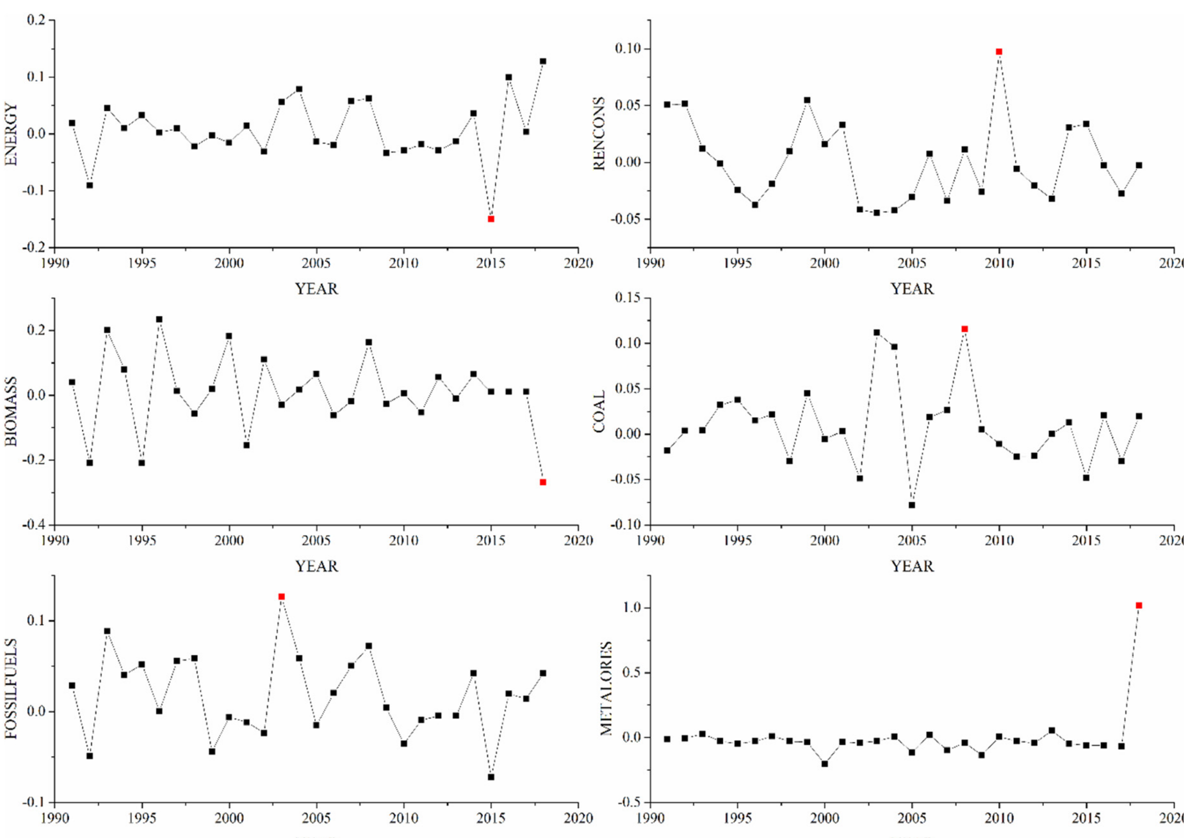

Fig. 5. Peak Analysis of % change in the annual rate. Legend: The *red* marker denotes the most prominent peak. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Vector autoregressive (VAR)-based optimal lag-order selection criteria.

Relationship		Optimal Lags	Cointegration
lnBIOMASS	lnENVPS	1	No
lnBIOMASS	lnTRADE	1	EG-J-Ba-Bo
lnCOAL	lnGDP	1	No
lnCOAL	lnPGDP	1	No
lnCOAL	lnENERGY	1	No
lnCOAL	lnFOSSILFUELS	1	No
lnCOAL	lnENVPS	1	No
lnCOAL	lnTRADE	1	EG-J-Ba-Bo
lnENEINT	lnRENCONS	1	No
lnENERGY	lnCOAL	1	Ba-Bo*
lnENERGY	lnRENCONS	1	No
lnENERGY	lnGDP	1	No
lnENERGY	lnPGDP	1	No
lnENERGY	lnMETALORES	1	No
lnENERGY	lnFOSSILFUELS	1	Bo*
lnENERGY	lnENVPS	1	J
lnENERGY	lnTRADE	1	No
lnENVPS	lnCOAL	1	Ba-Bo*
lnENVPS	lnGDP	1	EG-Bo*
lnENVPS	lnENERGY	1	J-Ba-Bo
lnENVPS	lnMETALORES	1	No
lnENVPS	lnFOSSILFUELS	1	Ba*
lnENVPS	lnBIOMASS	1	No
lnENVPS	lnTRADE	1	No
lnFOSSILFUELS	lnCOAL	1	No
lnFOSSILFUELS	lnGDP	1	No
lnFOSSILFUELS	lnPGDP	1	No
lnFOSSILFUELS	lnENERGY	1	No
lnFOSSILFUELS	lnENVPS	1	No
lnFOSSILFUELS	lnTRADE	1	EG
lnGDP	lnCOAL	1	No
lnGDP	lnENERGY	1	No
lnGDP	lnFOSSILFUELS	1	No
lnGDP	lnENVPS	1	No
lnMETALORES	lnENERGY	1	No
lnMETALORES	lnENVPS	1	No
lnMETALORES	lnTRADE	1	Ba*
lnPGDP	lnCOAL	1	No
lnPGDP	lnENERGY	1	No
lnPGDP	lnFOSSILFUELS	1	No
lnPM25	lnTRADE	1	No
lnPM25	lnENVPS	1	No
lnPM25	lnENEINT	1	No
lnPM25	lnRENCONS	1	No
lnRENCONS	lnENERGY	1	No
lnRENCONS	lnENEINT	1	EG
lnRENCONS	lnTRADE	1	No
lnTRADE	lnCOAL	1	EG-J
lnTRADE	lnRENCONS	1	No
lnTRADE	lnENERGY	1	No
lnTRADE	lnMETALORES	1	EG*
lnTRADE	lnFOSSILFUELS	1	EG-Ba-Bo
lnTRADE	lnBIOMASS	1	EG-J
lnTRADE	lnENVPS	1	No
lnBIOMASS	lnGDP	2	No
lnBIOMASS	lnPGDP	2	No
lnCOAL	lnENEINT	2	No
lnCOAL	lnMETALORES	2	EG*
lnENEINT	lnCOAL	2	Ba-Bo
lnENEINT	lnGDP	2	No
lnENEINT	lnPGDP	2	No
lnENVPS	lnPGDP	2	EG-J-Ba-Bo
lnFOSSILFUELS	lnRENCONS	2	J-Ba-Bo
lnGDP	lnENEINT	2	No
lnGDP	lnMETALORES	2	Ba-Bo
lnGDP	lnBIOMASS	2	No
lnGDP	lnTRADE	2	No
lnMETALORES	lnCOAL	2	Ba-Bo
lnMETALORES	lnRENCONS	2	No
lnMETALORES	lnGDP	2	No
lnMETALORES	lnPGDP	2	No
lnPGDP	lnENEINT	2	No
lnPGDP	lnMETALORES	2	Ba*
lnPGDP	lnBIOMASS	2	No

(continued on next page)

Table 2 (*continued*)

Relationship		Optimal Lags	Cointegration
lnPGDP	lnENVPS	2	J*
lnPGDP	lnTRADE	2	No
lnPM25	lnMETALORES	2	No
lnPM25	lnENERGY	2	No
lnPM25	lnPGDP	2	No
lnPM25	lnGDP	2	No
lnPM25	lnCOAL	2	No
lnRENCONS	lnMETALORES	2	EG-Ba-Bo
lnRENCONS	lnFOSSILFUELS	2	EG-J-Ba-Bo
lnTRADE	lnGDP	2	No
lnTRADE	lnPGDP	2	No
lnBIOMASS	lnRENCONS	3	No
lnCOAL	lnRENCONS	3	No
lnGDP	lnRENCONS	3	No
lnPGDP	lnRENCONS	3	No
lnPM25	lnFOSSILFUELS	3	No
lnPM25	lnBIOMASS	3	No
lnRENCONS	lnCOAL	3	No
lnRENCONS	lnGDP	3	Ba*
lnRENCONS	lnPGDP	3	No
lnRENCONS	lnBIOMASS	3	No
lnENVPS	lnRENCONS	4	J-Ba-Bo
lnGDP	lnPGDP	4	J-Ba-Bo
lnPGDP	lnGDP	4	J-Ba-Bo
lnRENCONS	lnENVPS	4	J
lnBIOMASS	lnENERGY	5	No
lnENERGY	lnBIOMASS	5	Ba-Bo*

Notes: *No* signifies no cointegration, *EG* means cointegration via Engle-Granger, *J* means cointegration via Johansen, *Ba* means cointegration via Banerjee and *Bo* means cointegration via Boswijk, * denotes 10% significant level.

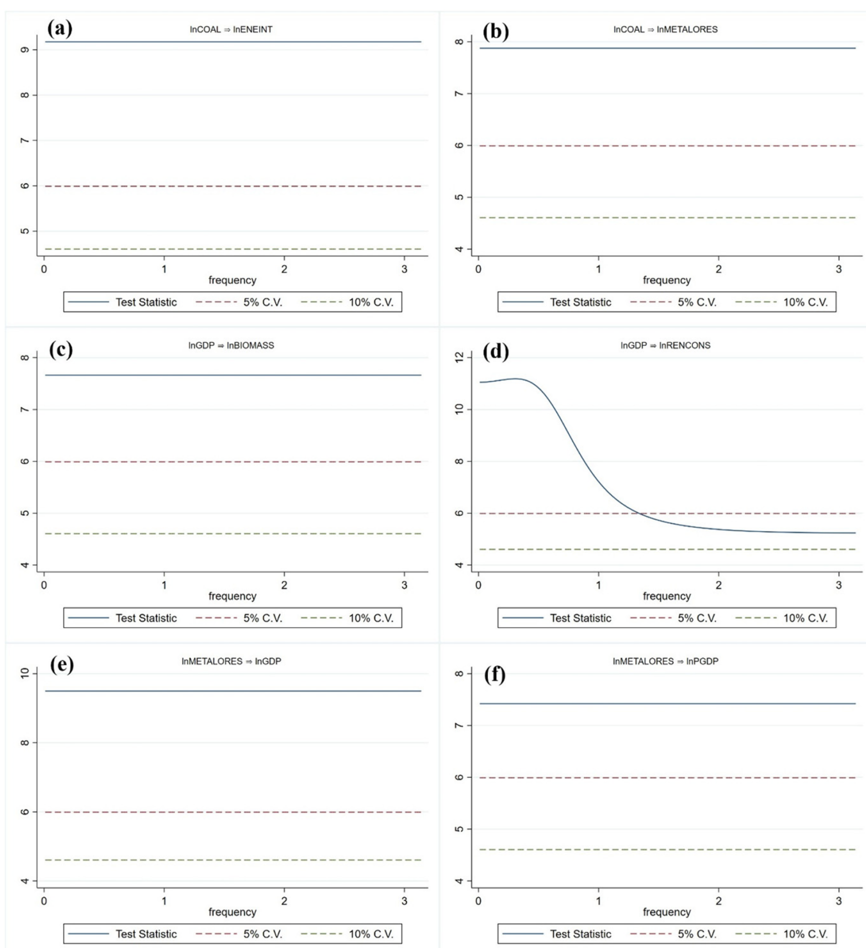

Fig. 6. Breitung-Candelon Spectral Granger-causality Test: Strong unidirectional causality from (a) lnCOAL → lnENEINT (b) lnCOAL → lnMETALORES (c) lnGDP → lnBIOMASS (d) lnGDP → lnRENCONS (e) lnMETALORES → lnGDP (f) lnMETALORES → lnPGDP.

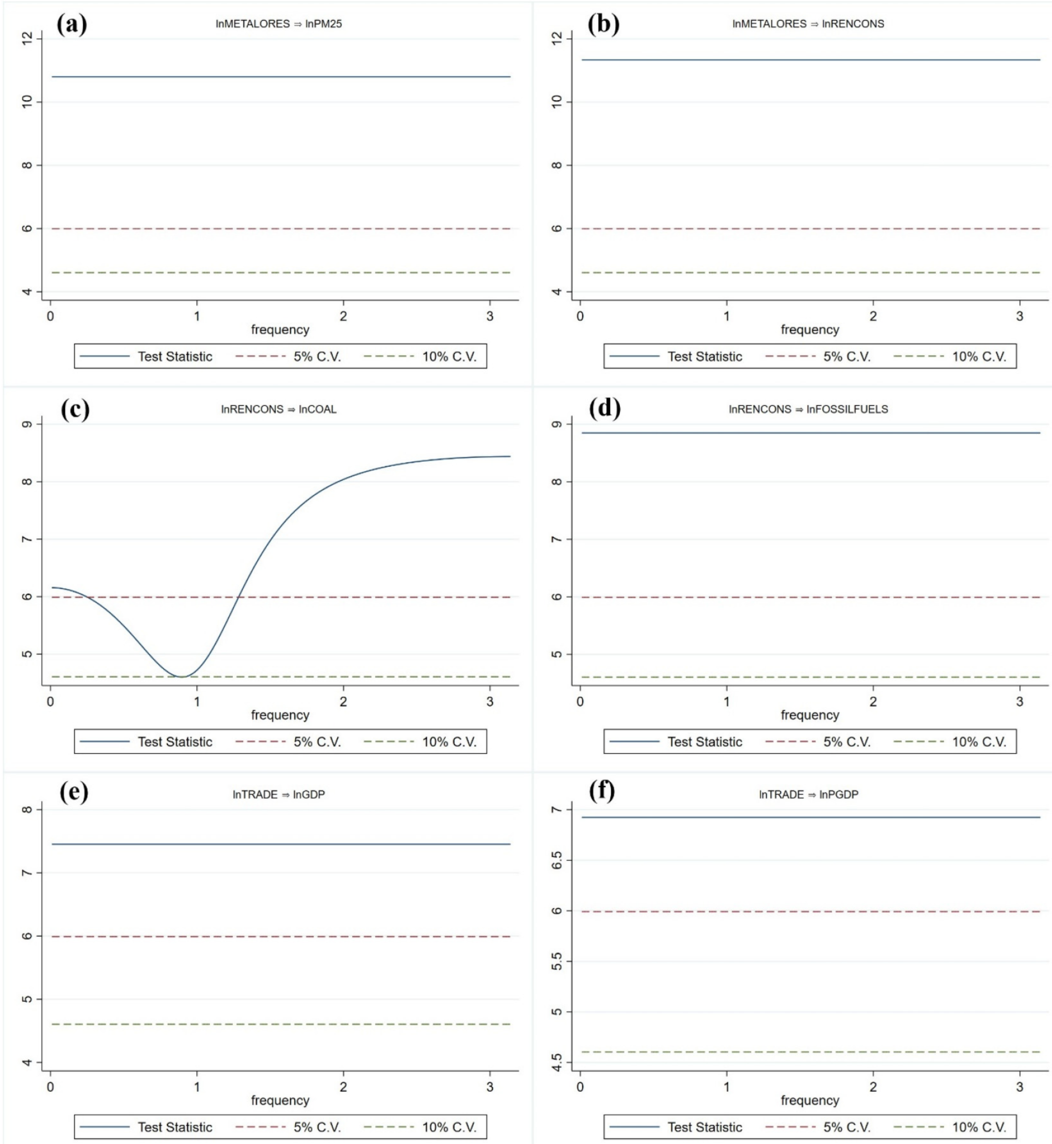

Fig. 7. Breitung-Candelon Spectral Granger-causality Test: Strong unidirectional causality from (a) lnMETALORES → lnPM25 (b) lnMETALORES → lnRENCONS (c) lnRENCONS → lnCOAL (d) lnRENCONS → lnFOSSILFUELS (e) lnTRADE → lnGDP (f) lnTRADE → lnPGDP.

ores constitute South Africa's domestic material consumption (Fig. 1). The 29-year domestic material consumption averages 170 million tonnes, 188 million tonnes and 139 million tonnes for Biomass, fossil fuels and metal ores respectively. The annual average consumption of coal, energy and energy intensity are ~80 million tonnes oil equivalent, ~2571 kg of oil equivalent per capita and ~ 10.3 MJ/$2011 PPP GDP respectively. For emphasis on the diversity of the energy portfolio, the average and maximum penetration of renewable energy is 17% and 19%, with a possibility of 81–83% dedicated to fossil fuels in the energy mix. The economic performance averages US$ 0.235 billion, US$ 4789 and 53.4% of GDP for economic growth, income level and trade respectively. The two environmental indicators namely ambient air pollution and environmental policy stringency have an average of ~535 Gg and 0.64 index. The Kurtosis statistic reveals that all the data series except ENVPS exhibit platykurtic distribution, which reflects in the Jarque-Bera test statistics. The Jarque-Bera test shows that all the variables except ENVPS fulfil the normality assumption. However, Bartlett's Kolmogorov-Smirnov test reveals that all the variables are normally distributed. On the contrary, Fisher's Kappa test reveals that the variables under examination have periodic components. As an additional pre-estimation technique, we examined the diagnostics of the time series variables presented in Figs. 2–3. The diagnostic tests comprise autocorrelation and partial autocorrelation for 25-time lags, with a corresponding Ljung-Box Q-statistic and *p-values* for the former. Figs. 2–3 show that all the variables have statistically significant (*p-value* < *0.01*) components for all the 25-time lags. Meaning that the diagnostics confirm the autocorrelation of non-zero time series variables. Next, a peak analysis of the data series was applied to examine the annual rate of change over the period. It can be observed in Fig. 4 that the maximum annual rate of change (prominent peak) in environmental policy stringency is ~217.39%, which occurred in 2009, coinciding with the economic recession in South Africa. A sharp annual rate of change in economic growth and income level occurred in 2003 at 50.86% and 49.91%, respectively. Agreeing with the economic recession and fragile recovery in South Africa, trade saw a downturn of about −23.94% in 2009. Ambient air pollution saw a maximum annual rate of change of ~7.14% in 2018 while energy intensity grew by 17.80% in 2017. In the same way, fossil fuel consumption increased by 12.65% in 2003, corresponding to the sharp upturn in economic growth and income level — revealing a fossil fuel embedded economic development (Fig. 5). While energy consumption

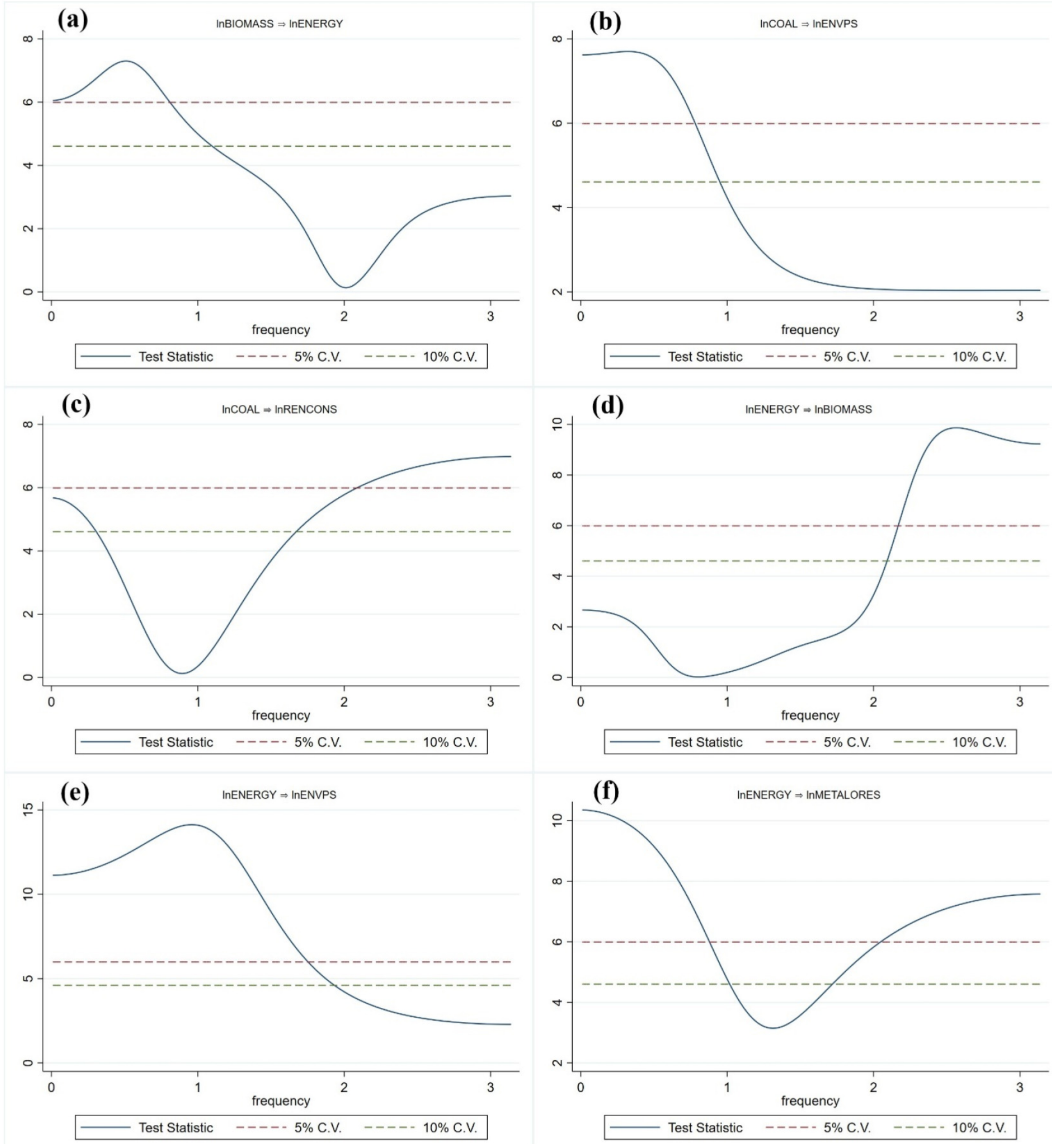

Fig. 8. Breitung-Candelon Spectral Granger-causality Test: Mixed unidirectional causality from (a) lnBIOMASS → lnENERGY (b) lnCOAL → lnENVPS (c) lnCOAL → lnRENCONS (d) lnENERGY → lnBIOMASS (e) lnENERGY → lnENVPS (f) lnENERGY → lnMETALORES.

declined by 15.02% in 2015, renewable energy consumption grew by 9.69% in 2010. The upward surge in renewable energy penetration can be attributed to South Africa's commitment at the Copenhagen agreement in December 2009 to decline climate change emissions, resulting in an energy Masterplan in 2010 that diversifies the energy portfolio (Department of Energy, 2015). Biomass energy consumption suffered a negative shock of 26.83% in 2018 while coal consumption saw an upward surge of 11.57% in 2008. Fig. 5 reveals a surge in metal ore consumption in 2018 with 101.78% annual rate of change.

Thus, the time diagnostic tests and the peak analysis suggest the Breitung-Candelon Spectral Granger-causality test as an appropriate method for the model estimation. The Breitung-Candelon Spectral Granger-causality test is robust in both stationary and non-stationary variables, hence, does not require an examination of the unit root properties and cointegration between the target variables and regressors.

3.2. Spectral causality test

To select appropriate lags for the model estimation, we used the vector autoregressive (VAR)-based lag-order selection criteria such as Schwarz Bayesian information criterion, sequential likelihood tests, Akaike information criterion, final prediction error, and Hannan and Quinn information criterion as pre-estimation techniques (Lütkepohl, 2005). The optimal lags [VAR(.)] selected for subsequent analysis are presented in Table 2. The study estimated 96 spectral causality models based on Hosoya (Hosoya, 1991) conditioning with automatic frequency selection. Five main conclusions are derived from the bivariate models based on the frequency (ω) interval $(0, \pi)$. Decisions from the Breitung-Candelon spectral Granger-causality test include strong unidirectional causality (Figs. 6–7), mixed unidirectional causality (Figs. 8–10), mixed-weak unidirectional causality (Fig. 11), very weak unidirectional causality (Fig. 12), and no causality (Fig. 13).

We observe in Figs. 6–7 that the null hypothesis of "*no predictability*" is rejected at 5% or 10% significance level across the horizon ranging from $\omega \in [0, 3.14]$. The results indicate that using VAR(2), coal consumption (lnCOAL) strongly predicts (*p-value* < *0.05*) the future contents of energy intensity (lnENEINT) and metal ore footprint (lnMETALORES) along with the entire frequency range, $\omega \in [0, 3.14]$ without fluctuations. At VAR(2) across $\omega \in [0, 3.14]$, economic growth (lnGDP) strongly predicts (*p-value* < *0.05*) biomass footprint (lnBIOMASS) without future

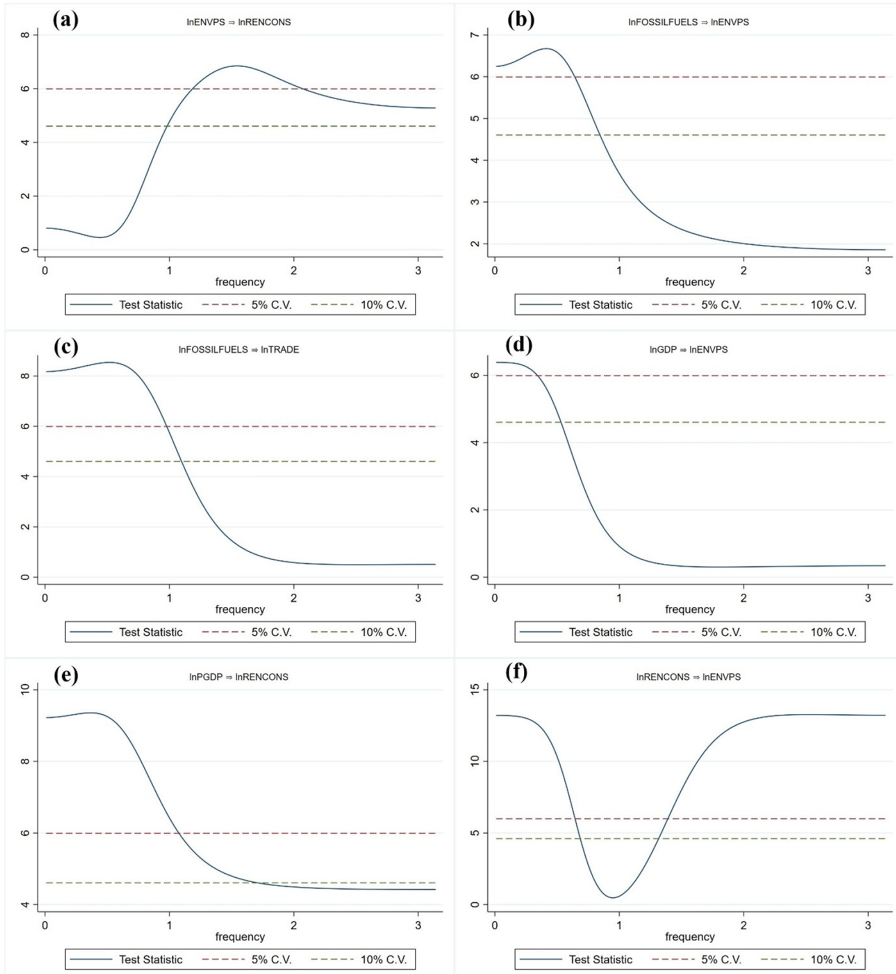

Fig. 9. Breitung-Candelon Spectral Granger-causality Test: Mixed unidirectional causality from (a) lnENVPS → lnRENCONS (b) lnFOSSILFUELS → lnENVPS (c) lnFOSSILFUELS → lnTRADE (d) lnGDP → lnENVPS (e) lnPGDP → lnRENCONS (f) lnRENCONS → lnENVPS.

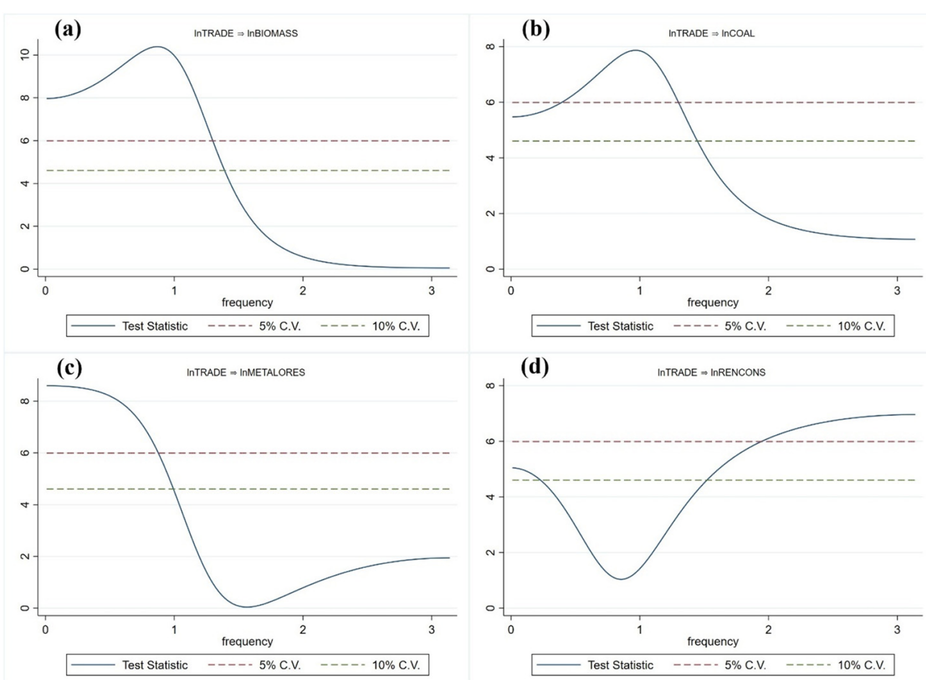

Fig. 10. Breitung-Candelon Spectral Granger-causality Test: Mixed unidirectional causality from (a) lnTRADE → lnBIOMASS (b) lnTRADE → lnCOAL (c) lnTRADE → lnMETALORES (d) lnTRADE → lnRENCONS.

volatilities. However, the prediction of renewable energy consumption (lnRENCONS) is affected by future volatilities (see Fig. 6 [d]). From a frequency range ω ∈ [0, 0.5], economic growth predicts the stability of renewable energy but first fluctuates significantly between frequencies ω ∈ [0.5, 1.2] and produces weak prediction afterwards, ω ∈ [1.2, 3.14]. There is strong evidence (*p-value* < *0.05*) that metal ore footprint predicts ambient air pollution (lnPM25), renewable energy consumption, economic growth and income level (lnPGDP) at VAR(2) along the entire horizon ω ∈ [0, 3.14], with no future fluctuations. Renewable energy consumption weakly predicts coal consumption at VAR(2) ω ∈ [0,1] but turns stronger (*p-value* < *0.05*) between frequencies ω ∈ [1, 3.14]. In contrast, renewable energy consumption shows a strong predictive (*p-value* < *0.05*) content for fossil fuel footprint (lnFOSSILFUELS) across entire frequency range ω ∈ [0, 3.14] without volatilities. Trade finds a strong predictive (*p-value* < *0.05*) content for future economic growth and income level at VAR(2) along the entire horizon ω ∈ [0, 3.14] with no fluctuations.

Contrary to Figs. 6–7 showing strong unidirectional causality, Figs. 8–10 show complexities of causal flows subjected to future fluctuations. At VAR(5) with frequency range ω ∈ [0, 0.8], we find strong evidence (*p-value* < *0.05*) that biomass footprint predicts energy consumption (lnENERGY), but turns weak at frequencies ω ∈ [0.8, 1.2] and die off completely after ω > 1.2 (Fig. 8[a]). There exists short-term evidence that coal consumption predicts future environmental policy stringency (lnENVPS) at VAR(1) across frequencies ω ∈ [0, 1] but diminishes after ω > 1.0 (Fig. 8[b]). We find a U-shape causality running from coal consumption to renewable energy consumption at VAR(3) between frequencies ω ∈ [0, 0.4; 1.8, 3.14] (Fig. 8[c]). At a frequency range ω ∈ [2.2, 3.14] based on VAR(5), we find strong evidence (*p-value* < *0.05*) that energy consumption predicts biomass footprint (Fig. 8[d]). At this point, we confirm short-term evidence of bidirectional causality between energy consumption and biomass footprint exposed to future volatilities (Fig. 8[a and c]). Short-term evidence exposed to future fluctuations in Fig. 8(e) shows that energy consumption predicts future environmental policy stringency at VAR(1) with frequency range ω ∈ [0, 1.9] but die off after ω > 1.9. A U-shape causal flow is validated from energy consumption to metal ore footprint at VAR(1) between frequencies ω ∈ [0, 1; 1.8, 3.14] (Fig. 8[f]). At VAR(4) with frequency range ω ∈ [0.9, 3.14], we find evidence that environmental policy stringency predicts renewable energy consumption (Fig. 9[a]). Short-term evidence of causal flow is confirmed from fossil fuel footprint to environmental policy stringency at VAR(1) with frequency range ω ∈ [0, 0.9], but diminishes after ω > 0.9 (Fig. 9[b]). The future fluctuations in Fig. 9 (c) reveals that fossil fuel footprint predicts future trade at VAR (1) with frequency range ω ∈ [0, 1.1] but die off after ω > 1.1. At a frequency range ω ∈ [0, 0.6] based on VAR(1), we find short-term evidence that economic growth predicts environmental policy stringency (Fig. 9 [d]). There exists a shred of temporary evidence that income level predicts future renewable energy consumption at VAR(3) across frequencies ω ∈ [0, 1.8] (Fig. 9[e]). We find a U-shape causality running from renewable energy consumption to environmental policy stringency at VAR(4) between frequencies ω ∈ [0, 0.8; 1.3, 3.14] (Fig. 9[f]). A similar temporary unidirectional causality is found running from trade to: biomass footprint [at VAR(1) with frequency range ω ∈ (0, 1.5)]; coal consumption [at VAR(1) with frequency range ω ∈ (0, 1.5)]; metal ore footprint [at VAR(1) with frequency range ω ∈ (0, 1.1)]; and renewable energy consumption [at VAR(1) with frequency range ω ∈ (1.6, 3.14)] (Fig. 10).

Weak evidence (*p-value* < *0.10*) of unidirectional causality presented in Fig. 11 shows a causal flow running from income level to biomass footprint [at VAR(2) with frequency range ω ∈ (0, 3.14)] and energy intensity [at VAR(2) with frequency range ω ∈ (0, 3.14)]. Besides, we find a piece of weak evidence (*p-value* < *0.10*) that biomass consumption predicts economic growth at VAR(2) with a frequency range ω ∈ [0, 3.14]. We find temporary weak unidirectional causality running from coal consumption to trade, fossil fuel footprint to coal consumption, economic growth to energy consumption, income level to energy consumption, and renewable energy to energy consumption (Fig. 12). Among the estimated models, we found 61 models based on Breitung-Candelon Spectral Granger-causality test that confirmed no causality. In brevity, 6 of such models are presented in Fig. 13. We found no causality running from biomass footprint to renewable energy, coal consumption to economic growth, energy intensity to renewable energy, environmental policy stringency to economic growth, renewable energy to ambient air pollution, and trade to fossil fuel footprint.

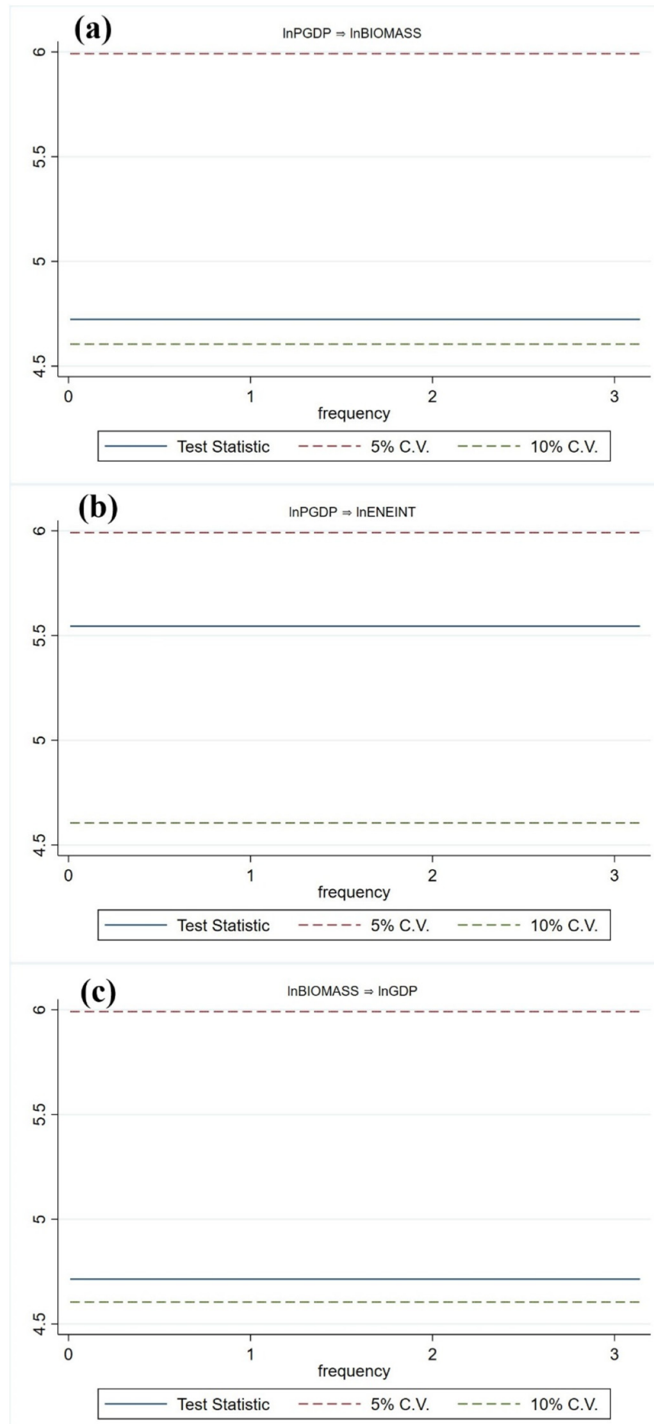

Fig. 11. Breitung-Candelon Spectral Granger-causality Test: Weak unidirectional causality from (a) lnPGDP → lnBIOMASS (b) lnPGDP → lnENEINT (c) lnBIOMASS → lnGDP.

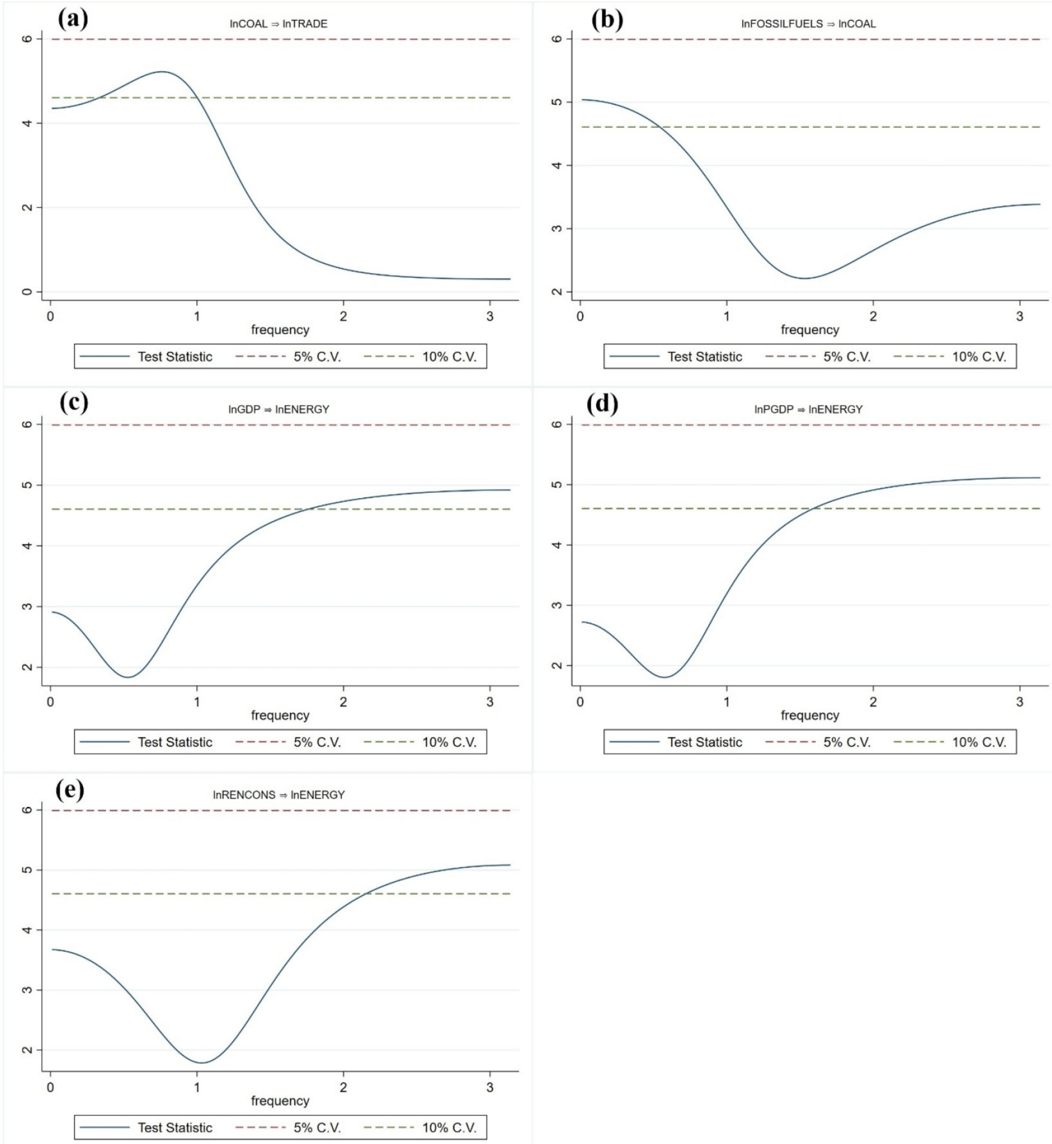

Fig. 12. Breitung-Candelon Spectral Granger-causality Test: Mixed-weak unidirectional causality from (a) lnCOAL → lnTRADE (b) lnFOSSILFUELS → lnCOAL (c) lnGDP → lnENERGY (d) lnPGDP → lnENERGY (e) lnRENCONS → lnENERGY.

To validate the estimated models, we examined the stability of the parameters within the time series estimation procedure over time using the novel cumulative test for parameter stability (Brown et al., 1975). As a model specification, we utilized the cumulative test of recursive residuals that produces graphical estimates with 95% confidence bands. The output of the time series validation technique presented in Figs. 14–15 shows that all the plots are within the 95% confidence bands, hence, confirming the stability of the estimated models.

4. Discussion

Coal consumption in South Africa contributes 85.98% (2018 estimate of World Bank (World Bank, 2020)) of the energy mix, the main fossil fuel energy technology that underpins the production-based economy. We found coal consumption as a strong predictor of energy intensity. This confirms a coal-driven energy-based economic structure with limited green inputs. Meaning that conservation measures and policies that restrict the consumption of coal without similar stable and sustainable alternative will hinder economic development. Similar studies have reported the coal consumption-led economic growth in India (Wolde-Rufael, 2010), Japan (Wolde-Rufael, 2010), South Africa (Wolde-Rufael, 2010), the US (Wolde-Rufael, 2010), China (Chandran Govindaraju and Tang, 2013), and OECD countries (Apergis and Payne, 2010).

Our study confirmed a strong and long-term metallurgical coal-controlled metal footprint through steelmaking. Countries with a high dependency on metallurgical industrialization often depend heavily on coal consumption. Iron and steel manufacturing and coal combustion are nonseparable — as coal is the main carbon source used in steel production. A similar study (Pokorná et al., 2016) found a strong positive correlation between steelmaking and coal combustion.

There exists a short-term mutualistic effect between biomass consumption and economic growth, thus, confirming the feedback hypothesis. A comparable feedback hypothesis between bioenergy and economic growth is found in Bildirici (Bildirici, 2013). Agrarian economies often depend heavily on the extraction of forest products for either legal or illegal export via international trade, which constitutes a portion of economic growth (Barrett et al., 2010). For example, China's craving for the endangered rosewood has triggered illegal trading of the forest commodity, affecting African forest reserves. It is reported that the

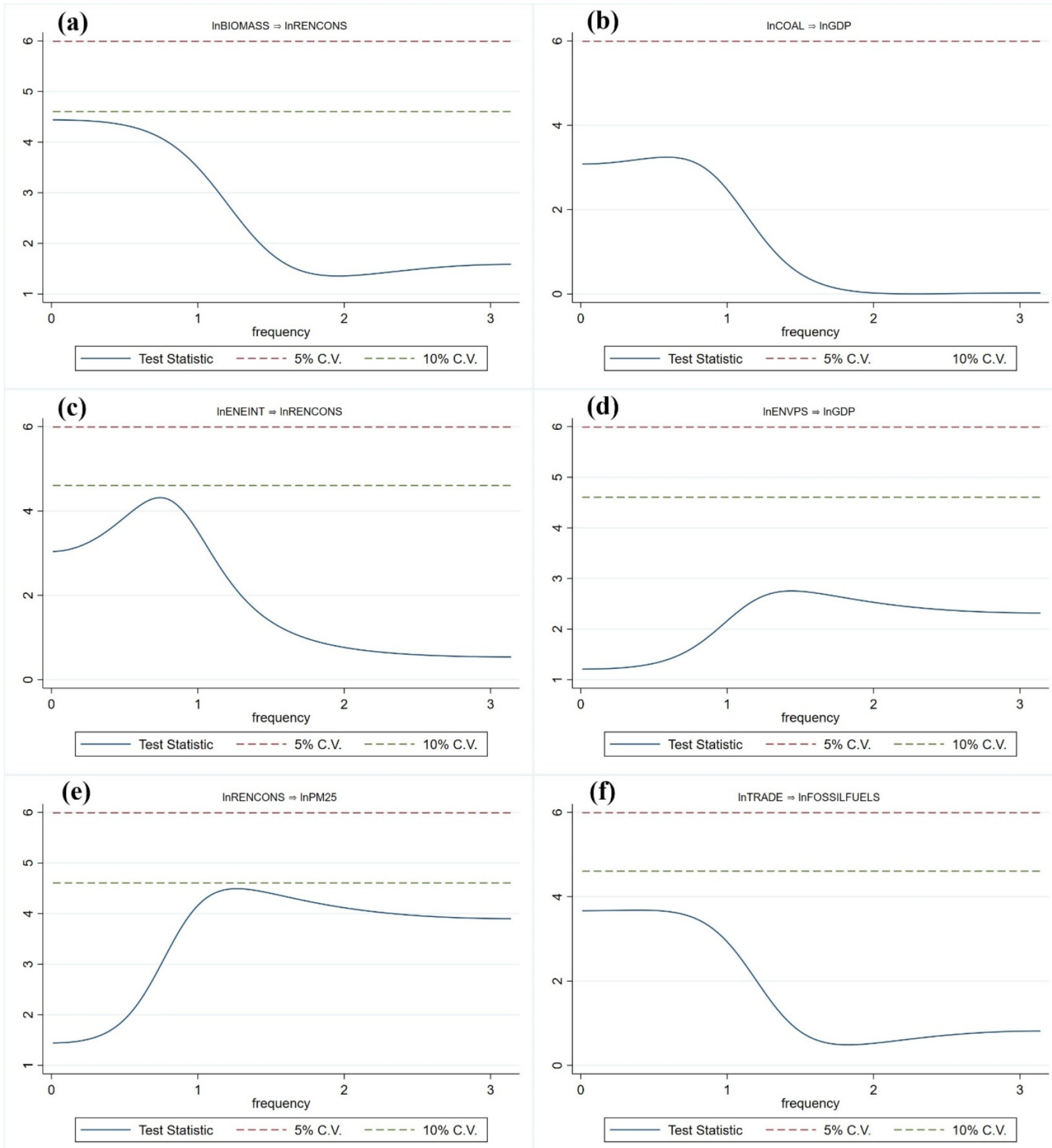

Fig. 13. Breitung-Candelon Spectral Granger-causality Test: No causality from (a) lnBIOMASS → lnRENCONS (b) lnCOAL → lnGDP (c) lnENEINT → lnRENCONS (d) lnENVPS → lnGDP (e) lnRENCONS → lnPM25 (f) lnTRADE → lnFOSSILFUELS.

illegal felling of endangered forest products increased a thousand-fold between 2009 and 2014 in Africa (Sandy and Edward, 2019). From another perspective, most African communities utilize the bioenergy function of biomass for cooking and heating purposes due to limited access to electricity (Sarkodie and Adams, 2020). In industrial-based economies, the energy-intensive economic structure is often characterized by domestic material consumption, including biomass resources extraction as raw materials for manufacturing processes, thus, explaining the bidirectional causality between biomass and economic growth.

Primary metal-based manufacturing processes underline carbonized and energy-intensive economic structure. This underscores our strong evidence that metal ore consumption predicts economic growth, income level and renewable energy consumption. It is reported that metal consumption has a strong relationship with wealth, because of the interconnectedness of metals to modern technological advancement (Graedel and Cao, 2010). High and booming investments in developing countries are reported to stem from metal consumption-led economic development (Zheng et al., 2018). The infrastructural systems of renewable energy technologies such as wind, solar, hydro, bioenergy, among others are built with extracted metals requiring more mining (Vidal et al., 2013). This means that metal consumption is a carrier process that transforms renewable energy technologies into usable commodities. Also, we found strong evidence to support metal consumption-led ambient air pollution. Metal production before consumption is characterized by several air pollution-embedded processes, ranging from, inter alia, raw material extraction, sintering operations (Kuramochi et al., 2012), coke production (Wei et al., 2018), steel production (Pokorná et al., 2016) via blast, ferromanganese blast, open hearth, basic oxygen and electric arch furnaces and Bessemer converters (Schueneman, 1963). There is evidence that metal production attributable air pollution affects communities through the effect of oxygen lances used in open-hearth furnaces, the magnitude of metal (steel and iron) mill emissions (Pokorná et al., 2016; Pelletier et al., 2017). Thus, without preventive measures, metal mill processes spur the total quantity of $PM_{2.5}$ and PM_{10} emitted into the atmosphere.

The long-term and strong effect of renewable energy-led fossil fuel consumption, and trade-controlled economic growth and income level speak volumes. Evidence of level relationship and unidirectional causality between renewable and fossil fuel energy consumption confirms both long- and short-run relationship. Besides, renewable energy was

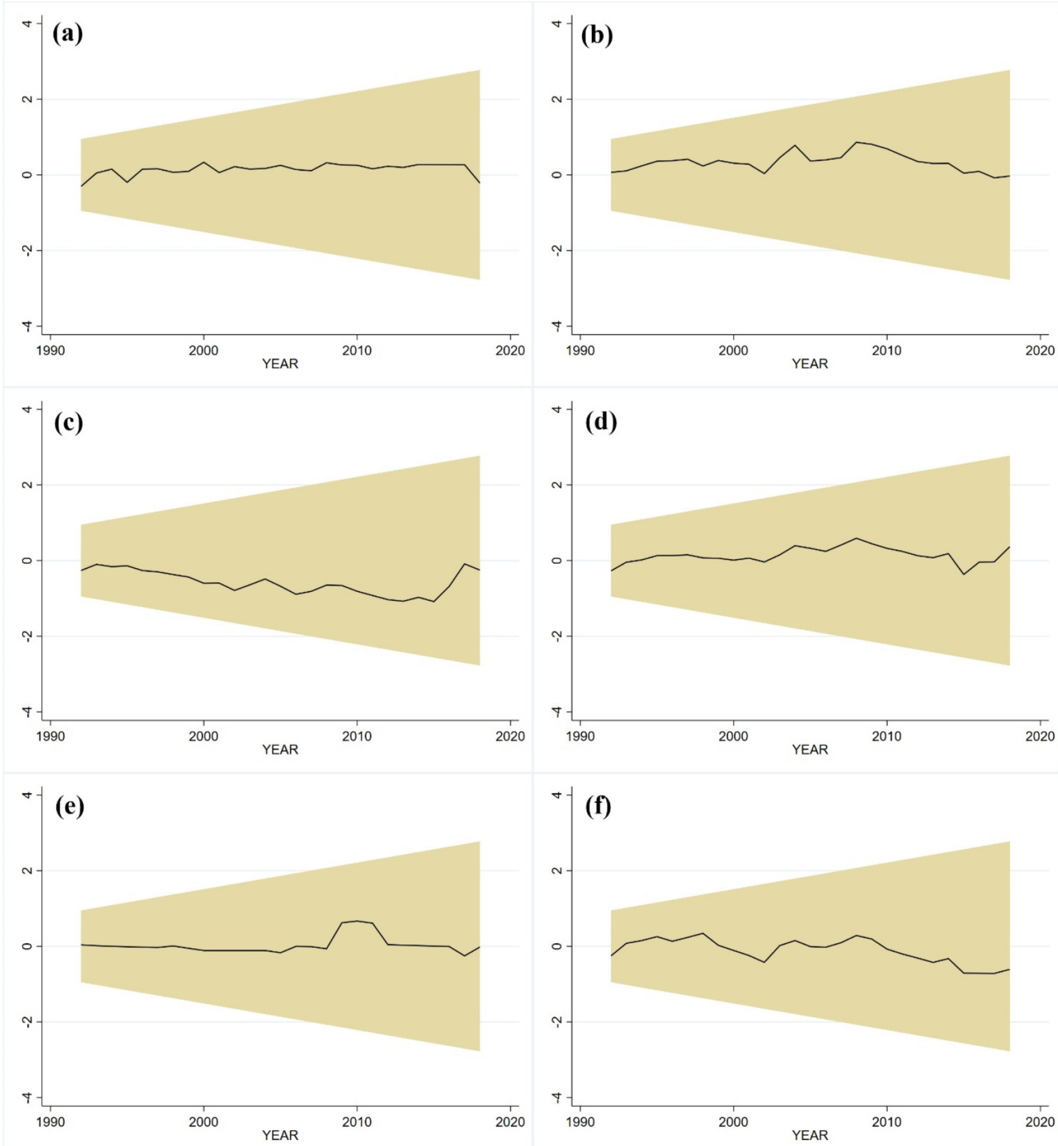

Fig. 14. Parameter stability using CUSUM test for (a) BIOMAS (b) COAL (c) ENEINT (d) ENERGY (e) ENVPS (f) FOSSILFUELS.

found to strongly predict coal consumption. This infers that the diversification of the energy portfolio with renewable energy sources will reduce fossil fuel footprint. We found a short-run relationship between renewable energy consumption and economic growth. This suggests a strong effect of wealth on renewable energy consumption. It is reported that cost is one of the major barriers affecting the market and patronization of renewables –especially in low-income countries (Owusu and Asumadu, 2016). While economic growth underpins renewable energy consumption, there may be other unobserved factors that might control or obstruct the causal effect. Our study confirms that trade is a catalyst for income and economic growth (Bhattacharya et al., 2016). Trade is known to facilitate import and export of goods and services across countries. Thus, trade acts as a conduit of shifting the production of goods and service to countries with comparative advantage (Makki and Somwaru, 2004).

5. Conclusion

This study assessed the causal effect of environmental factors, economic assessment and domestic material consumption in South Africa. Using the Breitung-Candelon spectral Granger-causality and parameter stability tests, we accounted for the direction of causality in a frequency domain. These tests, a similitude to machine learning algorithm with excellent predictive power – were necessary to examine sequential shocks not reported in traditional Granger-causality tests. From a policy perspective, the application of the spectral Granger-causality is useful for economies with limited and competing resources to make proper and timely resources allocation.

This study confirmed a coal-driven energy-based economic structure with limited green inputs. By extension, restrictive measures and policies that obstruct or limit coal consumption without a viable alternative will hamper economic development. A strong and long-term metallurgical coal-led metal footprint through steelmaking was confirmed. Because iron and steel manufacturing depend heavily on metallurgical coal combustion, the introduction of conservation policies might affect the metallurgical industry. Hence, technological improvement or upgrade of the coal infrastructure with carbon, capture and storage will decline the environmental and health effects. The existence of a feedback effect between biomass consumption and economic growth has policy implications. The magnitude of biomass consumption depends on the economic structure and vice versa. Biomass and economic growth play a complementary role, hence, environmental-

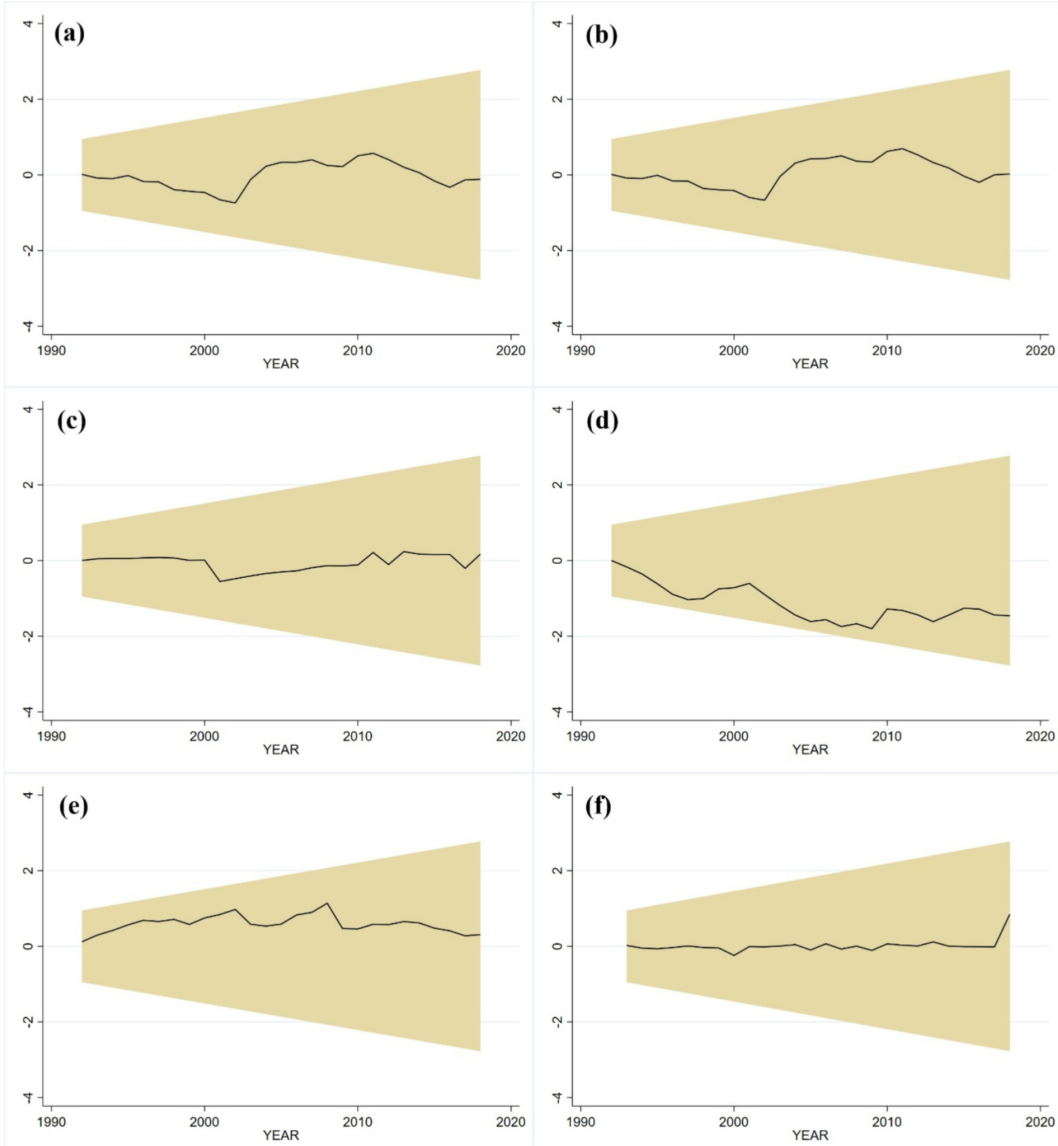

Fig. 15. Parameter stability using CUSUM test for (a) GDP (b) PGDP (c) PM 2.5 (d) RECONS (e) TRADE (f) METALORES.

related policies should be favourable to both. We found strong evidence that metal ore consumption predicts economic growth, income level and renewable energy consumption. Our empirical results found strong evidence to support the metal consumption-led ambient air pollution. Thus, the mitigation of ambient air pollution requires sustainable and technological upgrades that curtails pollution-embedded processes.

CRediT authorship contribution statement

Samuel Asumadu Sarkodie: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Software, Validation, Visualization, Writing - original draft, Writing - review & editing, Funding acquisition.

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.

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