IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals
ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2022, 12(3), 361-372.

Dynamic Connectedness between Renewable and Nonrenewable Energy Consumptions, Economic Growth and Carbon Dioxide Emissions in Vietnam: Extension of the TVP-VAR Joint Connected Approach

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Received: 08 January 2022 **Accepted:** 07 April 2022 **DOI:** https://doi.org/10.32479/ijeep.12956

ABSTRACT

We employ a time-varying parameter vector autoregression (TVP-VAR) combined with an extended joint connectedness approach to study interlinkages between renewable and nonrenewable energy consumption, economic growth, and CO_2 emission by characterizing connectedness of four markets starting from 1985 to 2019. Our results demonstrate that the financial crisis appears to have influences on the system-wide dynamic connectedness, which reaches a peak during 1989. The total directional connectedness suggests that nonrenewable and renewable sources of energy consumption tend to be net recipients of spillover shocks. Throughout the studied period, growth in the economy and CO_2 emissions seem to be influential net shock transmitters. Pairwise connectedness reveals that nonrenewable consumption primarily receives spillover effects of economic and environmental shocks. Since the crisis, CO_2 emission has been a net receiver of shocks from other variables.

Keywords: Nonrenewable and Renewable Energy Consumption, GDP, CO_2 Emission, Dynamic Connectedness, Joint Connectedness
JEL Classifications: C32, G12, Q43

1. INTRODUCTION

It has been argued with strongly backed up evidence that the environment is facing great harm due to the excessive and increasing amount of carbon dioxide (CO_2) emission in the atmosphere (Bölük and Mert, 2014; Shayanmehr et al., 2020a). With the growing amount of CO_2 in the atmosphere, the underlying reason for such phenomenon is reported and believed to be fossil fuel consumption as 90% of current CO_2 can be accounted for by such engagement and usage of such kind of energy (Shayanmehr et al., 2020b) according to the Joint Research Center of the European Commission (JRC). When consuming energy, greenhouse gasses such as CO_2 and SO_2 can cause severe damage to the environment (Murshed, 2020); therefore, the practice of using fossil energy can be reported to have a great responsibility to the deterioration of the environment. If strict energy consumption regulations are not imposed, the world may face catastrophic environmental disasters (Apergis et al., 2010). However, it is widely understood that energy has always been a crucial component in most businesses' manufacturing processes, making any reduction in its usage impractical. In light of this energy dependency, a conundrum has arisen due to the scarcity of resources, in particular fossil fuels (such as coal, oil, and natural gas). Energy demand increases rapidly, while supply is limited, posing the risk of resource depletion. This conflict creates problems for policymakers who incorrectly adjust energy supply and demand, especially when there are new energy sources, which is a grave issue for nations that rely on imported energy. The 1970s energy crisis and contemporary uprisings in Saudi Arabia serve as cautionary tales and possible dangers for a government unduly reliant on imported energy.

Renewable energy (e.g., solar, wind, hydroelectricity, biomass, biofuels, geothermal energy) and other types of renewable energy (e.g., tidal energy and wave energy) are gradually substituting fossil energy sources to address this issue since they reduce CO_2 emissions (Murshed et al., 2021). Renewable energy is regarded as a realistic solution for achieving a green economy while still ensuring long-term growth. Renewable and nuclear energy has long been recognized as non-carbon energy sources that can help battle climate change (Elliott, 2007). Furthermore, in both the production and consumption processes, substituting renewable energy sources for nonrenewable energy helps to increase energy security.

Economic expansion, environmental degradation, and energy usage are all intertwined, posing a constant and significant threat. Climate change and energy security have always been served as fascinating topics regarding energy consumption. Previous publications discussed the link between economic growth and a rise in energy consumption as well pollution emissions, and gave empirical evidence. However, practical knowledge on the interrelationships between these elements is still scarce. This shortage is more severe in developing countries due to a lack of relevant data. In this location, there has not been much study on renewable energy. To bridge the gap in the literature regarding nonrenewable energy, renewable energy consumption, environmental pollution, and economic growth, this study will examine their interconnectedness in the case of a country with a serious lack of data source.

To better understand the effects of nonrenewable energy and renewable energy consumption on the growth of economy and CO_2 emissions, this article examines Vietnam's environmental concerns from 1990 to 2019. Our choice is founded on scientific rigor. For starters, environmental degradation has become a severe problem (Ha et al., 2021). In order to achieve its goal of being a modern industrialized country with a high middle income by 2035, Vietnam, as a fast-emerging Southeast Asian economy, must choose between economic development and environmental protection. Recognizing the perils of seeking economic growth through policies, economists and politicians in Vietnam focus on environmental and energy issues. With the steady fall in the role of fossil fuels and the gradual increase in the percentage of renewable energy sources in the energy structure, our empirical study is expected to give novel solutions to the post-COVID-19 economy. Second, there is a scarcity of relevant data in Vietnam, which makes it difficult for academics to investigate these interconnections.

In this paper, we collect the yearly data of nonrenewable energy consumption, renewable energy consumption, CO_2 emission, and GDP per capita in Vietnam from 1985 to 2019. Our concentration is on interlinkages between economic growth, energy consumption, and pollution emission. Our study reveals critical findings by using the proposed application of a time-varying parameter vector autoregression (TVP-VAR) in combination with an extended joint connectedness approach. There is a shift in the role of each issue within our designed system over time. The total directional connectedness suggests that nonrenewable and renewable sources of energy consumption tend to be net recipients of spillover shocks. Throughout the studied period, growth in the economy and CO_2 emissions seem to be influential net shock transmitters. Pairwise connectedness reveals that nonrenewable consumption primarily receives spillover effects from all other markets. In contrast, renewable energy consumption and economic growth could be either a net transmitter or a net receiver. Since the crisis, CO_2 emission has been a net receiver of shocks from other variables.

The rest of the paper is organized as follows: In Section 2, related studies are discussed. Data sources, variable estimates, and methods are discussed in Section 3. Finally, in Section 4, the findings and policy implications are presented.

2. THE LITERATURE REVIEW

Until recently, the literature has examined the interrelationships between development, pollution, and the use of renewable and nonrenewable energy from three different angles. The first viewpoint looks into the relationship between economic growth and greenhouse gas emissions. The key hypothesis used to study this link is the Environmental Kuznets Curve (EKC). Lindmark (2002) discovered empirical evidence of EKC in Sweden during the 1870–1997 period, Acaravci and Ozturk (2010) in Denmark and Italy from 1960 to 2005, and Can and Gozgor (2017) in France during the 1964–2014 period. On the other hand, Mazur et al. (2015) asserted that the EKC theory had been disproven throughout the European Union. As a result, in order to address the situation in Vietnam – a developing country and a neglected part of the world when the issue of climate and energy is raised due to the aforementioned lack of data – the paper examines the relationship between the two mentioned aspects to address the situation in Vietnam.

The association between renewable energy consumptions and income growth is examined in the second point of view. In the short run, 20 OECD nations and 18 Latin American countries showed a bidirectional correlation between economic performance and renewable energy (Apergis et al., 2010), while renewable energy is reported to be a significant driver of GDP growth when data from 28 EU nations was investigated (Soava et al., 2018). Similar discoveries were discovered in Germany by Rafindadi and Ozturk (2017). Only one-way causation between GDP and renewable energy was explored by Cho et al. (2015) in 31 OECD countries. The results of these studies are inconsistent with little concern for a particular region of the world, with economic circumstances varying from Latin America to the European Union. On the other hand, the constancy with which some form of reciprocal or one-way interaction can be observed across works of the literature suggests that the pattern will most likely replicate itself in future contexts. As a result, this paper aims to investigate the link between renewable energy and Vietnamese income.

The last viewpoint elucidates the interconnectedness among income, carbon emissions, and renewable energy. According to Adewuyi and Awodumi (2017) and Lee (2013), the two-way interaction among dimensions is a significant source of concern. Menegaki (2011), on the other hand, employed a random-effects model for countries in the European region to validate a short run rather than long run two-way relationship between production and carbon emissions, as well as renewable energy and carbon emissions. Dong et al. (2018) looked at this link in 128 countries divided into six categories. In Europe and Eurasia, economic development and carbon emissions were bidirectional causal relationships, and renewable energy and CO_2 emissions were unidirectional causal relationships. Furthermore, Dong et al. (2020) demonstrated that these three factors had a two-way causal link. The conclusions are still set in the context of developed nations, leaving a void for emerging markets, despite the supporting data demonstrating the correlations between several factors of income-carbon emissions renewable energy.

Table 1 presents significant studies from three different perspectives. To investigate these inter-linkages between carbon emissions, energy consumption, and economic growth from these perspectives, popular methods such as Granger causality, vector autoregressive (VAR), error-correction model (ECM) causality, autoregressive distributed lag (ARDL), dynamic panel model, or spatial analysis were used, including Dong and Liang (2014), Kang et al. (2016), and Zheng et al. (2014), as shown in Table 1. In contrast, the study by Kang et al. (2016) used spatial panel data as a tool for examining the Environmental Kuznets Curves (EKC) theory in China. The study by Zheng et al. (2014) used a spatial panel data model to examine the geographic distribution of carbon intensity in China. A method of econometric estimation was used by Maddison (2006) to determine whether EKC exists for European countries. Overall, our literature review finds that no empirical study utilizing multivariate wavelet analysis to examine the inter-relationships between three fundamental problems in rising nations has been published (MWA). As a result, this work is the first to use the MWA to examine the relationship between economic development, carbon emissions, and renewable energy in the emerging economy.

3. DATABASE AND METHODOLOGY

3.1. Database

This paper uses the yearly data of nonrenewable energy consumption (*NEC*), renewable energy consumption (*REC*), CO_2 emission (*CO2*), and GDP per capita (*GDP*). While *GDP* is sourced from the World Bank database, we collect NEC, REC, and CO2 data from the Our World in Data database. The study concentrates on the period starting from 1985 to 2019. We calculate their growth rate and use them in the empirical analysis. We investigate the trend of these variables in the next section. Figure 1 demonstrates a pattern of these series.

As displayed in Table 2, the return of all studied markets is positive on average. In addition, renewable energy consumption has a more considerable variance than nonrenewable energy consumption, and therefore demand for renewable energy fluctuates the most during the selected sample. Notably, this paper finds that all series' distribution is highly leptokurtic. In other words, as compared to a normal distribution, the distribution of these variables has a shape with fatter tails, suggesting they do not follow a normal distribution as contended by Jarque and Bera (1980). Based on the ERS unit root test of Elliott et al. (1996), 1% significance level, these variables are statistically stationary. Lastly, the weighted portmanteau test of Fisher and Gallagher (2012) demonstrates an autocorrelation between their growth and squared percentage growth, thus we have strong evidence to utilize a TVP-VAR approach with a time-varying variance-covariance structure to estimate interlinkages of these variables. The main goal of this study is to investigate changes in the interlinkages of the series in the time from 1985 to 2019. Table 1 presents the statistics of these series.

3.2. Empirical Methodology

The most popular econometric technique used to examine interlinkage is one originally proposed by Diebold and Yilmaz (2012). The scholars employ this methodology to monitor contagions in a predetermined network to resolve the adverse effects of a specific economic shock. One limitation of the original approach relies on a rolling-window size chosen arbitrarily of time-variant interlinkage. Hence, several suggestions have been proposed to address this issue, such as using mean squared prediction error to determine the optimal window size (Antonakakis et al., 2020); or using the joint spillover index (Lastrapes and Wiesen, 2021). In this paper, we follow Balcilar et al. (2021) to employ a time-varying parameter vector autoregression (TVP-VAR) in combination with an extended joint connectedness approach to study interlinkages between four variables, namely nonrenewable energy consumption (*NEC*), renewable energy consumption (*REC*), CO2 emission (*CO2*), and GDP per capita (*GDP*).

First, the TVP-VAR connectedness approach in combination with the original technique of Diebold and Yilmaz (2012) is outlined in this section. In this article, we estimate a TVP-VAR model that has a lag length of order one, using the Bayesian information criterion (BIC):

$$y_t = M_t y_{t-1} + \epsilon_t \epsilon_t \sim N(0, \Sigma_t) \quad (1)$$

$$vec(M_t) = vec(M_{t-1}) + u_t u_t \sim N(0, R_t) \quad (2)$$

where y_t, y_{t-1} and ϵ_t are $Z \times 1$ dimensional vector and M_t and Σ_t are $Z \times Z$ dimensional matrices. $vec(M_t)$ and u_t are $Z^2 \times 1$ dimensional vectors whereas R_t is a $Z^2 \times Z^2$ multiple-dimensional matrix. According to this model, all parameters (M_t) as well as the relationship between successive series may fluctuate over time. A further assumption is that the variance-covariance matrices (Σ_t and R_t) also vary over time. A number of previous studies have revealed that the variances and covariances of financial markets are changing with time, resulting in varying market and investment risk over time.

Subsequently, the TVP-VMA model is written as follows:

$y_t = \sum_{h=0}^{\infty} N_{h,t}\epsilon_{t-1}$ where $N_0 = I_Z$ and ϵ_t denotes a symmetric white noise shocks that $Z \times Z$ time-varying covariance matrix $E(\epsilon_t \epsilon'_t) = \Sigma_t$ varies with time. Therefore, the L-step forecast error is as follows:

Table 1: Summary of previous studies

Paper	Period	Variables	Sample	Methodology	Main Conclusion
The relationship between economic growth and CO_2 emissions					
Pao and Tsai (2010)	1971–2005	GDP, CO2, EC	BRIC countries	Tests of VECM Granger causality tests and panel cointegration	CO2≥GDP
Cai et al. (2018)	1965-2015	CO_2, GDP, CE	G7	Tests of Granger causality and ARDL bounds	GDP×CO2
Mensah et al. (2019)	1990-2015	CO_2, GDP, GFCF, LF, NREC, OIL	Africa countries	Test of panel cointegration and ARDL by PMG	CO2≥GDP
Omri et al. (2015)	1990–2011	GDP, CO2, FDI, UR, GFCF, TO, ER	Global panel of 54 countries	Dynamic simultaneous-equation panel data	CO_2≥GDP
Salahuddin and Gow (2014)	1980–2012	GDP, CO_2, EC	Members of the Gulf Cooperation Council	Tests of Pedroni panel cointegration, Granger causality, and PMG-ARDL	GDP×CO_2
Fodha and Zaghdoud (2010)	1961–2004	GDP, CO_2, SO_2	Time series data for Tunisia	Tests of Johansen cointegration, ECM causality	GDP≥CO_2 (SHT and LT)
Jaunky (2011)	1980–2005	CO_2, GDP	36 countries with high incomes	Tests of VECM Granger causality and panel cointegration	GDP≥CO_2 (SHT and LT)
Al-Mulali and Che Sab (2012)	1980–2008	GDP, CO_2, EC, FD	19 studied countries	Tests of panel Granger causality, Pedroni cointegration	CO_2≥GDP (SHT and LT)
Azam (2016)	1990–2011	GDP, CO_2, HC, GS, FDI, EC	11 Asian countries	Panel model	CO_2≥GDP
Ahmed et al. (2017)	1971–2013	GDP, EC, P, TO CO_2	Five South Asian countries	Tests of panel cointegration tests and FMOLS	GDP≥CO_2 (LT)
Kais and Sami (2016)	1990–2012	GDP, CO_2, EC	Panel-country data	Panel model	GDP≥CO_2
Kang et al. (2016)	1997–2012	CO_2, GDP, GDP2, GDP3, TO, UR, EC, P	China	Spatial panel approach	GDP≥CO_2
Sarkodie and Strezov (2018)	1974–2013	GDP, GDP2, NREC, REC, CO_2, ENEI, ENEE	Australia	FMOLS, DOLS, CCR	GDP≥CO_2
The relationship between renewable energy and economic growth					
Kahia et al. (2017)	1980–2012	GDP, NREC, REC, LF, GFCF	11 MENA Net Oil Importing Countries	Tests of Panel Granger causality	GDP⇔REC (SHT)
Apergis and Payne (2010)	1985-2005	GFCF, REC, GDP, LF	OECD countries	Tests of FMOLS, panel cointegration, and Granger causality	GDP⇔REC (SHT and LT)
Apergis and Payne (2011)	1990-2007	GDP, NREC, REC, LF, GFCF	Emerging countries	Panel error correction, and FMOLS	GDP≥REC (SHT)
Apergis and Payne (2012)	1990–2007	NREC, REC, LF, GFCF, GDP	Panel country data	Panel error correction, and FMOLS	GDP⇔REC (SHT and LT)
Al-Mulali et al. (2014)	1980–2010	GDP, REC, NREC, LF, TO, GFCF	18 Latin American countries	VECM, Granger causality test, and DOLS	REC⇔GDP (SHT and LT)
Bhattacharya et al. (2016)	1991–2012	NREC, REC, LF, GFCF, GDP	38 countries	DOLS, FMOLS	57% of our selected countries REC≥GDP (LT)
Shahbaz et al. (2015)	1972Q1-2011Q4	GDP, REC, GFCF, LF	Pakistan	ARDL bounds test, Johansen cointegration, and VECM Granger causality test	REC⇔GDP (LT)
Dogan (2015)	1990-2012	GDP, REC, NREC, LF, GFCF	Turkey	ARDL bounds test, Johansen panel cointegration, and Gregory-Hansen cointegration tests	REC≥GDP (LT)

(Contd...)

Table 1: ***(Continued)***

Paper	Period	Variables	Sample	Methodology	Main Conclusion
Cho et al. (2015)	1990–2010	GDP, REC, GFCF, LF	31 OECD and 49 non-OECD countries	Panel VECM, FMOLS	Developed countries: GDP≥REC Less-developed countries: GDP⇔REC
Relationship between renewable energy and economic growth and CO_2 emissions					
Charfeddine and Kahia (2019)	1980–2015	GDP, CO_2, REC, GFCF, LF, FD	24 countries of MENA	Panel VAR model and Westerlund ECM panel cointegration tests	REC≥GDP REC≥CO_2
Pata (2018)	1974-2014	CO_2, GDP, REC, GDP2, FD, UR, HEC, AEC	Turkey	ARDL bounds test, FMOLS, Gregory-Hansen, and Hatemi-J cointegration tests	GDP≥CO_2 (SHT and LT)
Adewuyi and Awodumi (2017)	1980–2010	C) 2, GDP, REC, HC, FD, UR, TO, PC	West African countries	3SLS	REC⇔GDP GDP⇔CO_2 REC⇔CO_2
Shafiei and Salim (2014)	1980–2011	CO_2, REC, NREC, GDP, P, UR	OECD countries	ECM Causality, Johansen cointegration tests	REC≥CO_2 (LT)
Menyah and Wolde-Rufael (2010)	1960–2007	CO_2, REC, NEC, GDP	USA	Granger causality test (Toda-Yamamoto), VAR model	CO_2≥REC (LT) GDP⇔CO_2 (LT) GDP≥REC (LT)
Menegaki (2011)	1997–2007	CO_2, GDP, NREC, EM, REC	27 European Countries	RE, cointegration, and Granger causality test	CO_2⇔REC (SHT) CO_2⇔GDP (SHT) REC≥GDP (LT) CO_2≥GDP (LT)

CE: Clean energy use, GDP: Gross domestic product, NREC: Nonrenewable energy consumption, REC: Renewable energy consumption, CO_2: CO_2 emissions, HEC: Hydroelectricity consumption, NEC: Nuclear energy consumption, AEC: Alternative energy consumption, GFCF: Capital stock, FD: Financial development, UR: Urbanization, CRW: Combustible renewables and waste generation, OIL: Oil price, SO_2: Sulfur dioxide, ER: Exchange rate, R&D: Research and development expenditure, INV: Real investment, EM: Employment, SREC: Share of renewable energy consumption, CCR: Canonical cointegrating regression, OLS: Ordinary least squares, FMOLS: Fully modified ordinary least squares, DOLS: Dynamic ordinary least squares, RE: Random effects, VAR: Vector autoregressive, FE: Fixed effects, ARDL: The autoregressive distributed lag, VCEM: Vector error correction model, ENEI: Energy imports, ENEE: Energy exports, CCR: Canonical cointegrating regression, S: Material stocks, ST: Crude steel production, CE: Cement production, AM: Ammonia production, PG: Power generation, CAR: Car ownerships, NOx: Nitrogen oxide, SO_2: Sulfur dioxide, SEC: Ratio of value-added, SHT: In the short term, LT: In the long term; Indicate unidirectional relationship, ⇔: Indicates bidirectional relationship0, ×: Indicates no causal relationship

Figure 1: Consumption of nonrenewable and renewable energy, GDP and CO_2 emission returns

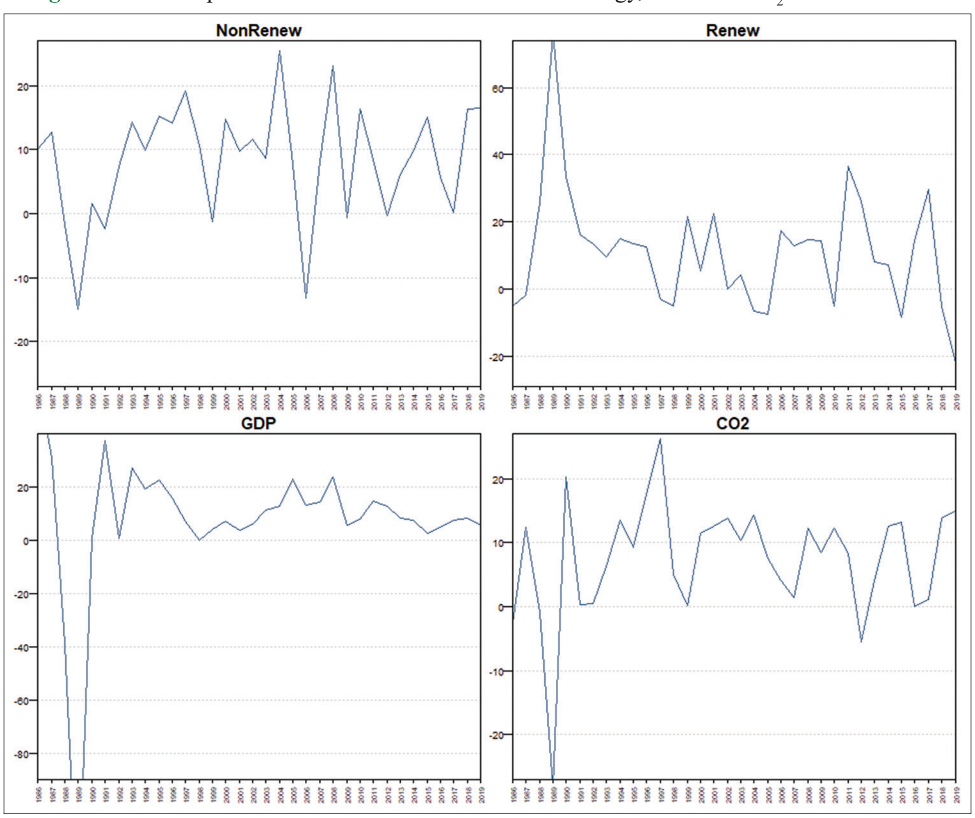


Table 2: Summary statistics

	Whole sample			
	NEC	REC	GDP	CO2
Mean	8.368	11.251	7.242	7.386
Variance	80.957	311.814	920.749	89.545
Skewness	–0.668* (0.000)	1.319*** (0.002)	–3.518*** (0.000)	–1.394*** (0.001)
Kurtosis	0.501*	3.638***	15.680***	4.189***
JB	2.884***	28.604***	418.475***	35.868***
ERS	–3.217*** (0.004)	–2.239*** (0.035)	–1.098*** (0.028)	–1.380*** (0.018)
Q (20)	21.719* (0.035)	14.555* (0.080)	10.751* (0.095)	12.369** (0.090)
Q^2 (20)	17.752*** (0.044)	3.450*** (0.009)	2.895*** (0.000)	13.417** (0.026)

$$\varphi_t(L) = y_{t+L} - E(y_{t+L}|y_t, y_{t-1}, \ldots) \quad (3)$$

$$= \sum_{l=0}^{L-1} N_{l,t}\epsilon_{t+L-l} \quad (4)$$

A matrix of forecast error covariance can be written as follows:

$$E((\varphi_t(L)\varphi'_t(L)) = N_{l,t}\sum\nolimits_t N'_{h,t} \quad (5)$$

The proposed framework relies on Pesaran and Shin (1998)'s L-step ahead generalized forecast error variance decomposition (GFEVD). The GFEVD, $gST_{ij,t}$ represents an impact of a shock stemming from variable *j* on variable *i* and can be written as follows:

$$\varphi_{ij,t}^{gen}(L) = \frac{E\left(\varphi_{i,t}^2(L)\right) - E[\varphi_{i,t}(L) - E(\varphi_{i,t}(L)) \mid \epsilon_{j,t+1}, \ldots, \epsilon_{j,t+1}]^2}{E\left(\varphi_{it}^2(L)\right)} \quad (6)$$

$$= \frac{\sum_{l=0}^{L-1}(e'_i N_{ltt} e_j)^2}{\left(e'_{jt} e_j\right).\sum_{l=0}^{L-1}(e'_i N_{ltt} N'_{lt}\, e_i)} \quad (7)$$

$$gST_{ij,t} = \frac{\varphi_{ij,t}^{gen}(L)}{\sum_{j=1}^{L}\varphi_{ij,t}^{gen}(L)} \quad (8)$$

where e_i denotes a $Z \times 1$ zero selection vector that have a unity on its *i*th position and $\varphi_{ij,t}^{gen}(L)$, (L), which represents a proportional reduction in the variance of the prediction error of variable i as a result of conditioning on the future shocks of variable *j*.

The $\sum_{j=1}^{Z} \varphi_{ij,t}^{gen}(L) \neq 1$ is normalized to unity, leading to the value of $gST_{ij,t}$. We write this metrics as follows:

$$X_{i\leftarrow,t}^{gen,from} = \sum_{j=1,i\neq j}^{Z} gST_{ij,t} \quad (9)$$

$$X_{i\rightarrow,t}^{gen,to} = \sum_{j=1,i\neq j}^{Z} gST_{ij,t} \quad (10)$$

The net total directional connectedness is presented as: $X_{i,t}^{gen,net} = X_{i\rightarrow\bullet,t}^{gen,to} - X_{i\leftarrow\bullet,t}^{gen,from}$. If $X_{i,t}^{gen,net} < 0\left(X_{i,t}^{gen,net} > 0\right)$, variable *i* implies a net receiver (transmitter) of shocks. In other words, variable *i* is driven by (is driving) other variables in the network.

The total connectedness index (TCI) demonstrates the interconnectedness within the network. We define the TCI as:

$$gST_t = \frac{1}{z}\sum_{i=1}^{Z} X_{i\leftarrow\bullet,t}^{gen,from} = \frac{1}{z}\sum_{i=1}^{Z} X_{i\rightarrow\bullet,t}^{gen,to} \quad (11)$$

where network spillovers with a higher degree have a greater value.

Lastly, the net pairwise directional spillovers can de represented as: $X_{i,t}^{gen,net} = gST_{ij,t}^{gen,to} - gST_{ij,t}^{gen,from}$. If $X_{ij,t}^{gen,net} > 0$, suggesting that series *i* has a more considerable influence on series *j*.

3.2.1. Technique with an extended joint connectedness

The $gST_{ij,t}$ and $jST_{ij,t}$ are assumed:

$$X_{i\leftarrow\bullet,t}^{jnt,from} = \sum_{j=1,i\neq j}^{Z} jST_{ij,t} \quad (12)$$

$$X_{\bullet\leftarrow i,t}^{jnt,to} = \sum_{j=1,i\neq j}^{Z} jST_{ji,t} \quad (13)$$

$$jSI_i = \frac{1}{z}\sum_{i=1}^{Z} X_{i\leftarrow\bullet,t}^{jnt,from} = \frac{1}{z}\sum_{i=1}^{Z} X_{i\rightarrow\bullet}^{jnt,to}$$

We follow (Lastrapes and Wiesen, 2021) to generalize the scaling approach, which the scaling factor η has differ by each row as follows:

$$\eta_i = \frac{X_{i\leftarrow\bullet,t}^{jnt,from}}{X_{i\leftarrow\bullet,t}^{gen,from}} \quad (14)$$

$$\eta = \frac{1}{z}\sum_{i=1}^{Z}\eta_i \quad (15)$$

Lastly, we can obtain:

- $jST_{ij,t} = \eta_i\, gST_{ij,t}$
- $jST_{ii,t} = 1 - X_{i\leftarrow\bullet,t}^{jnt,from}$
- $X_{i\rightarrow\bullet,t}^{jnt,to} = \sum_{j=1,j\neq i}^{Z} jST_{ij,t}$

Finally, allowing the scaling parameter to vary by row allows to compute the net total and pairwise directional connectedness measures as follows:

$$X_{i,t}^{jnt,net} = X_{i\rightarrow\bullet,t}^{jnt,to} - X_{i\leftarrow\bullet,t}^{jnt,from} \quad (16)$$

$$X_{ij,t}^{jnt,net} = gST_{ji,t} - gST_{ij,t} \quad (17)$$

4. RESULTS

This paper starts by reporting the average TCI values before displaying the pattern of the TCI over the studied period. By analyzing changes in the TCI's pattern from 1985 to 2019, we also evaluate the effects of the uncertain event on the interlinkages among the considered variables. In the following step, we also analyze net total connectedness and net pairwise connectedness, which help us achieve a more deeply insightful knowledge about the economic and environmental effects of renewable and nonrenewable energy consumption within our proposed system. It is worth noting that each variable can play a role of either a net shock transmitter or net shock receiver. Finally, for comparison purposes, we then follow Lastrapes and Wiesen (2021) to quantify the joint spillover index, which can be useful to explore the insights behind changes in interlinkages of these variables within the system.

4.1. Time-variant of Average Dynamic Connectedness

By concentrating over the 1985-2019 period, average results regarding interlinkages of diverse variables within the network of various variables are reported in Table 3. In this table, the volatility of a particular variable is accounted by its own shocks is reported by the diagonal element, and a contribution of this variable to others' volatility (FROM) and others to this variable's volatility (TO) are summarized in off-diagonal elements. Particularly, in Table 3, we outline each individual variable's contribution to a particular variable's forecast error variance in the rows, whilst columns correspond to the effect that one specific type of variable has on all other variables separately.

Considering the entire set of observations, the TCI average value is 57.90%, implying that fluctuations within this network can elucidate 57.90% of the variant in our network of considered variables. This result also suggests that nearly 42% of error variance within the system stems from idiosyncratic impacts. The last row of Table 2 indicates the role of each variable, meaning that, on net values, GDP and CO_2 emission play an inconsiderable role in transmitting effects and volatility of shocks to other variables within the system. By implication, nonrenewable and renewable Energy Consumption are net receivers of corresponding shocks, in which the most vital shock receiver is the NEC. The finding regarding GDP, CO_2 emission and energy consumption stays in line with many papers in the literature, such as Mezghani and Ben Haddad (2017), Mezghani et al. (2016) show that oil and non-oil GDP in Saudi Arabia play a role in net transmitters to energy consumption and CO_2 emissions. It is noted that the consumption of all types of energy in Iran is a net shock receiver from variables.

4.2. Time-variant of Total Connectedness

It would be instructive to note that the aforementioned average results only present a mere summary of interlinkages among considered variables within the system. In order to shed light on the influences of the crises on the interlinkages across a network of variables, it is vital to employ a more dynamic framework of analysis, which takes the time-variant of the TCI into account and reflects the time-variant of the role of studied variables within the network. For example, it is a prerequisite to consider changes in the behavior of a particular variable from a net shock transmitter to a net shock receiver and vice versa. This paper starts with the time-variant of total connectedness estimations presenting the intertemporal changes of the TCI as illustrated in Figure 2. It can be seen that the TCI values do not vary remarkedly across our studied sample period. The TCI tended to increase in the early years and peaked at about 65% in 1989. It would be worth noting that high values of TCI suggest high contagions between the diverse variables. However, the TCI values slightly declined to about 55% in 2019.

4.3. Time-variant of Net Total and Pairwise Directional Connectedness

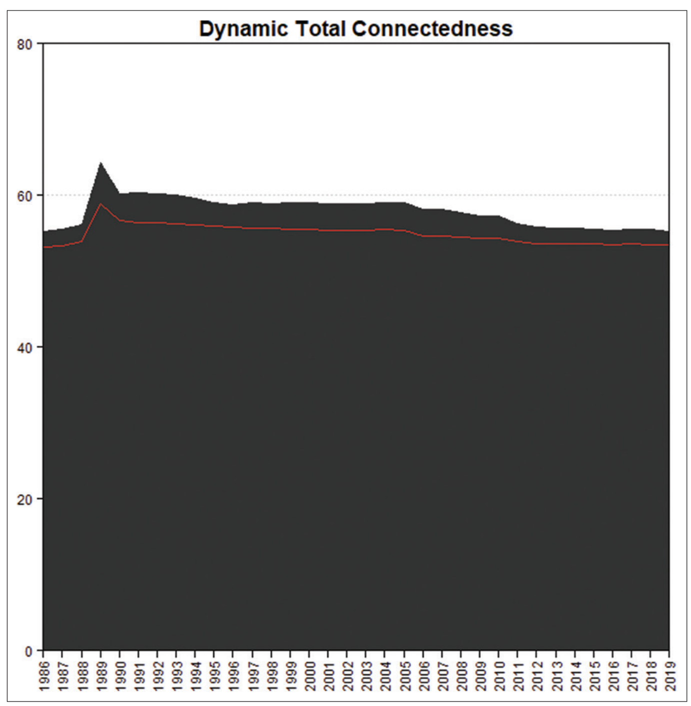
In the following analysis, we focus on net connectedness results, which can help us to classify a typical variable into a net shock transmitter or a net shock receiver. The current dynamic approach differs from the previous classification, which permits us to identify the process of shifting in each variable's role. In other words, the roles played by a specific variable as a net shock receiver and a net shock transmitter in the system at different times will be conditional on the time interval and the particular variable within the studied network.

Our study starts with the net total connectedness, which helps us detect a variant in the role of a variable throughout the separated periods. In the following, we outline our estimates regarding pairwise net connectedness. The investigation of pairs of

Table 3: Averaged joint connectedness

	Whole sample				
	NEC	REC	GDP	CO2	FROM
NEC	40.45	24.44	13.07	22.04	59.55
REC	22.97	33.61	23.11	20.31	66.39
GDP	11.38	21.05	50.55	17.02	49.45
CO2	20.83	18.79	16.59	43.80	56.20
TO	55.18	64.27	52.77	59.37	TCI
NET	–4.38	–2.11	3.32	3.17	57.90

Figure 2: Time-variant of total connectedness



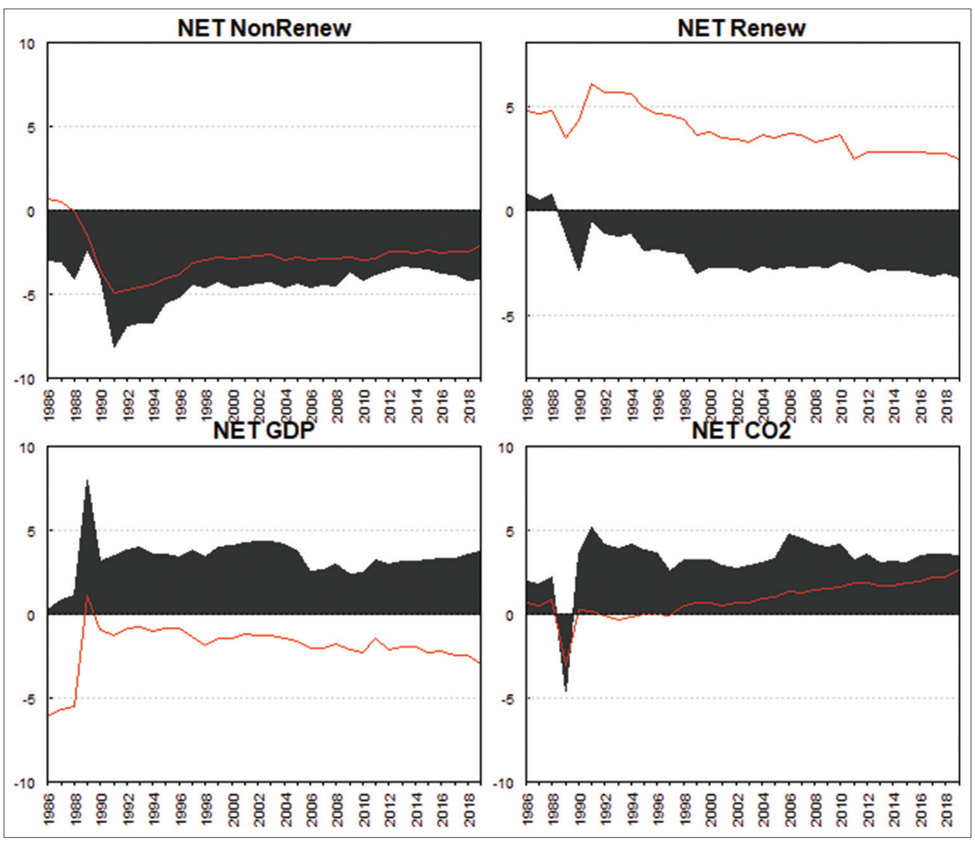
Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line)

considered variables allows us to indicate how their interlinkage has exchanged between these two potential roles over time. We plot estimated results in Figure 3. It is essential to recall that the positive and negative values reflect the net transmitting and receiving roles. Being consistent with main findings indicated previously by using net total connectedness results, nonrenewable energy consumption consistently acts as a net contagion shock receiver and receives the most shocks from the variable in 1991. The use of renewable energy is seen as a net transmitter for the first 2 years and largely variable shocks absorber after that because of the collapse of credit unions and the financial crisis in 1989.

The popularity of clean energy is increasingly dependent on shocks from GDP and other variables. Before 1989, the economy's stagnation with hyperinflation made the production cost of clean power high, so its role was highly faint compared to other variables. Renewable energy received many net shocks, especially in 1989, due to the large demand for electricity when the economy developed and the inauguration of the largest Hoa Binh Hydropower Plant. Therefore, all kinds of energy consumption depend heavily on variable shocks. GDP, by contrast, is a net transmitter over time and peaks in 1989. In spite of the Renovation policy in 1986, it was not until 1989 that effective policies were put into practice. For example, the government transferred land use rights to individual households, the state monopoly in foreign trade was abolished, and the stamp system and price controls were abolished. It gave GDP growth a jump and established the transmission of shocks to other variables in 1989. In particular, during the 2008 financial crisis, GDP transmits fewer shocks to variables. In 2008, Vietnam's economy faced many challenges due to inflation control, so the State Bank implemented a tight monetary policy. Besides, Vietnam also experienced a rapid increase in the trade deficit and a decline in the stock market. Because of rising costs, production stalled, and energy demand also decreased. CO_2 emission is a net transmitter for most of the time except from 1988 to 1990. This figure shows that GDP is heavily affected by CO_2 emission shocks.

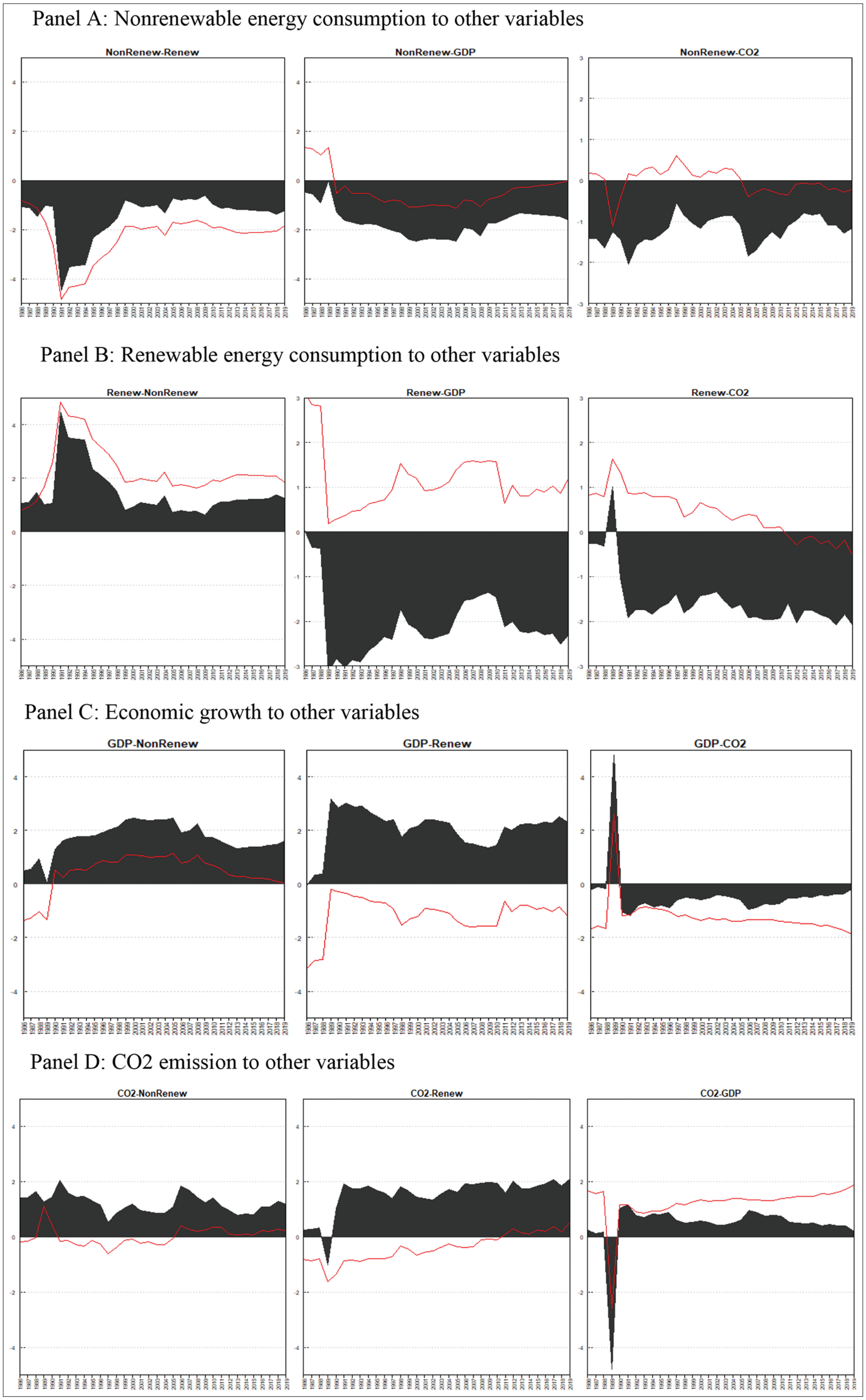
Subsequently, our study concentrates on net pairwise connectedness estimates, as displayed in Figure 4. We firstly look into contagion effects associated with *NER* to ascertain the critical role of *NER* within our considered network of diverse variables as shown in Panel A. Concerning the interrelation between *NER* and other variables, the consumption of nonrenewable energy is a persistent net shock receiver. In particular, *NER* receives the most shocks from *RER* in 1991 and gradually decreases after that. The shocks arising from *RER* have a more considerable effects on *NER* after the 2009 crisis. Panel B presents the spillover effects of renewable energy consumption on other variables. Notably, on net terms, the role of *RER* may exchange with CO_2 emission. Although *RER* exerts only a relatively substantial impact on CO_2 emission at the beginning of the time series, *RER* completely takes on the shocks from CO_2 emission since 1990. The consumption of renewable energy is also more dependent on GDP during crises. Concerning

Figure 3: Time-variant of net total directional connectedness



Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line)

Figure 4: Time-variant of net pairwise directional connectedness



Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line)

GDP and CO_2 emission, Panel C and D all reveal that these two variables may play time-varying roles with the remaining variables. It is observed that only during the financial crisis of 1989, the impact of GDP spread strongly affected CO_2 emission, and GDP is always a net receiver from CO_2 emission from 1990. It shows that at the beginning of development in 1989, Vietnam had a trade-off between economic growth and environmental degradation. CO_2 emissions are constantly increasing every year, of which the largest share is emissions from energy, followed by industry, agriculture, and waste, respectively. Like many other developing countries, Vietnam's manufacturing industry relies heavily on fossil energy and outdated technology. At the same time, there are many gaps in the policy on corporate responsibility for the environment, so CO_2 emission often plays the role of a net transmitter to GDP. The long-term and sustainable economic development strategy in Vietnam is required to reduce the proportion of polluting industries. In general, we reveal that all economic and environmental variables are significantly interrelated, hence it is vital to manage both economic and ecological strategies better simultaneously and appropriately to ensure economic development at a lower environmental cost.

5. CONCLUSIONS AND POLICY IMPLICATIONS

Our paper employs a network connectedness approach to estimate the interlinkages of four variables, namely the energy, crude oil, gold, and silver in a time-varying fashion using a TVP-VAR approach. We also follow Balcilar et al. (2021) approach that allows for more flexibility and enables us to attain the measures for net pairwise connectedness. Our focus is paid to detect the dynamic connectedness between nonrenewable and renewable energy consumption, economic growth and CO2 emission. In this paper, we collect the yearly data for the benchmark GDP volatility and CO2 emission volatility, nonrenewable and renewable energy consumption volatility, which starts from 1985 to 2019.

By using the full set of observations, our results show that all studied variables are considerably interconnected. The TCI value is approximately 57.90% when we use the whole sample. By using the time-variant of net total and pairwise directional connectedness analysis, we indicate the shift in the role of each variable within our designed system over time. However, except for the crisis of 1989, the GDP appears consistently as a net receiving of volatility shocks into the volatility of CO2 emission. The consumption of nonrenewable energy is always strongly affected by the shocks of CO2 emission, GDP and the use of renewable energy. The findings suggest that our developed network is exposed to high variable risk.

On the policy front, our findings provide vital implications for investors and authorities along with practices from the contagions across the diverse variables and their interlinkages. Insightful knowledge about key antecedents of the contagions among these variables, help policymakers design the most adequate policies to reduce these variables' vulnerabilities as well as minimize the spread of risk or uncertainty across these variables. Our findings show considerable interlinkages between four variables, thus emphasizing the potential risk of either low or high diversification for investors toward these variables. Our findings further underscore the increasing interlinkages within unexpected and highly uncertain events. In our findings, we demonstrate that there are influences of a shock in a typical variable on the entire network. Furthermore, the findings of this paper can also be useful for policy in an effort to enhance public welfare, which stems from the direct impact between nonrenewable and renewable energy consumption, economic growth and CO2 emission. It is vital to use the key insights that there are contentions of uncertainty and risk in energy variables to that on the economic growth and vice versa. Hence, it is a prerequisite to take them into account when designing policies for a vulnerable group as a way to enhance the welfare of society.

REFERENCES

Acaravci, A., Ozturk, I. (2010), On the relationship between energy consumption, CO_2 emissions and economic growth in Europe. Energy, 35(12), 5412-5420.

Adewuyi, A.O., Awodumi, O.B. (2017), Biomass energy consumption, economic growth and carbon emissions: Fresh evidence from West Africa using a simultaneous equation model. Energy, 119, 453-471.

Ahmed, K., Rehman, M.U., Ozturk, I. (2017), What drives carbon dioxide emissions in the long-run? Evidence from selected South Asian Countries. Renewable and Sustainable Energy Reviews, 70, 1142-1153.

Al-Mulali, U., Che Sab, C.N.B. (2012), The impact of energy consumption and CO_2 emission on the economic and financial development in 19 selected countries. Renewable and Sustainable Energy Reviews, 16(7), 4365-4369.

Al-Mulali, U., Fereidouni, H.G., Lee, J.Y., Sab, C.N.B. (2013), Examining the bi-directional long run relationship between renewable energy consumption and GDP growth. Renewable and Sustainable Energy Reviews, 22, 209-222.

Al-Mulali, U., Fereidouni, H.G., Lee, J.Y.M. (2014), Electricity consumption from renewable and non-renewable sources and economic growth: Evidence from Latin American countries. Renewable and Sustainable Energy Reviews, 30, 290-298.

Apergis, N., Payne, J.E. (2010), Renewable energy consumption and economic growth: Evidence from a panel of OECD countries. Energy Policy, 38(1), 656-660.

Apergis, N., Payne, J.E. (2011a), The renewable energy consumption–growth nexus in Central America. Applied Energy, 88(1), 343-347.

Apergis, N., Payne, J.E. (2011b), Renewable and non-renewable electricity consumption-growth nexus: Evidence from emerging market economies. Applied Energy, 88(12), 5226-5230.

Apergis, N., Payne, J.E. (2012), Renewable and non-renewable energy consumption-growth nexus: Evidence from a panel error correction model. Energy Economics, 34(3), 733-738.

Apergis, N., Payne, J.E., Menyah, K., Wolde-Rufael, Y. (2010), On the causal dynamics between emissions, nuclear energy, renewable energy, and economic growth. Ecological Economics, 69(11), 2255-2260.

Azam, M. (2016), Does environmental degradation shackle economic growth? A panel data investigation on 11 Asian countries. Renewable and Sustainable Energy Reviews, 65, 175-182.

Balcilar, M., Gabauer, D., Umar, Z. (2021), Crude oil futures contracts and commodity markets: New evidence from a TVP-VAR extended joint connectedness approach. Resources Policy, 73, 102219.

Bhattacharya, M., Paramati, S.R., Ozturk, I., Bhattacharya, S. (2016), The effect of renewable energy consumption on economic growth: Evidence from top 38 countries. Applied Energy, 162, 733-741.

Bölük, G., Mert, M. (2014), Fossil and renewable energy consumption, GHGs (greenhouse gases) and economic growth: Evidence from a panel of EU (European Union) countries. Energy, 74, 439-446.

Cai, Y., Sam, C.Y., Chang, T. (2018), Nexus between clean energy consumption, economic growth and CO_2 emissions. Journal of Cleaner Production, 182, 1001-1011.

Can, M., Gozgor, G. (2017), The impact of economic complexity on carbon emissions: Evidence from France. Environmental Science and Pollution Research, 24(19), 16364-16370.

Charfeddine, L., Kahia, M. (2019), Impact of renewable energy consumption and financial development on CO_2 emissions and economic growth in the MENA region: A panel vector autoregressive (PVAR) analysis. Renewable Energy, 139, 198-213.

Cho, S., Heo, E., Kim, J. (2015), Causal relationship between renewable energy consumption and economic growth: Comparison between developed and less-developed countries. Geosystem Engineering, 18(6), 284-291.

Diebold, F.X., Yilmaz, K. (2012), Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting, 28(1), 57-66.

Dogan, E. (2015), The relationship between economic growth and electricity consumption from renewable and non-renewable sources: A study of Turkey. Renewable and Sustainable Energy Reviews, 52, 534-546.

Dong, K., Dong, X., Jiang, Q. (2020), How renewable energy consumption lower global CO_2 emissions? Evidence from countries with different income levels. The World Economy, 43(6), 1665-1698.

Dong, K., Hochman, G., Zhang, Y., Sun, R., Li, H., Liao, H. (2018), CO_2 emissions, economic and population growth, and renewable energy: Empirical evidence across regions. Energy Economics, 75, 180-192.

Dong, L., Liang, H. (2014), Spatial analysis on China's regional air pollutants and CO_2 emissions: Emission pattern and regional disparity. Atmospheric Environment, 92, 280-291.

Elliott, G., Rothenberg, T.J., Stock, J.H. (1996), Efficient tests for an autoregressive unit root. Econometrica, 64(4), 813-836.

Fisher, T.J., Gallagher, C.M. (2012), New weighted portmanteau statistics for time series goodness of fit testing. Journal of the American Statistical Association, 107(498), 777-787.

Fodha, M., Zaghdoud, O. (2010), Economic growth and pollutant emissions in Tunisia: An empirical analysis of the environmental Kuznets curve. Energy Policy, 38(2), 1150-1156.

Ha, L.T., Nam, P.X., Thanh, T.T. (2021), Effects of bribery on firms' environmental innovation adoption in Vietnam: Mediating roles of firms' bargaining power and credit and institutional constraints. Ecological Economics, 185, 107042.

Jarque, C.M., Bera, A.K. (1980), Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economics Letters, 6(3), 255-259.

Jaunky, V.C. (2011), The CO_2 emissions-income nexus: Evidence from rich countries. Energy Policy, 39(3), 1228-1240.

Kahia, M., Aïssa, M.S.B., Lanouar, C. (2017), Renewable and non-renewable energy use-economic growth nexus: The case of MENA Net Oil Importing Countries. Renewable and Sustainable Energy Reviews, 71, 127-140.

Kais, S., Sami, H. (2016), An econometric study of the impact of economic growth and energy use on carbon emissions: Panel data evidence from fifty eight countries. Renewable and Sustainable Energy Reviews, 59, 1101-1110.

Kang, Y.Q., Zhao, T., Yang, Y.Y. (2016), Environmental Kuznets curve for CO_2 emissions in China: A spatial panel data approach. Ecological Indicators, 63, 231-239.

Lastrapes, W.D., Wiesen, T.F.P. (2021), The joint spillover index. Economic Modelling, 94, 681-691.

Lee, J.W. (2013), The contribution of foreign direct investment to clean energy use, carbon emissions and economic growth. Energy Policy, 55, 483-489.

Lindmark, M. (2002), An EKC-pattern in historical perspective: Carbon dioxide emissions, technology, fuel prices and growth in Sweden 1870-1997. Ecological Economics, 42(1), 333-347.

Maddison, D. (2006), Environmental Kuznets curves: A spatial econometric approach. Journal of Environmental Economics and Management, 51(2), 218–230.

Mazur, A., Phutkaradze, Z., Phutkaradze, J. (2015), Economic growth and environmental quality in the European Union countries-is there evidence for the environmental Kuznets Curve? International Journal of Management and Economics, 45(1), 108-126.

Menegaki, A.N. (2011), Growth and renewable energy in Europe: A random effect model with evidence for neutrality hypothesis. Energy Economics, 33(2), 257-263.

Mensah, I.A., Sun, M., Gao, C., Omari-Sasu, A.Y., Zhu, D., Ampimah, B.C., Quarcoo, A. (2019), Analysis on the nexus of economic growth, fossil fuel energy consumption, CO_2 emissions and oil price in Africa based on a PMG panel ARDL approach. Journal of Cleaner Production, 228, 161-174.

Menyah, K., Wolde-Rufael, Y. (2010), CO_2 emissions, nuclear energy, renewable energy and economic growth in the US. Energy Policy, 38(6), 2911-2915.

Mezghani, I., and Ben Haddad, H. (2017), Energy consumption and economic growth: An empirical study of the electricity consumption in Saudi Arabia. Renewable and Sustainable Energy Reviews, 75, 145–156.

Murshed, M. (2020), Electricity conservation opportunities within private university campuses in Bangladesh. Energy and Environment, 31(2), 256-274.

Omri, A., Daly, S., Rault, C., Chaibi, A. (2015), Financial development, environmental quality, trade and economic growth: What causes what in MENA countries. Energy Economics, 48, 242-252.

Pao, H.T., Tsai, C.M. (2010), CO_2 emissions, energy consumption and economic growth in BRIC countries. Energy Policy, 38(12), 7850-7860.

Pata, U.K. (2018), Renewable energy consumption, urbanization, financial development, income and CO2 emissions in Turkey: Testing EKC hypothesis with structural breaks. Journal of Cleaner Production, 187, 770-779.

Rafindadi, A.A. (2016), Does the need for economic growth influence energy consumption and CO2 emissions in Nigeria? Evidence from the innovation accounting test. Renewable and Sustainable Energy Reviews, 62, 1209-1225.

Rafindadi, A.A., Ozturk, I. (2017), Impacts of renewable energy consumption on the German economic growth: Evidence from combined cointegration test. Renewable and Sustainable Energy Reviews, 75, 1130-1141.

Salahuddin, M., Gow, J. (2014), Economic growth, energy consumption and CO_2 emissions in gulf cooperation council countries. Energy, 73, 44-58.

Sarkodie, S.A., Strezov, V. (2018), Assessment of contribution of Australia's energy production to CO_2 emissions and environmental degradation using statistical dynamic approach. Science of the Total Environment, 639, 888-899.

Shafiei, S., Salim, R.A. (2014), Non-renewable and renewable energy consumption and CO_2 emissions in OECD countries: A comparative analysis. Energy Policy, 66, 547-556.

Shahbaz, M., Loganathan, N., Zeshan, M., Zaman, K. (2015), Does renewable energy consumption add in economic growth? An application of auto-regressive distributed lag model in Pakistan. Renewable and Sustainable Energy Reviews, 44, 576-585.

Shayanmehr, S., Rastegari Henneberry, S., Sabouhi Sabouni, M., Shahnoushi Foroushani, N. (2020a), Climate change and sustainability of crop yield in dry regions food insecurity. Sustainability, 12(23), 9890.

Shayanmehr, S., Rastegari Henneberry, S., Sabouhi Sabouni, M., Shahnoushi Foroushani, N. (2020b), Drought, climate change, and Dryland wheat yield response: An econometric approach. International Journal of Environmental Research and Public Health, 17(14), E5264.

Soava, G., Mehedintu, A., Sterpu, M., Raduteanu, M. (2018), Impact of renewable energy consumption on economic growth: Evidence from European Union countries. Technological and Economic Development of Economy, 24(3), 914-932.

Zheng, X., Yu, Y., Wang, J., Deng, H. (2014), Identifying the determinants and spatial nexus of provincial carbon intensity in China: A dynamic spatial panel approach. Regional Environmental Change, 14(4), 1651-1661.