

THE IMPACT OF STOCK PRICES OF POLLUTING ENERGY SOURCES ON RENEWABLE ENERGY STOCK INDEX PRICES

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Abstract

Research background: The link between the price of polluting energy supplies and the renewable energy stock index may be intricate and subtle. Investors need to conduct thorough inquiries and analyses to completely understand the correlation between these industries.

Purpose: This study aims to explore the intricate dynamics between renewable energy stocks and conventional fossil fuel-based resources.

Research methodology: Our analysis encompasses daily data spanning from June 9, 2012, to March 31, 2023, extracted from the WilderHill New Energy Global Innovation Index (NEX), Crude Oil (WTI OIL),

Coal (COAL), and Natural Gas (NGAS). Key statistical tests include the Johansen co-integration test, the fully modified ordinary least squares (FMOLS) test, and the Granger causality test.

Results: The study shows a long-term co-integration relationship between renewable energy stocks and polluting energy sources. Oil prices positively impact the renewable stock index, while coal prices negatively affect it. Natural gas prices also positively correlate with the index, and short-term relationships exist with oil prices.

Novelty: The study provides valuable insights for investors, state authorities, and policymakers on optimising ESG portfolio diversification and sustainable development policies in energy, environment, and climate. It helps stakeholders understand investor behaviour, market trends, and policy impacts, enabling effective long-term investment strategies.

Keywords: renewable energy, polluting energy, ESG investing, risk management

JEL classification: C58, F64, Q49, Q56

Introduction

ESG (Environmental, Social, and Governance) is crucial for organisations to demonstrate their commitment to sustainability and moral decision-making. It addresses environmental problems, social injustices, and governance issues. Companies are not yet required to disclose their ESG efforts, but new European Union (EU) rules and international sustainability concerns have impacted the financial markets. ESG has become ingrained in major firms' cultures, necessitating specific skill sets and efficient resource allocation. Businesses may view ESG as an unpleasant requirement, but following guidelines can promote growth and enhance performance metrics (Kiehne, 2019; Perez et al., 2022). The natural development process begins with five phases: Roots, Development, Transition, Expansion, and Mainstream. The United Nations Climate Change Conference (COP21) resulted in the Paris Agreement, which put the international community and governments in charge of combating climate change. The agreement aims to achieve net-zero carbon emissions by 2030 and limit the increase in global average temperature to 1.5°C above pre-industrial levels. The efforts to create a low-carbon emission world gained momentum with the signing of the Paris Climate Agreement in 2015. The first scientific contributions to sustainability focus on using natural resources and their impact on quality of life (Marcuse, 1998; Jamieson, 1998; Nilashi et al., 2019). In the following period, relations with the next generation, which is the main target

group, and the economy, environment, and social fields were included in studies (Fisher et al., 2012; Anh et al., 2022; Rasoolimanesh et al., 2023; Bhatnagar et al., 2022).

The agreements and decisions aim was to create a human-friendly and sustainable environment. In this context, it can be seen that the most damaging factor to nature and the environment is the release of greenhouse gases. Therefore, many countries turn to renewable energy to reduce the greenhouse gases they emit, to cause less harm to the environment and nature, to reduce foreign dependency on energy, and to reduce increasing energy costs.

The energy requirements arising from industrialisation worldwide are mostly met with fossil fuels. Fossil fuels, also called dirty energy, are natural energy sources containing hydrocarbons and high levels of carbon. Coal, oil, and natural gas are prime examples of fossil fuels. The limited reserves of fossil fuels and their negative effects on people and the environment have led to the search for new energy sources. Solar, wind, geothermal, hydroelectric, and biomass energy sources are the leading renewable energy sources seen as alternatives to carbon-based energy sources.

The oil and energy crises of the 1970s had a negative impact on the economies of several nations, dealing severe blows to their economies. On the other hand, increasing carbon emissions due to the dirty energies used (oil types, natural gas, coal, etc.) and climate changes have also continued to affect world economies adversely. The fact that renewable energy sources are necessary for achieving sustainable growth and development has been brought to the attention of world leaders and politicians. Today, the foundation of sustainability and sustainable development is the green economy and renewable energy.

The global economy based on fossil fuels and the increase in greenhouse gas emissions are creating enormous changes in our climate system. The United Nations (UN) aims to ensure harmony and resilience in the fight against climate change and natural disasters, with the 13th goal of sustainable development (UNDP, 2023). The aim is to deliver a clean world without depriving future generations of today's opportunities and assets. For the world to achieve these goals, some critical issues need to be resolved. One of them is to completely abandon the world's dirty energy production habits that harm the environment and nature and to ensure their transition to environmentally friendly, renewable energy sources. This target is included in the 7th goal of the sustainable development goals (SDGs), which aims to provide universal access to affordable, reliable, and renewable energy services by 2030 (UNDP, 2023).

The share of renewable energy sources in primary energy sources was 12% in 2019. This rate is expected to increase to 35% by 2050 (BP, 2023). According to the International Energy Agency (IEA) data, more than 1.7 trillion of the 2.8 trillion energy investments will be

renewable energy investments. For every dollar invested in fossil fuels, 1.7 dollars is invested in clean energy (WEI, 2023).

The increase in demand for renewable energy investments attracts the attention of portfolio investors. Renewable energy stocks constitute a new asset class, especially for environmentally conscious market participants. Therefore, various indices worldwide include different renewable energy stocks. The WilderHill Clean Energy Index (ECO), the WilderHill New Energy Global Innovation Index (NEX), the Standard and Poor's (S&P) Global Clean Energy Index (SPGCE), and in the European market, the European Renewable Energy Index (ERIX) can be given as examples.

The growing investments in renewable energy and the rising returns on renewable energy stocks have garnered attention from investors and academics. However, only a few studies have examined the interaction between oil prices and renewable energy stock indices (Henriques, Sadorsky, 2008; Kumar et al., 2012; Managi, Okimoto, 2013; Geng et al., 2021; Umar et al., 2022). Previous literature has focused on the interaction between changes in oil prices and stock indices (Kumar, 2019; Wen et al., 2019; Chien et al., 2021; Liu et al., 2023; Hashmi et al., 2021). It focused only on oil prices as one of the dirty energy sources (Henriques, Sadorsky, 2008; Kumar et al., 2012; Managi, Okimoto, 2013; Jiang, Liu, 2021; Usman, 2023).

Investors and politicians increasingly require investments to consider ESG aspects and financial considerations, aiming to rebalance sustainability in a country or region. Diversification is essential to minimise risk and maximise holdings. Understanding the relationships between renewable energy stocks and fossil fuel-based energy resources is crucial for informed investment decisions. The pricing of polluting energy resources and the renewable energy stock index can be complex, and in-depth investigation is necessary to fully comprehend the connection between these industries. In line with this information, the aim of the study has been defined as determining the relationship between the renewable energy stock index and the prices of polluting energy resources. For this aim, the Wilder Hill New Energy Global Innovation Index (NEX) is used to represent the renewable energy stock index, while West Texas Intermediate Crude Oil (WTI OIL), coal, and natural gas (NGAS) futures data are used to represent polluting energy resources. The insights gained from this study can empower investors, policymakers, risk managers, researchers, and industry stakeholders to make more informed decisions, shape policies, and guide the transition toward a more sustainable energy future.

As a result, this study adds to the body of literature by integrating prices for natural gas and coal, besides oil prices, into the equation. Although we know that oil prices and the inventories of renewable energy sources are related (Usman, 2023; Umar et al., 2022), we included three distinct polluting energy sources in our study since it was believed that in addition to oil, natural

gas, and coal prices may also impact renewable stock values. Additionally, unlike other studies: (1) We used the NEX index to determine the impact of polluting energy sources on the performance of renewable energy stocks, (2) The data period from 26.12.2012 to 31.03.2023 was used, and (3) We conducted the fully modified ordinary least squares test, a cointegration-based regression method.

Following this introduction, Section 1 reviews the relevant literature on the relationships between dirty energy sources and clean energy stocks. Section 2 presents the dataset and some of its features. Section 3 explains the methodology used. Section 4 presents the empirical results. Section 5 compares the results with previous studies and provides recommendations.

1. Literature

Polluting energy sources have been the most basic energy source until today. The effect of the increase in oil prices manifests itself as an increase in production costs (Kim, Jang, 2023). Positive and negative shocks in crude oil prices have long-term asymmetric effects on different stock market indices (SP500, DJI, and FTSE), sustainability, and well-being. A short-term asymmetric relationship is seen in the United States(USA) market indices (S&P 500, DJI) (Jiang, Liu, 2021). Kumar (2019) investigated the effect of oil prices on stocks using linear and nonlinear methods and the results varied according to the methods used. While there is a one-way causality relationship between the stock index and oil prices with the linear method, the causality relationship between oil prices and the stock index is bidirectional in the nonlinear method.

Wen et al. (2019) investigated the relationship between the stock index and oil prices and found a unidirectional causality relationship between oil prices and some sector indices using the linear method. Lui et al. (2023) state that the nonlinear causality relationship is from oil prices to stocks in all sectors. The impact of shocks on oil prices varies depending on whether the shocks are expected or unexpected. Expected shocks have adverse effects, while unexpected shocks positively affect Chinese stock returns. Killian and Park (2009) show that the impact of an oil price increase on stocks can be good, inadequate, or largely insignificant, depending on the cause of the oil price increase. Considering the 2008 crisis, Bouri et al. (2022) conclude that the relationship between oil prices and stocks was positive during the crisis period.

Kuang (2021) observed a lack of risk and return characteristics of clean energy stocks compared to other stock segments and evaluated the comparison of clean energy stocks with “polluting energy” stocks using different optimisation techniques. Although clean energy outperforms “polluting energy” stocks, it outperforms the traditional equity market on a risk-

adjusted basis. At the same time, the study revealed that sub-sectors differ regarding risk and return potential. Shahzad et al. (2021) found that the US, European, and global energy market indices have remarkable asymmetric multifractality. The weak form of the Efficient Market Hypothesis (EMH) does not apply to the clean energy market, and the US clean energy stock market was the most active among the three markets evaluated.

Two perspectives exist on the relationship between oil prices and renewable energy stock returns. One suggests that rising oil prices decrease clean energy costs, increasing renewable energy stock returns. The other suggests that changes in oil prices do not impact renewable energy markets. (Wen et al., 2019). Henriques and Sadorsky's (2008) study found that changes in oil prices affect the ECO Energy Index returns, establishing a unidirectional causality relationship.

Some studies found a co-integration relationship between oil prices and the ECO index (Gargallo et al., 2021; Kumar, 2019). Managi and Okimoto (2013) found that the change in oil prices affects clean energy stock index prices. Due to wavelet coherency analysis, Nasreen et al. (2020) showed a weak correlation between oil prices and the clean energy stock index. Ozkan (2023) discussed how oil price fluctuations affect renewable energy stock returns. Using the ECO and NEX indices, the study shows that a negative oil supply shock positively affects clean energy stock returns, while an oil-specific demand shock affects it negatively.

There is a positive correlation between ECO and SPGCE index returns and oil prices (Wen et al., 2019; Micallef et al., 2023). Geng et al. (2021) took the ERIX index to represent clean energy stocks. He determined that crude oil prices and ERIX index changes move in the same direction. At the same time, the study shows that oil returns act as a net receiver of information in the crude oil-clean energy link system. According to Kumar et al. (2012), NEX, ECO, and SPGCE indexes positively correlate with oil prices. There is also a unidirectional causal relationship between oil prices and all indices included in the analysis.

The relationship between oil price and renewable energy stock differs significantly in subsectors of the renewable energy stock market (Kim, Jang, 2023). Specifically, biofuel and energy management stocks are the most related to oil prices, while stocks of wind, geothermal, and fuel cells are among the least related to oil prices. Reborade et al. (2017) examined the linear and nonlinear causality relationship between oil and different renewable energy stock index returns. A linear causal relationship between the variables could not be determined. On the other hand, a nonlinear causality relationship was found between energy stock indices and oil prices. In addition, a causal relationship between oil prices and some energy stock indices has also been determined.

Two different effects are expected from the decrease in oil prices (Aslan et al., 2022; Sahu et al., 2022). According to Aslan et al. (2022), the decrease in oil prices will have a negative impact on the shares of renewable energy companies as the demand for oil increases. On the other hand, Sahu et al. (2022) state that since the decrease in oil prices will increase the investment in renewable energy sources, it may increase the return on renewable energy stocks.

Bouri et al. (2019) found that crude oil and gold investments have weak haven properties against clean energy indices. However, few studies have examined other polluting energy sources other than oil prices. The ECO index has a negative relationship with oil prices in the long run but a positive relationship with natural gas prices. The causality test results show that the ECO stock index and oil and natural gas prices are mutually influential. In addition, causality test results showed that the ECO stock index and oil and natural gas prices were mutually influential (Xia et al. 2019). The connection between clean energy stocks and oil and natural gas prices during the COVID-19 pandemic is also investigated in the literature (Usman, 2023; Fu et al., 2022). Farid et al. (2023) examined the joint movement structure between clean energy stocks and polluting energies before and during the COVID-19 outbreak. They found a negative correlation between clean energy stocks and polluting energy prices in the pre-pandemic period but predicted a weak relationship during the pandemic. On the other hand, Umar et al. (2022) found a significant positive correlation between the SPGCE index returns and oil prices. The study found no significant positive correlation between wave gas prices and volatility spillovers between clean energy and oil markets in the short term, with weak volatility trends in the long term and increased volatility during crises.

Chun et al. (2022) found that coal price increases negatively impact the ERIX index, with wavelet coherence indicating a negative correlation between coal and ERIX prices over specific time scales and frequencies.

Xia et al. (2019) found that rising oil, natural gas, and coal prices boost the European Renewable Energy Index (ERIX) returns. However, Jiang and Liu (2021) found no causal relationship between these prices and clean energy stock indices. The study hypothesises that oil prices significantly positively affect NEX, SPGCE, and ERIX indices, while other energy sources have insignificant impacts.

High oil prices may increase the demand for renewable energy sources as investors shift towards renewables due to the rising costs of fossil fuels. Additionally, increases in coal prices may boost dependence on fossil fuels, which could reduce interest in the renewable energy sector, negatively impacting renewable energy stock prices. Consequently, it is anticipated that increases in oil and natural gas prices will lead to higher renewable energy stock prices, while increases in coal prices are expected to decrease renewable energy stock prices.

Therefore, based on the literature review, the following hypotheses were formed as follows:

- H₁: A co-integration relationship exists between the renewable energy stock price index and polluting energy sources.
- H₂: Oil prices positively affect the renewable energy stock price index.
- H₃: Coal prices have a negative effect on the renewable energy stock price index.
- H₄: Natural Gas prices positively affect the renewable energy stock price index.
- H₅: A causal relationship exists between the renewable energy stock price index and Crude Oil WTI prices.
- H₆: A causal relationship exists between the renewable energy stock price index and coal prices.
- H₇: A causal relationship exists between renewable energy stock price index and Natural Gas prices.

2. Data

The NEX index, which represents renewable energy stocks, and futures data of Crude Oil, Coal, and Natural Gas, which represents polluting energy sources, were analysed from 26.12.2012 to 31.03.2023 since the WilderHill New Energy Global Innovation Index data started from the 26.12.2012. The data of the variables was downloaded from the investing database. The logarithm of the daily data of the variables was taken and analysed with the Eviews 12 package program.

Figure 1 shows the evolution of daily prices and returns for renewable and polluting energy markets over time. Energy returns have changed significantly due to economic and financial events like the 2015 shale oil crisis, the COVID-19 pandemic, and the Russia-Ukraine war. The NEX index movements are similar to oil price movements, with a positive relationship between the two. However, there is a difference between the NEX index and gas price movements.

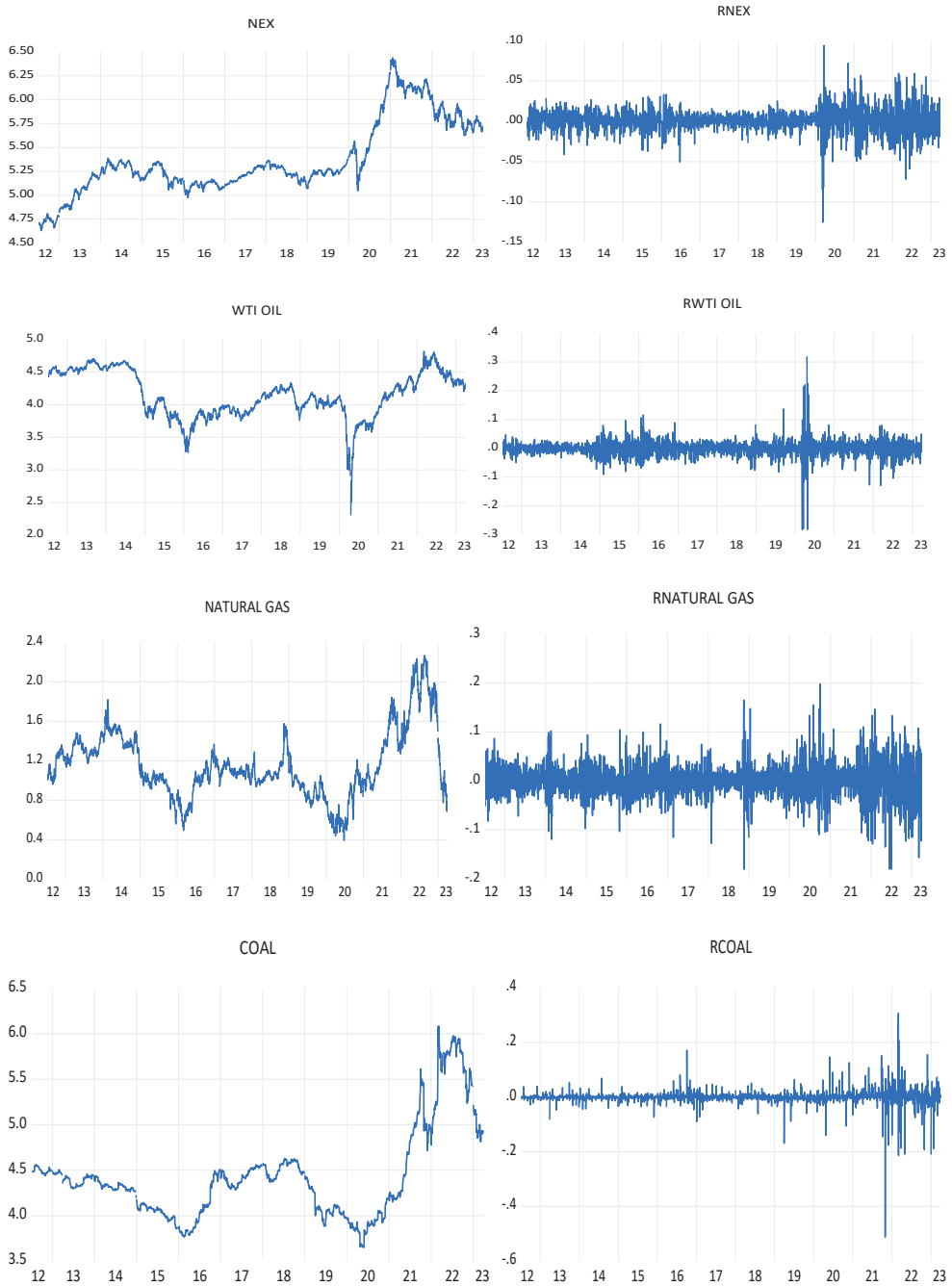


Figure 1. Time series plot of price and return

Source: author's compilation.

Descriptive statistics of the renewable stock price index and polluting energy resource prices are given below in Table 1. When we examined the skewness and kurtosis coefficients of the variables using the Jarque-Bera test statistic, it was seen that the variables did not follow the normal distribution. Results show that the null hypothesis (H_0) for the variables, which states that the variables conform to the normal distribution, was rejected at the 1% significance level. Therefore, the variables do not have a normal distribution.

We then calculated and presented in Table 1 the correlation coefficient values that will contribute to our knowledge about the direction and strength of the relationship between the variables. Results, consistent with the findings of some researchers (Kumar et al., 2012; Pham, 2019; Geng et al., 2021; Usman, 2023; Özkan, 2023) indicate a positive relationship between the renewable energy stock price index and the prices of polluting energy resources (oil prices). Also, it can be seen that coal prices interact more with the energy stock price index.

Table 1. Descriptive Statistics of Variables

	NEX	WTI OIL	COAL	NGAS
Mean	5.372858	4.148796	4.428533	1.159651
Median	5.257652	4.121960	4.347694	1.085865
Maximum	6.439558	4.817859	6.083018	2.266647
Minimum	4.628887	2.303585	3.653252	0.393393
Standard deviation	0.379491	0.351647	0.497851	0.339296
Skewness	0.852115	-0.439709	1.394761	0.738784
Kurtosis	3.065422	3.374342	4.726801	3.793872
Jarque-Bera	335.831500	105.471900	1242.709000	324.835100
Probability	0.000000	0.000000	0.000000	0.000000
Observation	2,771	2,771	2,771	2,771
Corr. With NEX	–	0.0567	0.4182	0.2665

Source: author's compilation.

Since the data used in the study are time series, it is necessary to determine whether the Series is stationary. When a non-stationary Series are analysed, a spurious regression problem arises, and the determined model coefficients become unreliable. For this purpose, the stationarity of the variables was tested by applying the Augmented Dickey-Fuller (ADF) unit root test developed by Dickey and Fuller (1979). ADF Unit Root Test results of the variables included in the study are given in Table 2.

Table 2. Results of Unit Root Test

Variables	Augmented Dickey-Fuller (ADF) Test				Stationary Level
	intercept		trend and intercept		
	level	difference	level	difference	
NEX	−1.651529	−11.438990*	−1.926352	−11.453030*	I(1)
WTI OIL	−1.045368	−9.730139*	−1.024798	−9.725164*	I(1)
COAL	−1.377435	−10.032730*	−1.909153	−10.057670*	I(1)
NGAS	−2.215086	−23.049810*	−2.167818	−23.053340*	I(1)

* Indicates statistical respective significance at the 1 percent level.

Source: author's compilation.

3. Research methodology

We used an econometric framework in three steps. We first carried out the Johansen co-integration test (because the variables were stationary at the first difference) to determine whether there is a long-term relationship between polluting energy resources and sustainable energy stock prices. As a second step, the Modified Least Squares (FMOLS) regression method was used to see the effect ratio of polluted energy sources on sustainable energy stock faults. This method is a parametric correction method that takes into account the correlation and endogeneity problems in the variables. It also allows us to check the robustness of the long-term predictions obtained from the Johansen co-integration test and to see the effect levels. As a third step, the causality relationship between the variables was examined with the Granger causality test based on the Vector Error Correction Model. The Granger causality test was chosen because this test determines which variables move first before following other variables.

3.1. Co-integration test

The co-integration test shows whether the variables act together in the long run. If the stationarity levels of the variables are the same, we tested whether they have a long-term relationship. The Johansen co-integration test, developed by Johansen (1988) and Johansen and Juselius (1990), tests the existence of a long-term equilibrium relationship between variables. This test is based on the vector autoregression model (VAR) analysis developed by Sims (1980). The VAR model is shown as follows (Sims, 1980; Brooks, 2008).

$$y_t = \beta_1 y_{(t-1)} + \beta_2 y_{(t-2)} + \dots + \beta_3 y_{(t-3)} + u_t \quad (1)$$

where y_t is the $n \times 1$ vector of $I(1)$ variables, and u_t is the white noise vector of the residuals. The above VAR model needs to be converted to an error correction model (VECM) to use the Johansen Test. Since this transformation is done, the VECM model can be written as follows:

$$\Delta y_t = \Pi y_{t-k} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \dots + \Gamma_{k-1} \Delta y_{t-(k-1)} + u_t \quad (2)$$

where

$$\Pi = \left(\sum_{i=1}^k \beta_i \right) - I_g \quad \text{and} \quad \Gamma_i = \left(\sum_{j=1}^i \beta_j \right) - I_g \quad (3)$$

where $\Pi y - (t - k)$ is the error correction, where $\Pi = \alpha \times \beta'$; The components of the matrix α are short-term correction parameters for long-term relationships which are implemented in the matrix β' .

Johansen's co-integration test statistic is based on two likelihood ratio tests of at most cointegrating relationships among variables and is based on trace statistic and eigenvalues, respectively. Trace test statistics investigate the co-integration relationship as r , and the maximum eigenvalue test statistics investigate the co-integration relationship as $r + 1$ (Johansen, 1990; Sims, 1980; Brooks, 2008; Shahbaz, 2009).

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^g \ln(1 - \hat{\lambda}_i) \quad (4)$$

$$\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \quad (5)$$

The calculated test statistics values are compared with the asymptotic critical values developed by Johansen-Juselius. If the test statistic value exceeds the critical value, then the null hypothesis of no co-integration is rejected. Therefore, it is concluded that there is a long-run equilibrium relationship.

3.2. Co-integration regression test

The traditional co-integration methods used to reveal the long-term relationships between variables in time series analysis have been replaced by the fully modified ordinary least squares (FMOLS) method developed by Phillips and Hansen (1990) due to the internal problem that arises in the estimation process and the inability to interpret the long-term coefficients obtained. The FMOLS estimation method is a semi-parametric correction method that considers the

correlation and internality problems arising from the co-integration relationship between the variables (Shahbaz, 2009; Priyankara, 2018). In addition, this method is also used to find the robustness of the predictions of traditional co-integration methods (Johansen, 1988).

The correlation and endogeneity problems in the variables often cause deviations in the OLS estimates from the time series regressions. The analyses use completely modified OLS methods to account for these issues. These methods are widely used to estimate variables' co-integration coefficients and adjust asymptotic internality and serial correlations (Chun et al., 2022; Shahbaz, 2009; Philips 1990; Priyankara, 2018).

This method yields consistent parameters even with small sample sizes, overcomes the problems of endogeneity, serial correlation, omission of variable bias, and measurement errors, and allows heterogeneity in long-term parameters (Shahbaz, 2009; Priyankara, 2018). The FMOLS co-integration method, just like traditional co-integration methods, is based on the condition that the variables used are stationary in difference. However, the possibility of interpreting the obtained coefficients offers a significant advantage.

The FMOLS first modifies the variables and estimates directly to eliminate the existing nuisance parameters. Assume an $n + 1$ – dimensional time series vector process (y_t, x_t') with the cointegrating equation.

$$y_t = x_t' \beta + D_t' \gamma + v_{1t} \quad (6)$$

where $D_t = (D_{1t}', D_{2t}')'$ are deterministic trend regressors, and the n stochastic regressors x_t are governed by the system of equations:

$$x_t = \Gamma_{21}' D_{1t} + \Gamma_{22}' D_{2t} + \varepsilon_{2t} \quad (7)$$

$$\Delta \varepsilon_{2t} = v_{2t} \quad (8)$$

Let $\hat{v}_{1t}$ be the residuals obtained after estimating equation (6). The $\hat{v}_{2t}$ may be obtained indirectly as $\hat{v}_{2t} = \Delta \hat{v}_{2t}$ from the level regression equation (7) or directly from the difference regressions:

$$\Delta x_t = \hat{\Gamma}_{21}' \Delta D_{1t} + \hat{\Gamma}_{22}' \Delta D_{2t} + \hat{v}_{2t} \quad (9)$$

Let $\hat{\Omega}$ and $\hat{\Lambda}$ be the long-run covariance matrices computed using the residuals $\hat{v}_t = (\hat{v}_{1t}, \hat{v}_{2t})'$. The modified data can then be defined as:

$$y_1' = y_t - \hat{\omega}_{12} \hat{\Omega}_{22}^{-1} \hat{v}_2 \quad (10)$$

And an estimated bias correction term of

$$\hat{\lambda}_{12}^+ = \hat{\lambda}_{12} - \hat{\omega}_{12} \hat{\Omega}_{22}^{-1} \hat{\Lambda}_{22} \quad (11)$$

The FMOLS estimator is expressed as follows:

$$\hat{\theta}_{FMOLS} = \begin{bmatrix} \hat{\beta} \\ \hat{\gamma}_1 \end{bmatrix} = \left(\sum_{t=2}^T Z_t Z_t' \right)^{-1} \left(\sum_{t=2}^T Z_t y_t^+ - T \begin{bmatrix} \hat{\lambda}_{12}^{+'} \\ 0 \end{bmatrix} \right) \quad (12)$$

y_t^+ and $\hat{\lambda}_{12}^+$ are the endogeneity and series correlation correction terms, respectively. The FMOLS estimator is asymptotically neutral and has an asymptotically normal distribution (Shahbaz, 2009; Apergis, Payne, 2014; Bashier, Siam, 2014; Priyankara, 2018).

3.3. Causality test

According to Engle and Granger (1987), if there is co-integration between the variables, it is possible to discuss at least a unidirectional causality relationship between them. The fact that the variables are stationary in their first difference and their integration degree is I(1) enables the vector error correction model (VECM) to be used for a causality analysis. To determine the direction of possible causality in the VAR model, error correction terms (ECT) should be included in the VECM model, where each variable is used as an independent variable. The vector error correction model is shown as follows (Brooks, 2008):

$$\Delta Y_t = \alpha_1 + \sum_{i=1}^p \beta_{1i} \Delta X_{t-i} + \sum_{i=1}^p \gamma_{1i} \Delta Y_{t-i} + \phi ECM_{t-1} + u_{1t} \quad (13)$$

$$\Delta X_t = \alpha_2 + \sum_{i=1}^p \beta_{2i} \Delta X_{t-i} + \sum_{i=1}^p \gamma_{2i} \Delta Y_{t-i} + \phi ECM_{t-1} + u_{2t} \quad (14)$$

In the model, the ECM represents the error correction term. Therefore, the coefficient before the error correction term is expected to be negative, between zero and minus one, and statistically significant. In this case, it is stated that there will be a long-run causality relationship between the variables. At the same time, the negative value and statistical significance of the ECM coefficient show that the short-term deviations between the variables disappear in the long term, and the variables come to equilibrium together in the long term.

In the model, p indicates the lag length, and u_{1t} and u_{2t} error terms are supposed to be white noise, distributed with null average and constant variance, and whose common variance is null. Equation (13) indicates the causality from X to Y, and equation (14) indicates the causality from Y to X. H0 hypothesis in equation (13); If $\beta_{1i} = 0$, X is not the cause of Y, hypothesis H1;

If $\beta_{1i} \neq 0$, X is the cause of Y. H0 hypothesis in equation (14); If $\gamma_{2i} = 0$, Y is not the cause of X, hypothesis H1; If $\gamma_{2i} \neq 0$, Y is the cause of X.

In equation (13), the dependent variable is first included in the model with the appropriate lag number. Then, the other variable is included in the model with the same lag number. There are error square sums of these models. Then, the F statistic developed by Wald (the Wald test) is calculated (Gujarati, 2001).

$$F_{calc} = \frac{(ESS_r - ESS_{ur}) / m}{ESS_{ur} / (n - k)} \quad (15)$$

where ESS_r is the sum of the squares of the error terms in the constrained relationship, ESS_{ur} is the sum of the squares of the error terms in the unconstrained relationship, m is the number of lagged variables left out, n ; the sample size, and k the number of parameters estimated in the unconstrained regression.

The value of F_{calc} is compared with the value of the F-table at a chosen significance level with degrees of freedom ($m; n - k$). If the value of F-calc is greater than the value of the F-table, the null hypothesis is rejected. If it is small, the null hypothesis is accepted.

3.4. Empirical models

The co-integration regression model was used to determine how polluting energy sources affect the renewable energy stock price index in the long run. The model equation established for this purpose is as follows.

$$NEX = \alpha_7 + \alpha_{71}WTIOIL + \alpha_{72}COAL + \alpha_{73}NGAS + \varepsilon_{7t} \quad (16)$$

The causal relationship and the direction of the relationship between renewable energy stock prices and polluting energy resource prices were investigated with the Vector Error Correction Model (VECM) proposed by Engle and Granger (1987). According to the VECM model, the changes in the dependent variable, the changes in the explanatory variables, and the error correction coefficient as a lagged function were created as follows.

$$\Delta NEX_t = \alpha_1 + \sum_{i=1}^p \beta_{1i} \Delta NEX_{t-i} + \sum_{i=1}^p \gamma_{1i} \Delta WTIOIL_{t-i} + \psi_1 ECM_{t-1} + \varepsilon_{1t} \quad (17)$$

$$\Delta WTIOIL_t = \alpha_2 + \sum_{i=1}^p \beta_{2i} \Delta WTIOIL_{t-i} + \sum_{i=1}^p \gamma_{2i} \Delta NEX_{t-i} + \psi_2 ECM_{t-1} + \varepsilon_{2t} \quad (18)$$

$$\Delta NEX_t = \alpha_3 + \sum_{i=1}^p \beta_{3i} \Delta NEX_{t-i} + \sum_{i=1}^p \gamma_{3i} \Delta COAL_{t-i} + \psi_3 ECM_{t-1} + \varepsilon_{3t} \quad (19)$$

$$\Delta COAL_t = \alpha_4 + \sum_{i=1}^p \beta_{4i} \Delta COAL_{t-i} + \sum_{i=1}^p \gamma_{4i} \Delta NEX_{t-i} + \psi_4 ECM_{t-1} + \varepsilon_{4t} \quad (20)$$

$$\Delta NEX_t = \alpha_5 + \sum_{i=1}^p \beta_{5i} \Delta NEX_{t-i} + \sum_{i=1}^p \gamma_{5i} \Delta NGAS_{t-i} + \psi_5 ECM_{t-1} + \varepsilon_{5t} \quad (21)$$

$$\Delta NGAS_t = \alpha_6 + \sum_{i=1}^p \beta_{6i} \Delta NGAS_{t-i} + \sum_{i=1}^p \gamma_{6i} \Delta NEX_{t-i} + \psi_6 ECM_{t-1} + \varepsilon_{6t} \quad (22)$$

4. Findings

4.1. Results of the co-integration test

The fact that the time series are stationary of the same order does not mean that they always move together in the long run. After determining that the Series are stationary at the first differences, the co-integration method developed by Johansen (1988) and Johansen and Juselius (1990) was used to confirm the H1 hypothesis, which expresses the existence of a long-term equilibrium relationship between the variables. To perform a co-integration test, an unconstrained Vector autoregressive (VAR) model should be estimated with the variables used in the model, and the lag number of the model should be determined. In determining the appropriate number of delays, LR (Likelihood Ratio), FPE (Final Prediction error), AIC (Akaike Information Criteria), SC (Schwarz), and HQ. (Hannan Quinn) criteria were used (Vide Table 3).

Table 3. Determining Appropriate Lag Length

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2,102.244	NA	5.42e-05	1.529034	1.537631	1.532140
1	26,086.120	56,274.41000	7.11e-14	-18.922770	-18.879790	-18.907240
2	26,167.020	161.27850	6.79e-14	-18.969890	-18.892520*	-18.941940*
3	26,187.400	40.57200	6.76e-14	-18.973070	-18.861310	-18.932700
4	26,206.340	37.64583	6.75e-14	-18.975200	-18.829060	-18.922410
5	26,221.400	29.88104	6.75e-14	-18.974520	-18.793980	-18.909300
6	26,233.950	24.86552	6.77e-14	-18.972010	-18.757090	-18.894370
7	26,259.600	50.77386	6.72e-14	-18.979020	-18.729710	-18.888960
8	26,280.400	41.09781*	6.70e-14*	-18.982510*	-18.698800	-18.880020

* Indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at the 5% level) FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information, HQ: Hannan- Quinn information criterion.

Source: authors' compilation.

The estimated VAR model's appropriate lag length is two, based on the SC criterion. The position of the AR characteristic polynomial inverse roots within the unit circle was examined to see whether the VAR model estimated for two lag lengths contains a unit root. It is clear from Figure 2 that all the inverse roots of the AR characteristic polynomial lie within the unit circle. The fact that the inverse roots are within the unit circle revealed that the predicted model exhibited a stationary structure.

Johansen's co-integration test was used to determine the existence of a long-term relationship between the renewable energy stock index and polluting energy resource prices. The linear intercept and trend model was determined as the most appropriate in the co-integration test performed with the determined lag length. The Model's results are given in Table 4.

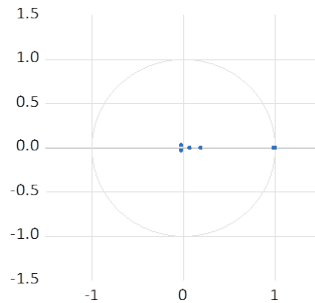


Figure 2. Inverse roots of AR characteristic polynomial

Source: authors' compilation.

Table 4. Co-integration test results

Hypothesis	Trace Statistic	0.05 Critical Value	Prob.**
$r = 0^*$	64.635200	63.87610	0.0431
$r \leq 1$	27.454340	42.91525	0.6546
$r \leq 2$	13.582480	25.87211	0.6918
$r \leq 3$	4.734141	12.51798	0.6349
Hypothesis	Max-Eigen Statistic	0.05 Critical Value	Prob.**
$r = 0^*$	37.180860	32.11832	0.0110
$r \leq 1$	13.871860	25.82321	0.7334
$r \leq 2$	8.848338	19.38704	0.7399
$r \leq 3$	4.734141	12.51798	0.6349

* Denotes rejection of the hypothesis at the 0.05 level.

** MacKinnon-Haug-Michelis (1999) p-values.

Source: authors' compilation.

When Table 4 is examined, according to the maximum eigenvalue and trace statistics obtained from the Johansen co-integration test, the H_0 hypothesis is rejected; the hypothesis that predicts at least one co-integration vector is accepted at the 5% significance level. According to these results, it is consistent with some studies in the literature (Charemza, Deaman, 1993; Managi, Okomoto, 2013; Farid et al., 2023) that there is a long-term equilibrium relationship between the renewable energy stock price index and polluting energy resource prices during the analysed period. Afterward, the first cointegrating vector on NEX normalised cointegrating coefficients was estimated, as reported in Table 5.

Table 5. Normalised cointegrating coefficients

Variables	Coefficient	Standard error	t-Statistics
WTI OIL	-0.065310	0.30183	0.21638
COAL	1.734591	0.31179	5.56333*
NGAS	-2.532706	0.40327	6.28042*
@TREND	-0.000791	0.00012	6.59166*

* Indicates statistical respective significance at the 1 percent level.

Source: authors' compilation.

The normalised equation was estimated as below:

$$\text{NEX} = 0.065310\text{WTIOIL} - 1.734591\text{COAL} + 2.532706\text{NGAS} + 0.000791\text{@TREND}$$

Normalised Cointegrating Coefficients reveal the long-run relationship between polluting energy sources and the renewable energy stock index. According to the normalised equation, it is seen that there is a positive relationship between oil prices and the renewable energy stock index in the long run, but this relationship is not statistically significant. A significant negative relationship exists between the renewable energy stock index and coal prices in the long run. In addition, in the analysis, it has been determined that there is a significant positive relationship between natural gas prices and the renewable energy stock index in the long run. Before concluding the long-run coefficients from the Johansen co-integration test, the analysis was repeated to account for the robustness of the long-run parameters by re-estimating the coefficients via FMOLS.

4.2. Results of FMOLS

Testing the sensitivity of the long-term parameters obtained from the Johansen co-integration test is essential. In the study, equation (8) was re-estimated using the FMOLS test developed by Phillips and Hansen (Philips and Hansen, 1990) to find the robustness of the predictions. The estimation results are presented in Table 6.

Long-term coefficients obtained from the FMOLS regression and Johansen co-integration tests have the same effect on the renewable energy stock index. R^2 and adjusted R^2 in the FMOLS regression model show that changes in polluting energy sources explain about 72% of the changes in the renewable stock index.

Table 6. Result of the FMOLS Regression

Variables	Coefficient	Standard error	t-Statistics	Probability
WTI OIL	0.280722	0.054004	5.198187	0.0000
COAL	-0.455122	0.055671	-8.175211	0.0000
NGAS	0.522726	0.071519	7.308862	0.0000
C	4.928337	0.198575	24.818520	0.0000
@TREND	0.000498	2.11E-05	23.564900	0.0000
R-squared	0.716673		Adjusted R-squared	0.716263

Source: authors' compilation.

The FMOLS regression equation was estimated as follows.

$$\text{NEX} = 4.928337 + 0.280722\text{WTIOIL} - 0.455122\text{COAL} + 0.522726 \times \text{NGAS} + 0.000498\text{@TREND}$$

When the FMOLS regression test results in Table 6 are examined, it is seen that there is a significant and positive relationship between WTI OIL and Natural Gas prices and the energy stock price index in the long run. The results prove the correctness of the H2 and H4 hypotheses. While a 1% increase in WTI OIL price causes an increase in the energy stock price index by 0.28%, a 1% increase in the NGAS price causes the energy stock price index to increase by 0.52%. In addition, it was determined that there is a significant and negative relationship between COAL prices and the renewable energy stock price index. This result shows that the H3 hypothesis is not valid. A 1% increase in COAL prices causes a 0.45% decrease in the energy stock price index.

4.3. Results of the causality test

Although the co-integration analysis shows a long-term relationship between the variables, it does not provide any information about the direction of causality. The validity of the H5, H6, and H7 hypotheses, which state that there is a causal relationship between the renewable energy stock price index and the polluting energy resource prices, and the direction of the relationship were investigated with the Granger causality test based on the Vector Error Correction Model (VECM) proposed by Engle and Granger (Sims, 1980). The causality test results are presented in Table 7.

Table 7. Results of the Granger Causality Test

Hypothesis	X2 Statistic	Probability	Direction of Causality
WTI OIL does not Granger cause NEX	3.452555	0.1779	WTIOIL $\leftarrow$ NEX
NEX does not Granger cause WTI OIL	14.063190	0.0009	
COAL does not Granger cause NEX	8.852605	0.0120	COAL $\rightarrow$ NEX
NEX does not Granger cause COAL	1.116693	0.5722	
NGAS does not Granger cause NEX	4.819777	0.0898	NGAS $\rightarrow$ NEX
NEX does not Granger cause NGAS	1.118268	0.5717	

Source: authors' compilation.

When Table 7 is examined, the null hypothesis that WTI OIL prices do not have Granger causality on the renewable energy stock price index cannot be rejected. However, the null hypothesis that the renewable energy stock price index has no Granger causality on WTI OIL prices is rejected at the 1% significance level. The Granger causality test results show a unidirectional causality relationship between the renewable energy stock price index and the WTI OIL prices. The causality test results determined a unidirectional causality relationship between coal prices and the renewable energy stock price index. Likewise, a unidirectional causality relationship was found between natural gas prices and the renewable energy stock price index.

Discussion and conclusions

Consistent with the findings of studies by Managi et al. (2013), Kocaarslan and Soytaş (2019), and Fu et al. (2022), we have shown that polluting energy sources and renewable energy stocks have a long-term co-integration relationship. Our other findings reveal that the increase

in oil prices positively affects the renewable stock index relationship. This is consistent with the results obtained by Jiang and Liu (2021), Kumar et al. (2012), Managi and Okimoto (2013), Usman (2023), Geng et al. (2021), Umar et al. (2022), Özkan (2023) and Sahu et al. (2022). This can be explained by the investors' tendency to invest in the renewable energy stock price index due to the expectation that the search for new energy sources will increase with oil price increases. Also, consistent with the findings of Chun et al. (2022), we find that coal prices significantly and negatively affect the renewable stock index, but the effect is weak. We believe that there is no meaningful explanation for other polluting energy sources to be positive and coal to be negative (Koaarslan, Soytaş, 2019; Adom et al., 2015). Similarly to studies by Jiang and Liu (2021), Sahu et al. (2022), and Chun et al. (2022), we show that natural gas prices significantly and positively affect the renewable stock index, but the effect is a weak relationship. When the effect rates are compared, it can be seen that natural gas prices affect stock prices more than oil prices. This situation is considered because of the prominence of natural gas consumption due to the Russia-Ukraine war in the examined period.

Finally, similarly to some studies by Jiang and Liu (2021), Henriques and Sadorsky (2008), Kumar et al. (2012), Pham (2019), and Sahu et al. (2022), we show that the causality test results reveal a short-term relationship between the renewable stock index and oil prices. Moreover, as reported by Reboredo et al. (2017), we find a unidirectional causality relationship between the renewable energy stock price index and WTI OIL prices. In contrast, studies by Henriques and Sadorsky (2008) and Kumar et al. (2012) find a causal relationship between WTI OIL prices and the renewable energy stock price index. The reason why these studies differ from the results of our study is that the analysis periods vary. In addition, a one-way causality relationship was found between coal prices and the renewable energy stock price index and between natural gas prices and the renewable energy stock price index.

The study's findings provide valuable insights for energy policy and investment strategies, particularly for renewable and dirty energy market participants. The findings show that energy stocks are not independent of dirty energy prices. This means that the green initiatives and climate actions taken by policymakers worldwide are insufficient to strengthen renewable energy investments in financial markets. Therefore, governments and policymakers worldwide should emphasise promoting green initiatives such as subsidising renewable energy technologies, applying tax reductions on renewable energy profits, and encouraging employment in the renewable energy sector. The findings also provide significant insights into asset allocation and risk management. For example, considering the connections between the two markets, there is no diversification advantage between renewable and dirty

energy markets. It is not recommended for portfolio investors and risk managers to use dirty energy sources and renewable energy stocks for portfolio diversification. Moreover, the results indicate that renewable energy stocks do not offer a safe haven for investments in dirty energy resources.

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