ANALYSIS OF THE RELATIVE PERFORMANCE OF CLEAN ENERGY STOCK INDICES

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ABSTRACT

This study examines the dynamic relationships between return differentials of traditional and clean energy stock indices. The analysis employs the nonlinear autoregressive distributed lag model (NARDL) using return differentials between the Nasdaq Composite Index and the Nasdaq Clean Edge Green Energy Index, as well as between the Morgan Stanley Capital International All Country World Index (MSCI ACWI) and the S&P Global Clean Energy Index. Monthly data spanning from January 2014 to January 2024 are utilised. Findings illustrate the impacts of crude oil prices, average temperatures, gold prices and real risk-free rates on return differentials. For model selection at a significance level of 5%, a model including trend and intercept terms was preferred using the stepwise regression criterion. Diagnostic tests confirm the adequacy of model specifications and validate that error term assumptions were not violated. According to NARDL model results, a statistically significant long-term cointegration relationship is found between relative performance of clean energy index return and average temperatures, crude oil prices, real risk-free rates and gold prices. The Wald test reveals asymmetric relationships between crude oil prices and return differentials in both models. According to the model results, an increase in crude oil prices positively affects the returns of the clean energy index, whereas a decrease in crude oil prices reduces the relative performance of the clean energy index. Positive deviations in average temperatures decrease the relative performance of the clean energy index, whereas negative deviations increase its relative performance. Moreover, an increase in gold prices enhances the relative performance of the clean energy index. Robustness checks of the methodology were conducted, confirming the stability of the coefficients. The CUSUM test results also indicate that the coefficients maintain their stability in the long term.

Keywords: clean energy index, NARDL, co-integration, relative performance.

1 INTRODUCTION

Climate change around the world poses a threat to global markets and natural environments. The increase in global warming in recent years, the increase in the economic activities of countries, problems with oil supply, and the macroeconomic and financial risks caused by the increase in oil prices have become indicators that turning to clean energy has become a necessity. It is noteworthy that the sensitivity of both society and governments has increased with global warming caused by the increase in greenhouse gas emissions in the world and the fact that this situation leads to long-term changes in weather conditions. The decrease in energy demand that started with the 2019 COVID pandemic, the subsequent recovery in the markets and the fluctuation in energy prices, and the continuation of price uncertainty caused by the Russia–Ukraine war that started in 2022, have affected countries from different perspectives and triggered an increase in interest in renewable energy sources.

The increase in oil prices may cause deteriorations in macroeconomic indicators. This situation becomes even more dire, especially for net energy importing countries. Increasing oil prices will cause an increase in production costs, resulting in a decrease in household income levels in an inflationary environment and deterioration of economic stability [1]. As a result, increasingly depleted and non-renewable energy resources cause uncertainty and destabilisation in country economies.

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With the increasing transition to renewable energy, each country's budget balance will be affected differently, directly related to its own conjuncture. In particular, the revenues of oil-exporting countries will decrease and this will lead to deteriorations in budget balances. Countries' ability to reduce their financial risks in the transition from exhaustible energy sources to renewable energy sources and to continue this process without compromising economic growth depends on taking rapid action in the field of renewable energy. It is especially important for countries with high production volumes that direct the world economy and developing countries that need financing resources for renewable energy investments, which still have relatively high costs, to cooperate in this process.

Although today, the energy demand that increases with the economic growth of countries is largely met by fossil fuels, sensitive countries that participate in international agreements to increase the use of renewable energy will contribute to reducing carbon emissions in the world, with the decrease in renewable energy investment costs over time.

Risks created by uncertainty in energy prices and supply affect economies not only on a macro scale, but also on a micro basis by reducing the profitability of companies. In financial markets, where uncertainty and risk perception have a positive interaction with each other, this process is an element that will cause portfolio investors to experience return losses and therefore increase sales pressure in the market [2]. In this context, it is important for investors to have more information about financial assets based on renewable and clean energy so that they can make more accurate decisions in the portfolio management process.

The increase in the number of businesses that want to ensure a sustainable ecological order and nature-sensitive investments globally has increased the desire of investors who are concerned about the future of the world to invest in businesses that support sustainable practices. However, both developed and developing countries, trying to control the recently increasing inflation, have started to encourage green energy investments in order to purify their economies from the effects of energy prices that create inflationary pressure, and this has caused green financial investments to become more attractive for portfolio investors.

The relationship of green stocks, investment instruments or clean stock market indices with macroeconomic variables has been examined in various studies, but it has been noticed that there is a gap in investigating the relationship between the return difference between the renewable energy index and the traditional stock market index and macroeconomic variables. The second part of the study includes a literature study examining the relationships between portfolio investments in the field of renewable energy and macroeconomic indicators. The third section includes the data used in the study and the methodology used to analysed the impact of macroeconomic indicators on the difference between the renewable energy index and the traditional stock market index. While the fourth section includes the analysis results and comments, the last section includes the results and recommendations of the study.

2 LEGISLATION

The idea of 'net zero' emerged from research in the late 2000s that examined how the atmosphere, oceans and carbon cycle respond to CO_2 emissions [3]. These studies have shown that the only way to stop global warming is to reduce CO_2 emissions to net zero. The concept of net zero formed the basis of the Paris Agreement's goals. The agreement states that a balance should be achieved between 'anthropogenic emissions and greenhouse gas emissions in the second half of this century.' Many companies have pledged to reach net zero emissions by 2050. Such pledges are often made at a corporate level. Both governments and international agencies encourage businesses to contribute to a national or international net zero pledge. The International Energy Agency states that to reach net zero by 2050, $4 trillion per year in low-carbon fossil fuel substitutes will be needed worldwide [4]. On average,

Table 1: Clean energy regulations by country.

Regulation name	Target of the regulation	Year of regulation	Issuing institution
Renewable Energy Directive III	Set a target of 42.5% renewable energy share by 2030.	2023	European Commission
European Green Deal	A comprehensive strategy to combat climate change and promote sustainable energy transition At least 55% less net greenhouse gas emissions by 2030, compared to 1990 levels.	2023	European Commission
Inflation Reduction Act	Provides financial support for renewable energy investments and energy efficiency incentives.	2022	U.S. Congress
REPowerEU Plan	Increase the renewable energy target to 45% by 2030; reduce the EU's dependence on Russian fossil fuels.	2022	European Commission
Clean Energy Strategy	A strategy targeting a 50% reduction in carbon emissions and increasing renewable energy use by 2030.	2022	Japanese Government
Climate Change Act	Australia's greenhouse gas emissions reduction targets of a 43% reduction from 2005 levels by 2030 and net zero by 2050.	2022	Australian Federal Government
American Jobs Plan	Includes investments in clean energy infrastructure and energy efficiency improvements.	2021	U.S. Government
Energy Efficiency Directive	Aim for a 11.7% reduction in energy consumption by 2030.	2021	European Commission
Decarbonised Gas and Hydrogen Markets	Regulations for decarbonised gas markets and hydrogen markets.	2021	European Commission
Energy Efficiency Directive Update	Increase energy efficiency to meet 2030 targets.	2021	European Commission
European Climate Law	Aim to make the EU carbon neutral by 2050.	2021	European Commission
Fit for 55 Package	A set of regulations aiming to reduce carbon emissions by 55% by 2030 to meet the EU's climate targets.	2021	European Commission
500GW Nonfossil Fuel Target	Aims to generate 50% of its energy from renewable sources by 2030.	2021	India
New Energy Vehicle Industry Development Plan	Target 50% of vehicles sold by 2035 to be new energy vehicles.	2020	Government of the People's Republic of China

* The data in the table were compiled by the authors from the official websites of the relevant regulatory authorities and other official sources.

around 29% of companies in EU member states have set or achieved a net zero target, but these figures can vary significantly across different industries, countries and company sizes [5]. In this context, various international and national regulations have developed strategies aimed at achieving net zero emissions. These regulations are designed to promote the energy transition, reduce carbon emissions, and support investments in renewable energy. Table 1 presents a detailed overview of regulations that play a significant role in achieving these goals and cover policies from different regions. These regulations represent important steps both in international agreements and national laws and strategies.

3 LITERATURE

Portfolio managers' interest in green energy markets has been increasing over time, and with renewable energy initiatives to be implemented globally, the demand for green financial assets will likely increase further over time. There are studies in the literature that analyse clean energy investments using different perspectives and methods.

Kumar et al. [6] analysed the effects of oil and carbon prices on the stock prices of clean energy firms by estimating VAR model. According to the Granger causality test results, it was determined that the variation in the three indices of clean energy stocks was explained by past movements in oil prices, stock prices of high-tech companies and interest rates. Managi and Okimoto [7] examined the relationships among oil prices, clean energy stock prices, and technology stock prices and found a positive relationship between oil prices and clean energy prices after structural breaks. Ferrer et al. [8] in their study, where they examined the time and frequency dynamics of the connections between stock prices of US clean energy companies, crude oil prices and a number of important financial variables, they showed that most of the connection occurred in very short-term movements, while the long-term effect was less important. Additionally, a significant bidirectional relationship between clean energy and technology stock prices was found, especially in the short term. Sadorsky [9] used multivariate GARCH models to model conditional correlations and to analyse the volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies. In the study, where the dynamic conditional explanation model was found to be the most suitable model for the data, results were revealed showing that the stock prices of clean energy companies are more highly correlated with technology stock prices than with oil prices. Dutta [10] evaluated whether the variance in alternative energy stock returns could be explained by using the information content of the crude oil volatility index (OVX), which is an indicator of oil price uncertainty, it was revealed that clean energy stock returns are quite sensitive to OVX shocks. Geng et al. [11] analysed the dynamic effects of oil price changes on the stock returns of clean energy companies and concluded that there is a high level of interdependence between the returns of crude oil and the returns of clean energy companies. Maghyereh et al. [12] used the multivariate GARCH method to find the bidirectional return and risk transfer from oil and technology to the clean energy market and concluded that contagions are more evident in long time periods. Reboredo et al. [13] examined the co-movement and causality relationships between oil and renewable energy stock prices, and as a result of their analysis, they found that the dependence between oil and renewable energy returns was weak in the short term but strengthened in the long term.

Kocaarslan and Soytas [14] investigated the asymmetric connection between oil prices, interest rates and stock prices of clean energy/technology companies and revealed the asymmetric effects between variables by using the nonlinear autoregressive distributed lag (NARDL) model. The study shows that clean energy stock investments increase with speculative attacks due to rising oil prices in the short term, but that increasing oil prices have a negative effect on clean energy stock prices in the long term and this effect is asymmetric.

Avazkhodjaev et al. [15] examined the asymmetric effect of renewable energy production and clean energy prices on green economy stock prices with a non-linear ARDL approach and concluded that renewable energy production prices have a positive effect on green economy stock prices. However, it has been shown that negative shocks outweigh positive shocks in renewable energy production and clean energy. Zaghdoudi et al. [16] examined the asymmetric effects of oil price shocks on coal and renewable energy consumption in China in the long and short term. In the study using the FNARDL specification, it was concluded that there is a cointegration relationship between coal energy consumption, renewable energy consumption, oil price and economic growth, and that increases in oil prices cause an increase in renewable energy consumption in China in both the short and long term. Mishra and Acharya [17] investigated the asymmetric effect of oil prices on stock returns of renewable energy companies in India by applying panel NARDL. They concluded that in the long run, the oil price has an asymmetric effect on the stock returns of independent renewable product and service companies and that the market return is more volatile than the stock returns of renewable energy companies. Reboredo et.al. [18] used continuous and discrete wavelets to reveal the co-movement and causality between oil and renewable energy stock prices. They found that the dependence between oil and renewable energy returns is weak in the short term for the period 2006–2015, but gradually strengthens in the long term, especially for the period 2008–2012. Also, they found mixed evidence for causality from oil to renewable energy prices. Pham [19] investigated whether the relationship between oil price and clean energy stocks is homogeneous across sub-sectors of the clean energy stock market. As a result, it was found that the relationship between oil price and clean energy stocks varies greatly across sub-sectors of clean energy stocks, with biofuel and energy management stocks being the most dependent on oil prices. Dawar et al. [20] employed a quantile-based regression approach to examine the association between crude oil and renewable energy stock prices. In their study, which included crude oil prices (WTI market) and Wilderhill Energy Index, MAC Global Solar Index and S&P Global Clean Energy Index as variables, they examined the asymmetric effect of oil returns on clean energy stock returns under various market conditions and found that falling oil returns have a strong effect on index returns, while rising oil returns have a small effect. Elsayed et al. [21] use wavelet quantile correlation and cross quantilogram analysis, to examine the interrelationship between green bonds, clean energy, socially responsible stocks and variants of oil shocks. As a result, they concluded that the stocks used in the study showed protection against oil shocks in the medium to long term. Khalfaoui et.al. [22] employed a spillover and dependency network analysis to determine how much the US stock market returns are dependent on climate change-related risks by using green index, carbon price, general and climate uncertainty. The findings of the study revealed that the indices of clean energy and new energy innovation industry and climate policy uncertainty are the driving forces of the transmission spillover network, especially in extreme market scenarios, and the effects of green index, carbon price, general and climate uncertainty are found to be more pronounced in recession and boom markets. Li et al. [23] applied ARDL/NARDL model to assess whether the climate risks affect dirty and clean energy stock prices correlations by controlling for business cycles, funding liquidity, USD values, and oil market sentiments. Findings from the study demonstrate the strengthened potential of clean energy stocks to hedge against dirty energy stocks in the face of rising climate risks and increased fossil fuel price volatility.

4 METHODOLOGY AND DATA

In the study monthly data was used between the terms of 2014 January and 2024 January. In order to analyse the dynamics between the clean energy sector and the overall stock market performance, indices with similar characteristics were selected. While the S&P Global Clean Energy Index used in the study measures the performance of global clean energy companies, the MSCI ACWI includes companies with a wide range of sectoral diversity globally. The S&P Global Clean Energy Index is a major index that evaluates the performance of companies in the clean energy sector. This index covers companies that invest in and operate in clean energy globally. The index is weighted based on companies' contributions to clean energy and their market performance. The companies are evaluated on their areas of operation, financial performance, and adherence to sustainability standards. The MSCI ACWI index provides coverage of global markets, including companies from both developed and developing countries. The MSCI All Country World Index is a comprehensive global equity index that includes companies from 23 developed and 24 emerging markets. It covers a broad spectrum of large and mid-cap companies, representing about 85% of the global equity investment opportunities. Companies are selected based on market capitalisation, liquidity, sectoral distribution, and country representation. The index is weighted by market capitalisation and has broad coverage without focusing on a specific country or sector. Therefore, it is useful to evaluate the relative performance of the clean energy sector against the overall performance of the global market. Since both indices have global coverage, they are used in the comparison to understand how the clean energy sector is performing globally compared to the overall market performance. The Nasdaq Clean Edge Green Energy Index targets companies in the clean energy sector and tracks innovations, technologies and financial performance in this area. The index is evaluated based on companies' contributions to clean energy and their financial performance. To be included in the index, companies must meet specific financial criteria and engage in certain activities related to clean energy. With a special focus on the clean energy sector, it is an appropriate index to examine developments in this sector and the overall performance of companies in this area in more detail. The Nasdaq Composite Index includes all stocks traded on the Nasdaq exchange with technology and growth-oriented companies, providing a broad market representation. The index is weighted by market capitalisation, meaning companies with larger market values have a higher weight in the index. The composition of the index is determined by the market value and trading volume of the stocks. This index can be used to measure overall market trends and performance, providing a convenient reference point for comparing the performance of clean energy companies to the overall market. Since both indices focus on the technology and innovative sectors, they are used in the model as a suitable benchmark to see the performance of clean energy technologies compared to the overall technology sector. The use of these two different index groups together is useful for comparing clean energy companies with the general market and for better understanding the performance factors in the clean energy sector. The variables used in the model are listed below:

- $spreadnas_t$; data is calculated by subtracting the logarithmic return of the Nasdaq Clean Edge Green Energy Index from the logarithmic return of the Nasdaq Composite Index;
- $spreadspc_t$; data is calculated by subtracting the logarithmic return of the S&P Global Clean Energy Index from the logarithmic return of the MSCI ACWI;
- $ltmp_{\mathrm{t}}$; logarithm of New York average temperature;
- $lons_t$; logarithm of gold price per ounce;
- $lcop_t$; logarithmic crude oil prices;
- $realrf_t$; data is calculated by subtracting U.S. consumer price index rate from the yield of the 3 months U.S. Treasury Bill Rate.

The linear ARDL model introduced by Pesaran and Shin [24] and Pesaran et al. [25] was later developed by Shin et al. [26] to take into account asymmetric relationships and was introduced to the literature as the non-linear ARDL (NARDL) model. The NARDL approach is a modelling approach to detect nonlinear relationships by taking into account short- and long-term asymmetries between relevant variables. In this approach, the focus is on the short and long-term asymmetric relationship between variables and the effects of 'negative' and 'positive' changes in the explanatory variables on the dependent variable are determined.

The asymmetric cointegration regression used in the study which based on Schorderet [27] and Shin et al. [26] is defined as follows:

$$y = \beta^{+}x_t^{+} + \beta^{-}x_t^{-} + u_t \tag{1}$$

where β^{+} and β^{-} are the long-term parameters, x_t is the $k \times 1$ vector and is divided into the following elements.

$$x_t = x_0 + x_t^{+} + x_t^{-} \tag{2}$$

The partial sum processes of positive and negative changes in x_t^{+} ve x_t^{-}, x_t are shown as follows:

$$x_t^{+} = \sum_{j=1}^{t} \Delta x_j^{+} = \sum_{j=1}^{t} \max\left(\Delta x_j^{t}, 0\right) \, and \, x_t^{-} = \sum_{j=1}^{t} \Delta x_j^{-} = \sum_{j=1}^{t} \max\left(\Delta x_j^{t}, 0\right) \tag{3}$$

When eqn (1) is associated with the ARDL (p, q) model, the following asymmetric error correction model (AECM) is obtained.

$$\Delta y_t = \rho y_{t-1} + \theta^{+}x_{t-1}^{+} + \theta^{-}x_{t-1}^{-} + \sum_{j=1}^{p-1} \varphi \Delta y_{t-j} + \sum_{j=0}^{q} \left(\pi_j^{+} \Delta x_{t-j}^{+} + \pi_j^{-} \Delta x_{t-j}^{-}\right) + e_t$$
$$j = 1, \ldots., p \tag{4}$$

In eqn (4) $\theta^{+} = -\rho\beta^{+} \, and \, \theta^{-} = -\rho\beta^{-}, \pi_t^{+} = -\beta^{+}\varphi_i + \psi_{2i}, \pi_t^{-} = -\beta^{-}\varphi_i + \psi_{2i}$.

In eqns (3) and (4), 't' indicates the time, 'i' indicates the delay of the series, and 'j' indicates the period for which the cumulative total is taken. Although the NARDL method, which takes into account the asymmetric cointegration relationship, is not used when the variables are I(2), it allows cointegration analysis regardless of whether the explanatory variables are I(0) or I(1), as in the ARDL approach [26]. Therefore, in the first stage, stationarity analyses are performed for the variables in the model and the degree to which the variables are integrated is decided. After the stationarity tests, the following steps are briefly followed in the NARDL cointegration approach. First, eqn (4) is estimated by least squares.

Then, with the F test developed by Pesaran et al. [25] and Shin et al. [26], the null hypothesis of $\rho = \theta^{+} = \theta^{-} = 0$ for eqn (4) is tested, thus investigating whether there is a long-term relationship between the levels of the variables y_t, x_t^{+}, x_t^{-}. In the next stage, the Wald test is used to test whether there is long-term symmetry $\theta = \theta^{+} = \theta^{-}$ and short-term symmetry $\left[(1)\pi_i^{+} = \pi_i^{-} \; for \; all \; i = 1,2, \ldots, q \; or \; (2) \sum_{i=0}^{q} \pi_i^{+} = \sum_{i=0}^{q} \pi_i^{-}\right]$.

If it is decided that there is no symmetry, eqn (4) is used in the last stage and the asymmetric dynamic multiplier effects of a unit change in x_t^{+} and x_t^{-} on the dependent variable y_t are obtained using the following equations:

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial y_{t-j}}{\partial x_t^+}, \quad m_h^- = \sum_{j=0}^{h} \frac{\partial y_{t-j}}{\partial x_t^-}, \quad h = 0,1,2,\ldots$$

5 NARDL MODEL RESULTS

In this study, variables influencing the relative performance between Nasdaq Composite Index and Nasdaq Clean Edge Green Energy Index, as well as between MSCI ACWI and S&P Global Clean Energy Index, were analysed. In both models, the dependent variable was the return differential between traditional stock indices and clean energy stock indices.

In the first model, the dependent variable was the return differential between S&P Global Clean Energy Index and MSCI ACWI (All Country World Index); S&P Global Clean Energy Index measures the performance of global clean energy companies. MSCI ACWI includes companies with diverse sectoral representation globally. Due to their global coverage, both indices were used for comparative analysis to understand how the clean energy sector performs globally relative to the overall market.

In the second model, the dependent variable was the return differential between Nasdaq Clean Edge Green Energy Index and Nasdaq Composite Index; Nasdaq Clean Edge Green Energy Index includes companies operating in the clean energy sector. Nasdaq Composite Index generally covers technology and growth-focused companies. Both indices focus on technology and innovative sectors, making them suitable benchmarks for comparing the performance of clean energy technologies against the overall technology sector.

To measure the relative performance of S&P Global Clean Energy Index and Nasdaq Clean Edge Green Energy Index against their traditional counterparts, explanatory variables such as average temperatures, crude oil prices, real risk-free rates, and gold prices were used in the NARDL (nonlinear autoregressive distributed lag) model. The study employed various econometric tests and model selection criteria. Except for the average temperature variable, it was concluded that all series were non-stationary at the level but stationary at the first difference based on ADF (augmented Dickey–Fuller), PP (Phillips–Perron), and KPSS (Kwiatkowski–Phillips–Schmidt–Shin) tests. The NARDL model utilised a maximum of 12 lags, and models with trend and intercept terms were selected using stepwise regression criteria.

According to the NARDL model results (via Pesaran test), a statistically significant long-term cointegration relationship was found between the relative performance of companies in the clean energy index and average temperatures, crude oil prices, real risk-free rates, and gold prices. This indicates the presence of long-term equilibrium relationships in the market.

Diagnostic tests (Jarque–Bera, Harvey Heteroskedasticity, ARCH, Ramsey RESET, Breusch–Godfrey LM tests) provided valid results, confirming the appropriateness of the model and that error terms satisfied necessary assumptions presented in Table 2. Both models exhibited white noise error terms with no autocorrelation, constant variance, and normal

Table 2: NARDL diagnostic test results.

Test type	Model 1		Model 2	
	Test stat.	**Prob.**	**Test stat.**	**Prob.**
Jarque–Bera	5.134	0.077	0.007	0.997
Heteroskedasticity Breusch–Pagan–Godfrey F	0.919	0.626	0.840	0.739
Breusch–Godfrey serial correlation LM F	0.296	0.589	0.631	0.431
Ramsey RESET Test F	0.577	0.452	0.162	0.689
Heteroskedasticity Harvey F	0.947	0.585	1.089	0.387
Heteroskedasticity ARCH F	0.018	0.894	1.374	0.244

exhibited white noise error terms with no autocorrelation, constant variance, and normal distribution based on diagnostic tests. Model specification was deemed appropriate according to the Ramsey RESET test. Those results lead us to conclude that we have obtained efficient, consistent, and unbiased estimators.

The CUSUM graphs demonstrating the long-term stability of the coefficients obtained in both models are presented in Figs 1 and 2.

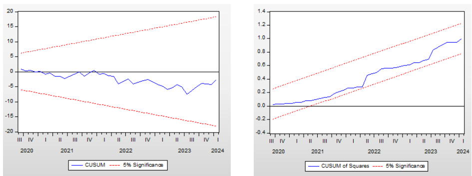

Figure 1: CUSUM Test of Model 1.

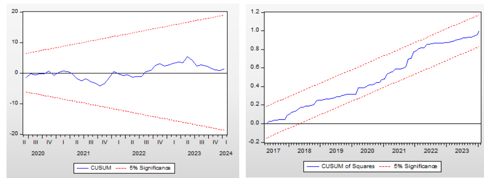

Figure 2: CUSUM Test of Model 2.

Wald tests in both models identified asymmetric relationships between crude oil prices and relative performance of the clean energy index. However, average temperatures were found to have a symmetric effect on the relative performance of the clean energy index in both models.

In practice, the most commonly used methods to test the stationarity level of series are Dickey and Fuller [28], Extended Dickey and Fuller (ADF) [29], Phillips and Perron (PP) [30] and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) [31] tests. In the ADF and PP test basic hypothesis, it is claimed that there is a unit root as opposed to the alternative hypothesis that the series is stationary.

It was found that the average temperature variable is stationary at the level with a significance level of 1% according to the PP and KPSS tests, whereas it is not stationary at the level according to the ADF test but stationary at the first difference. Thus, except for the temperature variable, it was determined that all other variables are non-stationary at the level but stationary at the first difference as presented Table 3.

Table 3: ADF, PP and KPSS unit root test results.

	PP	**Prob.**	**ADF**	**Prob.**	**KPSS**
$spreadnas_t$	−9,215	0.000	−8,994	0.000	0,174
$spreadspc_t$	−8,244	0.000	−8,250	0.000	0,146
$lons_t$	−0.569	0.872	−0.633	0.858	1.162
$ltmp_t$	−4.220	0.001	−2.534	0.110	0.064
$lcop_t$	−2.466	0.126	−2.440	0.133	0.253
$realrf_t$	−0.224	0.931	−1.129	0.703	0.588
$\Delta spreadnas_t$	−52,277	0.001	−10,725	0.000	0,203
$\Delta spreadspc_t$	−40,621	0.000	−10,085	0.000	0,180
$\Delta lons_t$	−11.860	0.000	−11.827	0.000	0.099
$\Delta ltmp_t$	−5.888	0.000	−12.168	0.000	0.060
$\Delta lcop_t$	−9.144	0.000	−8.433	0.000	0.164
$\Delta realrf_t$	−6.688	0.000	−3.108	0.029	0.202

* According to KPSS (1992); 1%; 0.739 5%; 0.463 10%; 0.347 null hypothesis indicates the absence of a unit root at the significance level.

Table 4 includes the linear ARDL model estimation results for Nasdaq and S&P. For both difference series, F-values are (2.51) and (1.98) at 1% and 5% levels, respectively. Pesaran et al. [25], the null hypothesis that there is no cointegration between the dependent variables and the estimators cannot be rejected. One of the possible reasons for the absence of a long-run cointegration relationship in the estimated ARDL models may be due to the lack of linearity among the variables. Granger and Yoon [32] developed the term hidden cointegration and suggested that hidden cointegration exists between the series when the positive and negative elements of two time series are cointegrated with each other. Shin et al.'s [26] NARDL model allows examining the short-term and long-term response and finding hidden cointegration between variables.

Table 4: ARDL and NARDL cointegration test results.

Model 1	Model 2	1%		5%		10%	
		I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
Nasdaq FARDL = 2.51	S&P FARDL = 1.92	4.89	6.16	3.67	4.84	3.16	4.23
Nasdaq FNARDL = 31.69	S&P NARDL = 24.83	3.6	4.9	2.87	4	2.53	3.59

Table 5 shows the long-term asymmetry Wald test results of the Nasdaq and S&P return difference series. According to the Wald test statistics (120.8517 and 62.453) for Nasdaq and S&P respectively, the null hypothesis (H_0) claiming a long-term symmetric relationship between crude oil prices and the dependent variable has been rejected. Thus, it is accepted that crude oil prices have an asymmetric relationship with Nasdaq and S&P in the long term. Similarly, based on the Wald test statistics results for average temperature (2.725748 and −0.087231) for Nasdaq and S&P respectively, the null hypothesis (H_0) claiming a long-term symmetric relationship for temperature has been accepted. Therefore, it was concluded that there is no asymmetric relationship between temperature and Nasdaq and S&P in the long term.

Table 5: Long run asymmetry Wald test results.

Model 1	$W_{LR,LCOP}$	120.851	0.000
	$W_{LR,LTMP}$	2.725748	0.106
Model 2	$W_{LR,LCOP}$	62.453	0.000
	$W_{LR,LTMP}$	0.087231	0.769

$$\Delta SPREADNAS_t = \mu + \alpha SPREADNAS_{t-1} + \gamma_1^- LTMP_{t-1}^- + \gamma_1^+ LTMP_{t-1}^+ + \vartheta LONS_{t-1} + \gamma_2^- LCOP_{t-1}^- + \gamma_2^+ LCOP_{t-1}^+ + \pi REALRF_{t-1} + \theta @TREND + \varepsilon_t \tag{5}$$

$$\Delta SPREADSPC_t = \mu + \alpha SPREADSPC_{t-1} + \gamma_1^- LTMP_{t-1}^- + \gamma_1^+ LTMP_{t-1}^+ + \vartheta LONS_{t-1} + \gamma_2^- LCOP_{t-1}^- + \gamma_2^+ LCOP_{t-1}^+ + \pi REALRF_{t-1} + \theta @TREND + \varepsilon_t \tag{6}$$

Eqns (5) and (6) display the positive and negative partial sums calculated using the disaggregation method. They test the existence of a long-term cointegration relationship between the dependent variables of Model 1 and Model 2, and the variables of crude oil price and average temperature, measuring the magnitude of positive and negative elements. Additionally, eqns (5) and (6) indicate the presence of asymmetries in both the short and long term, or solely in the long term or short term. The presence of long-term cointegration in this model is determined by testing the null hypothesis that the combined delayed level coefficients of the variables are all equal to zero.

The long-term coefficient findings of the NARDL model are presented in Table 6. It is observed that all coefficients, except for the trend variable, are significant. According to Model 1 findings, it has been concluded that a 1% decrease in average temperature will result in a 0.641% increase in relative clean energy performance. Furthermore, it has been determined that a 1% increase in average temperature will lead to a 0.468% decrease in relative clean energy performance. Low temperature generally creates a positive effect, while high temperature can negatively impact performance due to various reasons. These factors are crucial considerations in shaping the operational and financial strategies of clean energy companies. The absence of an asymmetric relationship between average temperature change and the relative performance of clean energy companies indicates that temperature increases or decreases have an equally effective impact in the clean energy sector. This suggests that temperature changes have balanced and symmetrical effects on clean energy production. The lack of an asymmetric relationship between temperature change and the performance of clean energy companies supports a stable environmental impact perception and planning capability within the sector. This underscores the importance for stakeholders in the sector to consider temperature changes when developing long-term strategies.

Table 6: NARDL long run coefficients.

Model 1: Nasdaq				**Model 2: S&P**			
Variable	**Coef.**	***t*-stat.**	**Prob.**	**Variable**	**Coef.**	***t*-stat.**	**Prob.**
$spreadnas_{t-1}$	−2.464	−14.133	0.000	$spreadspc_{t-1}$	−1.487	−12.451	0.000
$ltmp^{-}_{t-1}$	0.641	3.722	0.001	$ltmp^{-}_{t-1}$	0.598	2.877	0.006
$ltmp^{+}_{t-1}$	0.468	4.303	0.000	$ltmp^{+}_{t-1}$	0.561	4.270	0.000
$lons_{t-1}$	−0.511	−4.353	0.000	$lons_{t-1}$	−0.855	−5.622	0.000
$lcop^{-}_{t-1}$	−0.626	−8.067	0.000	$lcop^{-}_{t-1}$	−0.344	−4.994	0.000
$lcop^{+}_{t-1}$	−0.283	−4.323	0.000	$lcop^{+}_{t-1}$	−0.063	−1.054	0.297
$realrf_{t-1}$	0.033	4.717	0.000	$realrf_{t-1}$	−0.004	−0.55	0.585
$@trend$	0.002	0.217	0.830	$@trend$	−0.004	−0.423	0.675
C	2.485	3.174	0.003	C	5.311	5.348	0.000

*In Model 1, the return difference obtained by subtracting the Nasdaq Clean Edge Green Energy index return from the Nasdaq Composite index return was used as the dependent variable. In Model 2, the return difference obtained by subtracting the S&P clean energy index return from the MSCI AWCI index return was used. As independent variables in both models; Average temperature, crude oil prices, ounce gold price, real risk-free interest rate are included. In the model, the maximum number of lags is taken as 12. The General to specified method was used as the model selection criterion. In Model 1, all variables except trend are significant, while in Model 2, all variables except trend and real risk free are significant.

When crude oil prices decrease by 1%, relative clean energy performance decreases by 0.626%, whereas a 1% increase in oil prices leads to a 0.283% increase in performance. Clean energy sources are generally more expensive than fossil fuels. Therefore, a drop in oil prices makes clean energy less attractive, leading to a decrease in its performance. Thus, it is concluded that a potential negative shock in oil prices has a greater impact compared to a positive shock. Rising oil prices make clean energy sources more competitive, which in turn increases the performance of clean energy. The long-term coefficients confirm an asymmetric effect of oil prices on return differentials. A decrease in oil prices could enhance the competitiveness of renewable energy sources and increase returns in this sector.

An increase of 1% in gold prices leading to a 0.511% increase in relative clean energy performance can be explained by general economic uncertainties and shifts in investment preferences. Investors may seek safe havens with rising gold prices, thereby increasing the attractiveness of alternative investments in the clean energy sector. Consequently, clean energy companies' performance can benefit positively from increases in gold prices. On the other hand, a 1% increase in risk-free interest rates resulting in a 0.033% decrease in relative clean energy performance can be associated with increased financing costs for renewable energy projects. Higher interest rates may raise the costs of financing clean energy projects, negatively impacting returns in the sector. According to the model results, if the return differential between clean energy and the benchmark stock index increases in the previous period, a decrease in the return differential is expected in the current period; in other words, an increase in relative clean energy performance is anticipated. These findings highlight the complex effects of financial and economic factors on clean energy indices, emphasising the importance of considering these factors when developing strategies within the sector.

The results of Model 2 are similar to those of Model 1; it has been determined that increases in average temperature negatively affect the relative performance of the clean energy index. However, it has been found that decreases in average temperature positively impact the relative performance of clean energy. According to the results of Model 2, when average temperatures increase by 1%, the relative performance of clean energy decreases by 0.561%, while when average temperatures decrease by 1%, the relative performance increases by 0.598%. While temperature increases negatively impact clean energy performance by increasing energy demand and reducing clean energy production efficiency, temperature decreases positively impact performance by balancing energy demand and increasing clean energy efficiency.

It has been determined that when crude oil prices decrease by 1%, relative clean energy performance decreases by 0.344%, while an increase in oil prices by 1% results in a performance increase of 0.063%. Based on the comparison of Model 2's results, it has been determined that Nasdaq's relative clean energy performance responds more strongly to increases and decreases in oil prices compared to S&P's relative clean energy performance. A decrease in crude oil prices tends to reduce clean energy index performance. When oil prices decrease, the return differential between indices increases. Low oil prices can increase profitability for companies while potentially reducing competitiveness for clean energy companies. Conversely, an increase in oil prices leads to improved clean energy index performance. These results indicate that high oil prices can provide a competitive advantage to clean energy companies.

The previous period's value of relative clean energy performance has a negative coefficient (−1.487), indicating that the performance of the previous period affects the current period's performance in the opposite direction. If the return difference between clean energy and the benchmark stock index increases in the previous period, a decrease in the return difference is expected in the current period; in other words, the relative performance of clean energy is expected to improve.

In conclusion, the findings highlight the significant influence of crude oil, average temperature, gold prices and risk-free rate on both sectors performance.

6 CONCLUSION

This study highlights the significant impacts of crude oil and gold prices on energy sector performance, and also analyses the effects of temperature changes on the clean energy index performance. According to the findings of the NARDL model in this study, decreases in crude oil prices make clean energy less attractive, whereas increases enhance clean energy performance. Moreover, increases in gold prices have a negative impact on clean energy companies' performance due to general economic uncertainties and shifts in investment preferences. Temperature changes exhibit symmetric effects on clean energy performance; while temperature increases negatively affect energy demand and production efficiency, decreases positively influence performance. Increases in the risk-free interest rate have a dampening effect on sector returns by raising financing costs for renewable energy projects. These findings underscore the importance of considering these factors when planning strategies within the clean energy sector.

Rising crude oil prices tend to positively impact clean energy index returns. High oil prices can increase demand for clean energy technologies or enhance the competitiveness of clean energy alternatives. Therefore, profitability and performance of clean energy companies are typically positively affected by high oil prices. Conversely, decreasing oil prices reduce the relative performance of clean energy indices. Lower oil prices may increase the cost advantage of traditional energy sources, complicating market competition for clean energy companies. Rising gold prices enhance clean energy index performance. Gold prices often move inversely with global economic uncertainties or inflation concerns. In such cases, high gold prices may increase investors' search for safe havens, potentially benefiting clean energy index performance. Increased market uncertainty typically leads to higher demand for energy as predictability in energy prices decreases.

Positive deviations in average temperatures (i.e., warm weather conditions) generally negatively impact clean energy index company performance. Negative deviations in average temperatures (i.e., cold weather conditions), on the other hand, positively affect clean energy index company performance. It has been determined that positive and negative shocks in average temperatures have a symmetric effect on clean energy index relative performance in the long term. Warm weather conditions may reduce the need for clean energy solutions by increasing energy demand or directing it towards traditional energy sources. In this case, declining demand and competitive conditions may lower clean energy company performance. These financial perspectives are crucial for understanding the impact of macroeconomic factors on clean energy indices.

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