# The impact of carbon and fossil fuel prices on renewable energy companies' stock prices: New evidence from piece-wise approach

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**Abstract**

This study aims to elucidate the relation between oil, gas, coal, carbon prices and the clean market index. We adopt a piece-wise linear approach and assume that each piece represents a unique structural mechanism. We utilize an optimization model that endogenously finds cut-off dates on non-stationary data along with the model coefficients for each period. Our findings highlight that the clean market index is positively related to stock market performance and negatively related to carbon and oil prices. The direction of the effects of gas and coal, on the other hand, are found to be alternating among the break periods. Moreover, predictor importance of the factors also changes through the timeline. Empirical evidence indicates that splitting the time series data into pieces according to their distinct structural characteristics improves the prediction performance and it is imperative to better understand the behavior of the renewable energy market. By doing so, we aim to provide insights for policy makers on how to utilize the leverage effect of financial markets to empower renewable energy companies.

**Keywords**: renewable energy companies, financial markets, carbon prices, fuel prices, structural break, piece-wise linear regression.

**JEL classification**: G11, G15, G17

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## 1. Introduction

Incidents such as wildfires, abrupt hailstorms, and the occurrence of the hottest days in July vividly manifested the severe ramifications of global warming. UN Secretary-General António Guterres has characterized this epoch as the termination of the global warming era and the commencement of a 'global boiling' era (the Guardian, 2023). The sixth assessment report released by the Intergovernmental Panel on Climate Change (IPCC) in 2021 asserts that climatic changes are irreversible, yet concerted endeavors to mitigate global warming can shape the future and avert more adverse consequences. Greenhouse gases, particularly carbon dioxide, constitute the primary

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catalyst for global warming, underscoring the imperative of decarbonizing the economy as a pivotal measure in combating climate change. A low-carbon economy is defined as an economic system that minimizes the emission of greenhouse gases, specifically carbon dioxide. The key sector in facilitating the transition to a low-carbon economy is the energy sector. The International Energy Agency (IEA) report of 2022 states that the energy sector surpasses the industry, transportation, and building sectors in global carbon dioxide emissions. According to the report, notably, the energy sector exhibited the most significant increase in emissions, registering a 1.8% upsurge to an all-time high in 2022, compared to previous years primarily attributed to emissions emanating from electricity and heat production. Clean energy enterprises, utilizing renewable resources such as solar, wind, hydropower, and biofuel, represent the exclusive alternative to fossil fuel-based energy production and are integral to the shift towards sustainable energy systems. The transition to renewable energy assumes heightened significance for the European Union (EU), particularly considering geopolitical events, such as Russia's invasion of Ukraine, which underscored vulnerabilities associated with dependence on Russian natural resources. According to the IEA's 2022 report, renewable energy production has attained record levels, constituting 90% of the growth in global total electricity generation. Consequently, numerous studies in literature have examined the role of clean energy companies in the energy market, scrutinizing their financial performance and the factors influencing their stock performance. Despite this, there remains a notable gap in the literature concerning the insufficient exploration of carbon prices as a determinant of clean energy companies' performance, especially within the European market. Notably, the European Union stands out as the world's most ambitious region in terms of emission reduction and combating climate crises, further underscored by the European Emissions Trading System's status as the largest carbon market globally.

The Emission Trading System (ETS) stands out as a pivotal market-oriented mechanism for mitigating carbon emissions. The inception of the European Union Emission Trading System (EU ETS) in 2005 marked a concerted effort to impose a cost on carbon emissions for energy companies throughout its four sequential phases. Across each phase, the European Commission, drawing from insights gained in preceding periods, introduces innovations designed to enhance market efficiency and further curtail emission volumes. The fourth and concluding phase witnessed the implementation of the Market Stability Reserve (MSR) mechanism, strategically devised to prevent entities, particularly those within the energy sector with elevated carbon emissions, from accumulating excess carbon permits. Through this mechanism, the European Commission aims to enhance market stringency, precluding pronounced declines in carbon prices by mitigating emission allowance surpluses. Consequently, carbon permits, constituting a significant cost for energy enterprises, are anticipated to wield substantial influence over the energy market by the year 2030. A robust association is expected between the financial performance of clean energy firms, exempt from carbon permit expenses, and carbon prices, particularly within the European context.

This study seeks to investigate the influence of carbon prices, fossil fuel prices, and stock market index on European clean energy companies. We employ an optimization model based on dynamic programming that distinguishes the structural mechanism shifts through the timeline and offers cut-off dates of these shifts. The model uses a piece-wise linear regression approach and finds the cut-off dates of the structural breaks by minimizing the total squared errors. Although dynamic programming approaches are computationally challenging and not time efficient, we utilize a heuristic approach that is grounded on column generation, so that the model approach is even applicable to very long time series data. The contribution of this study is three-fold. First, it determines the cut-off dates of structural shifts endogenously with a rigorous modelling study within reasonable time limits. Second, the model coefficients of piecewise linear regression provide interpretability as opposed to the most machine learning algorithms that offer a black box representation. Third, we study the results further with predictor importance graphs for different numbers of structural breaks (i.e. 3 and 4), where the relative importance of the factors is presented. This enables policy makers to unveil the behavioral change in stock market index on European clean energy companies as a function of carbon and fossil fuel prices on a timeline. Moreover, the modelling approach we offer is versatile such that the users can impose different numbers of structural breaks that are defined according to the granularity level they prefer. Therefore, they can evaluate the effectiveness of the interventions that have been applied at a particular time frame or in a short period of time.

The subsequent structure of the study is outlined as follows: In the second section, existing studies examining the factors influencing the stock performance of renewable energy companies are summarized, and the gaps in the literature are identified. The third section elucidates the data utilized in the study, providing an explanation of the data and sharing summary statistics. The fourth section details the statistical background of the methodology employed in the study. The fifth section presents empirical findings and discusses the implications of the results. The final section summarizes the findings and presents policy recommendations.

## 2. Literature review

There are only few studies on the relation between clean energy companies and carbon prices. The existing literature mainly focuses on the impact of fossil fuel prices on the clean energy companies globally by using WilderHill Clean Energy Index (ECO) and there is no agreement on how the fossil fuel market and clean energy market is related. The pioneer study in the literature by Henriques & Sadorsky (2008) examines the clean energy market and its relationship with technology and oil market. This study documents that interest rates, oil prices and stock market performance of technology firms have impact over clean energy stocks although the effect of oil prices is not that strong as expected. Maghyereh et al. (2019) employ MGARCH model to analyze the return and risk transmission between oil prices, clean energy and clean energy technology markets. While they find strong relations between renewable energy and clean energy technology markets, return transmission from oil to clean energy market exists in the long run. Inchauspe et al. (2015) apply the state-space model with time-varying coefficients and use monthly data for the period August 2001 to February 2014. They find that MSCI World index and technology stock index is more influential on the stock market performance of clean energy firms. The results reveal weak impact of oil prices on the stock returns of renewable energy companies, but they suggest that the influence of oil is more pronounced since 2007. Ferrer et al. (2018) analyze the frequency and time dynamics of connectedness among clean energy, conventional energy and technology stocks and oil prices along with some other financial indicators in the period from January 2003 to September 2017 in the USA. The results of the study suggest no significant impact of oil prices on the stock market performance of clean energy companies and that the clean energy market and technology market are connected. From January 2003 to June 2015, Bondia et al. (2016) apply non-linear cointegration tests to analyze the relation between clean energy stocks and technology stocks, oil prices and interest rates and they ascertain long run relation among the variables. They also find short run causality running from technology stocks, oil prices and interest rates to clean energy stocks but that no causality exists in the long run from the variables to clean energy stocks. Sadorsky (2012a) applies multivariate GARCH model using data ranging from January 2001 to December 2010. It is found that there is dynamic conditional correlation between clean energy companies and oil prices, but that technology market is more influential on the renewable energy. Nasreen et al. (2020) use FIGARCH-a-cDCC model and FIGARCH-DECO model over the period December 2000 to June 2018 and document the strong connection between technology and clean energy market and underline that oil is not a major driver of clean energy stock prices. Between November 2003 to March 2018, Elie et al. (2019) analyze if oil and gold are effective hedge for clean energy stocks with blended copulas approach and they find that these commodities are only weak hedges for the clean energy indices. About the riskiness of clean energy market, Sadorsky (2012b) find that increasing oil prices has positive effect on the systematic risk of renewable energy company stocks between the years 2001-2007.

There is a body of literature which is in line with the expectations and suggests that the oil price is an important factor explaining the financial risk of clean energy stocks. Dutta (2017) examines how the risk of clean energy stocks is affected by the oil price volatility between May 2007 and June 2016. The results demonstrate that the volatility of clean energy stock return is strongly related with the oil price volatility. Managi and Okimoto (2013) apply MSVAR considering structural changes and asymmetry for the period January 2001 to February 2010 and suggest that clean energy market is positively affected by both the technology stocks and oil prices. For the period May 2005 to April 2015, Ahmad (2017) finds that clean energy and technology stocks mostly move in the same direction, so they are not good hedge and that oil is better in hedging for clean energy stocks. Kocaarslan and Soytas (2019) consider the asymmetric impact of oil prices and apply NARDL approach between January 2004 to January 2018. They document that an increase in oil prices with speculative attacks positively affects the clean energy stocks in the short run but that the impact of rising oil prices is adverse in the long run. About the impact of natural gas prices and coal prices, there are limited number of studies. Fu et al. (2022) evaluate the impact of global financial stress, oil price, gold prices, and natural gas prices on the global renewable energy stocks by utilizing quantile autoregressive distribute lag approach between January 2008 and April 2021. They ascertain that, under bullish market conditions, oil prices exhibit an adverse effect on the performance of renewable energy stocks, while natural gas prices demonstrate a favorable impact on the clean energy stocks in bearish market conditions in the long run. Bibi et al. (2022) report positive impact of coal and oil prices and negative impact of natural gas prices on the global clean energy stocks both in the short run and long run by utilizing ARDL method between February 2011 and February 2020. Sun et al. (2019) analyze the impact of coal, oil and natural gas prices on the Chinese new energy companies and document weak impact of fossil fuels and no impact of carbon prices on the clean energy stocks. Gu et. a. (2020) reveal that there is bi-directional volatility transmission between coal prices and clean energy companies in China from January 2008 to February 2019. Song et al. (2019) show that the influence of oil is more conspicuous compared to the effects of coal and natural gas on the global clean energy stocks. They posit that the impact of coal has manifested only in recent times, while the impact of natural gas is weak on the clean energy stocks.

There are a few studies exploring the European renewable energy companies and the factors affecting their pricing. With multivariate quantile dependence approach, Reboredo and Ugolini (2018) examine how the oil, gas, coal and electricity prices affect the stock market performance of the European Renewable Energy index (ERIX) in the EU and ECO Clean Energy Index for the USA in the period 2009-2016. They find that energy prices affect the renewable energy companies' stock prices. They reveal that oil prices play an important role in the clean energy market in the USA while the stocks of clean energy companies are mainly affected by the electricity prices in the EU. Reboredo (2015) analyses the ERIX together with other clean energy indices and finds significant impact of oil prices on the renewable energy stock risk between 2005 and 2013. It is argued that the increasing oil prices spurred the interest of investors in the renewable energy market and that it encourages the development of the sector. Reboredo et al. (2017) use the ERIX with other renewable energy indices from January 2006 to March 2015 and examine the co-movement and causality between stock return of clean energy sector and oil prices for the period 2006-2015. They document a strong relation between oil prices and clean energy sector and that the interaction between oil and clean energy is growing strong in the long run. The impact of oil, gold prices and financial stress on clean energy prices in USA and in Europe are analyzed by He et al. (2021) in November 2003-January 2020 period with Quantile Autoregressive Distributed Lag approach. They find negative impact of gold prices and financial stress on the clean energy stocks while volatility of oil prices is found to be positively related with clean energy market in the long run. Xia et al. (2019) explore the effect of fossil fuels on ERIX with network approach from April 2008 to July 2019. They argue that clean energy market is the determinant in fossil energy market in Europe and that renewable energy market has the potential to reshape the energy systems in the world.

The interest in the interaction between carbon prices and clean energy gains momentum in the literature in the last decade. Kumar et al. (2012) estimate a VAR model for the period April 2005 to November 2008 and examine the relation between clean energy and technology stocks, oil prices and carbon prices. They conclude that high technology market and oil prices impact the clean energy market, but carbon prices have no effect on the stock market performance of clean energy firms. Ahmad et al. (2018) estimate the time varying hedge ratios between clean energy stocks and some financial variables like VIX, European carbon prices and oil prices for the period March 2008 to October 2017 and apply MGARCH models. They find that VIX (Volatility Index), OVX (Crude Oil Volatility Index) and oil are good hedges and interestingly they find no strong impact of carbon prices on the clean energy stocks. Dutta et al. (2018) use bivariate VAR-GARCH model to study the relation between

EUA, ECO and ERIX from July 2009 to December 2017. They find that clean energy prices and carbon prices are not strongly correlated, and the volatility of carbon prices and clean energy prices are only linked in Europe. Tiwari et al. (2022) analyze the connectedness and spillover between green bonds, carbon prices, solar and wind indices and global clean energy index between January 2015-September 2020 and find that clean energy market is the net transmitter of shocks.

The existing literature focuses on the relation between global clean energy companies and fossil fuel energy market while the studies focusing on the EU ETS and European renewable energy prices are limited. To the best of our knowledge, there is only one study that examines the impact of carbon prices along with Stoxx 600 Europe using TVP-VAR methodology (Qiu et al., 2023). They examined the impacts of Brexit, the launch of the European Green Deal and COVID-19 pandemic between 2014-2021. In this study, we analyze the impact of the EU carbon prices on the clean energy index considering the fourth phase of the EU ETS as a factor shaping the market. Besides carbon prices, this study also investigates the influence of fossil fuel prices and stock market indices on European clean energy market. The contribution of the study is two-fold: policy and methodology oriented. It elucidates the interplay between key determinant factors in the clean energy market, providing information for policy implications. On the other hand, the model used in this study accounts for structural shifts and, opposite to the literature, endogenously finds cut-off dates for a predetermined number of structural breaks. To the best of our knowledge, this study marks the inaugural implementation of Bai and Perron's well-established structural break estimation method (1998, 2003), specifically tailored to minimize estimation errors globally in the context of the clean energy market.

## 3. Data

The analysis covers the period from January 1, 2021, and July 31, 2023, with the specified dates aligned with the fourth phase of the European Emission Trading System. As a proxy for the European clean energy firms, we used the NASDAQ OMX Clean Energy Europe index as the independent variable in the model. The inaugural factor to be incorporated into the model is the stock market factor, deemed paramount in accordance with the recommendations posited by the Capital Asset Pricing Model (Sharpe, 1963). To represent the stock market index, we considered NASDAQ EURO 50 index. ICE Carbon Emission Futures contract is used to represent the carbon prices. For the oil price, we used the most extensively used Brent spot price. Dutch TTF Natural Gas Futures is considered to represent the natural gas price factor. Finally, Newcastle Coal Futures is included as the proxy for coal prices. To ensure all the series are traded in the same currency, the series denominated in USD (Newcastle Coal Futures, Brent Spot, NASDAQ OMX Clean Energy Europe) converted to Euro currency by daily Euro/USD exchange rate. All the data is compiled from investing.com.

The stationarity characteristic of the series is tested with Augmented Dicky Fuller Test for two models namely Intercept and Intercept & Trend and the results are shared in Table 1 Panel A. All the series have unit root at the level which suggest the existence of structural breaks. We share the descriptive statistics in Panel B. Finally, Panel C shows the correlation coefficients among the series.

*Table 1 – Unit Root Test results and Summary Statistics*

| **Panel A: Augmented–Dickey–Fuller test** | | | | | | |
|---|---|---|---|---|---|---|
| | **Clean energy index** | **Stock market Index** | **EUA** | **Oil price** | **Natural gas price** | **Coal price** |
| **Intercept** | -2.44 (0.1301) | -1.96 (0.3065) | -2.25 (0.1874) | -1.88 (0.3399) | -2.14 (0.2281) | -1.28 (0.6419) |
| **Intercept and Trend** | -2.770321 (0.2089) | -1.999136 (0.6002) | -2.999314 (0.1331) | -1.415186 (0.8560) | -1.998760 (0.6004) | -0.540537 (0.9815) |
| **Panel B: Descriptive statistics** | | | | | | |
| **Mean** | 1607.18 | 999.99 | 72.14 | 76.75 | 79.32 | 218.80 |
| **Std. Deviation** | 112.53 | 73.55 | 17.59 | 17.84 | 57.54 | 120.59 |
| **Skewness** | -0.32 | -0.39 | -0.64 | 0.38 | 1.23 | 0.49 |
| **Kurtosis** | 2.66 | 1.97 | 2.21 | 2.25 | 4.43 | 1.74 |
| **Number of observations** | 672 | 672 | 672 | 672 | 672 | 672 |
| **Panel C: Correlation matrix** | | | | | | |
| **Clean energy Index** | 1.00 | 0.57 | -0.50 | -0.73 | -0.56 | -0.79 |
| **Stock market Index** | 0.57 | 1.00 | 0.25 | -0.41 | -0.49 | -0.56 |
| **EUA** | -0.50 | 0.25 | 1.00 | 0.63 | 0.38 | 0.50 |
| **Oil price** | -0.73 | -0.41 | 0.63 | 1.00 | 0.72 | 0.87 |
| **Natural gas price** | -0.56 | -0.49 | 0.38 | 0.72 | 1.00 | 0.83 |
| **Coal price** | -0.79 | -0.56 | 0.50 | 0.87 | 0.83 | 1.00 |

## 4. Methodology

This study explores the potentially time-variant impact of carbon and fossil fuel prices and stock market index on the European clean energy market. To do so, we utilize the multiple structural change model approach introduced by Bai and Perron (1998, 2003). This approach estimates multiple structural changes in linear models. Our aim is to determine cut-off dates indicating when structural changes occur and estimate the corresponding linear model parameters for each regime. To better expose such a model, let us consider the following multiple linear regression model with $m$ cut-off points corresponding to $m+1$ structural breaks (i.e. regimes).

$$y_t = c_k + \beta_k x_t + \epsilon_t \qquad t \in [l_k + 1, u_k] \tag{1}$$

where $k \in [1, m+1]$ and stands for the structural break period, $y_t$ denotes the dependent variable (clean energy index) at time $t$, $x_t \in \mathbb{R}^6$ represents the vector of independent variables – namely time index, stock market index, carbon, oil, gas, and coal prices, $\beta_k$ and $c_k$ respectively refer to the coefficient vector and the constant for a structural break $k$, and $\epsilon_t$ denotes the error term at time $t$. Also, $l_k$ and $u_k$ respectively refer to lower and upper time bounds of regime $k$ for $1 \leq k \leq m+1$. We use the convention that $l_1 = 0$ and $u_{m+1} = T$ simply referring that the first regime starts with the first observation, whereas the last regime ends with the last observation. Also, each regime must be disjoint, i.e. $u_i \leq l_j$ for $i \leq j$, and collectively exhaustive, that is, their union yields the entire set of observations, i.e. $u_i = l_{i+1}$.

Here, the bounds of regimes, i.e. $[l_k + 1, u_k]$, and associated regression parameters are unknown. Therefore, one aims to compute the cut-off points and corresponding estimation parameters. The computational approach developed by Bai and Perron (2003) is a dynamic programming model that eventually computes the optimal cut-off points along with the corresponding estimation parameters.

The dynamic programming model can be seen as a variant of the infamous shortest path problem in a directed acyclic graph that entails finding the shortest path having exactly $m$ hops (edges) in a graph $\mathcal{G}(\mathcal{V}, E)$ where vertices represent time indices, i.e. $\mathcal{V} \in \{1, \dots, T\}$ and edges stand for each regime, i.e. $E \in \{(i,j) | i \in \mathcal{V}, j \in \mathcal{V},\ i < j\}$. Now, let $\mathcal{C}(i,j)$ denote the squared residuals of the multiple linear regression model computed in regime $(i,j]$ and $\mathcal{S}(r,j)$ represent the sum of squared residuals corresponding to the optimal partitioning of the time frame $[1,j]$ using $r$ regimes. As such, the shortest path problem can be formulated as follows.

$$\mathcal{S}(r,j) = \min_{i|i<j}\{\mathcal{C}(i,j) + \mathcal{S}(r-1,i)\} \tag{2}$$

where

$$\mathcal{C}(i,j) = \textstyle\sum_{t=i+1}^{j}(y_t - \hat{y}_t)^2 \tag{3}$$

and $\mathcal{S}(0,j) = 0$ for any $j \in \mathcal{V}$. Here, the optimal sum of squared residuals of having $m$ regimes on the given dataset is found by computing $\mathcal{S}(m,T)$.

It is observable that the dynamic programming model given above requires solving a large number of least square equations, making it computationally inefficient. In fact, the complexity of the dynamic program has already been shown to be $\mathcal{O}(n^2d^2 + n^2m)$ where $n$ refers to the number of observations in the dataset and $d$ denotes the number of independent variables (Acharya et al., 2016). These findings indicate that it may be unable to compute the parameters of interest for even small sized datasets. Due to the aforementioned computational issues, we opt for using the computationally efficient heuristic method introduced by Tunc and Genc (2021). This method relies on a mathematical programming heuristic known as the column generation, which enables smart filtering of options and solving only a small subset of least square equations. Specifically, there is no need to compute the least squares of every possible regime that could establish the partition. Instead, the method begins with a relatively small subset of potential regimes and then iteratively extends the subset as necessary. By doing so, it provides the user with the opportunity to work with large datasets. Both of those methods work with a predetermined number of break points. That is, the number of breaks, i.e. the number of regimes, are exogenous. Within a particular regime $k$, i.e. for $t \in [l_k + 1, u_k]$, the traditional least-squares approach is employed, and unknown values displayed in Equation 4 are found for each regime $k \in \{1,2,\dots,m+1\}$, where $m$ denotes the number of cut-off points.

$$Clean\ index_t = c + \beta_{time\ index}t + \beta_{index}marketindex_t + \beta_{carbon}carbon_t + \beta_{oil}oil_t + \beta_{gas}gas_t + \beta_{coal}coal_t + \epsilon_t \quad (4)$$

Bai (1997) shows that the estimator minimizing the sum of squared residuals maximizes Wald-type statistics as well. As such, the aim of the method used in this study is to minimize the sum of squared residuals across all structural breaks.

## 5. Empirical findings

We have applied piece-wise linear regression method with different number of structural breaks, namely, 3 and 4. For the coherence of the results and comparison purposes, we also report the case where no breaks are considered. Clean energy index is taken as dependent variable, while stock market index, carbon, oil, gas and coal prices are taken as independent variables. We have also included time index increasing by 1 on each consecutive day. The estimation results of these models are displayed in Figure 1 within 4 equal time frames for a better visual representation. Note that the figure displays data on daily basis and no smoothing is done. As the figure shows, there are too many ripples in the data and linear regression approach is unable to mimic those ripples, especially when they are sharp in magnitude. However, when we apply structural breaks, an obvious improvement is observed. Increasing the number of breaks also improves the model performance. However, we keep our analysis restricted to 3 and 4 number of breaks, because we do not want to sacrifice the practicality for a higher granularity. Yet, one can still get the idea how number of breaks enhance the performance of the estimation model by comparing the results of 3 and 4 breaks.

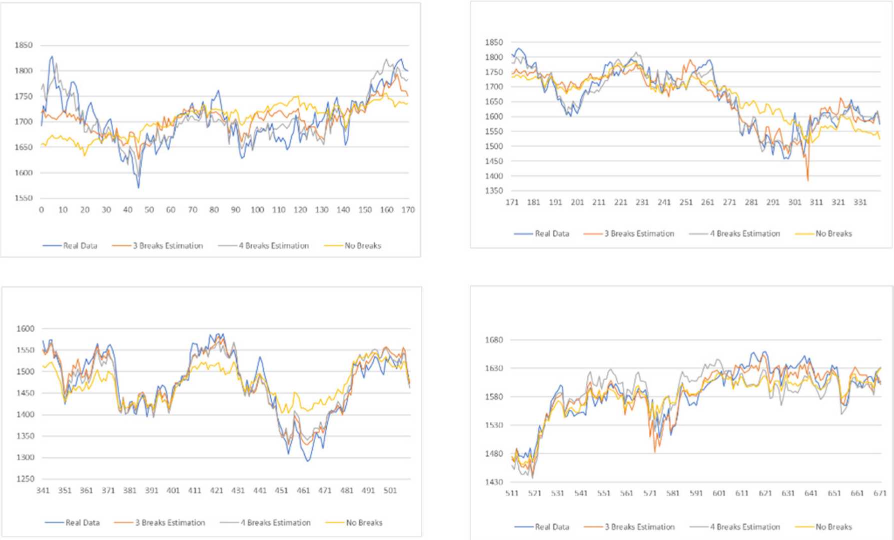
We summarize the error measures of those models in Table 2 together with $R^2$ values. These measures indicate that 'no break' case, namely multiple linear regression, is reported with the minimum error terms, nevertheless, with the smallest value for explanatory power, i.e. $R^2$=84%. As it is seen in Figure 1, it is the case that displays the worst performance in terms of catching up with the real data where sharp ripples are present. By minimizing total error terms, it can only comply with the general trend in the data, in other words, it can estimate the real data only when a smoothing is applied. When we elaborate on piece-wise linear regression models, we observe that total measures for residuals slightly increase, but it reveals better catch up with the ripples along with higher explanatory values. As it can be seen from Figure 1 and $R^2$ values reported in Table 2, estimation model with 4 breaks showcases a very high level of catch up with the real data, even displaying some overlaps in particular times.

*Table 2 – Error and $R^2$ Measures*

| | MAD | MAPE | MSE | RMSE | $R^2$ |
|---|---|---|---|---|---|
| **NO BREAK** | 105,30 | 6.91% | 17776 | 133.33 | 0.84 |
| **3 BREAKS** | 106.02 | 6.99% | 18912 | 137.52 | 0.93 |
| **4 BREAKS** | 109.61 | 7.19% | 19276 | 138.84 | 0.96 |

MAD: Mean absolute deviation; MAPE: Mean absolute percentage error; MSE: Mean square error; RMSE: Root mean square error

*Figure 1 – Renewable energy companies stock index*




Results of no break case is reported in Table 3. As we have discussed earlier, piece-wise linear regression model provides a high interpretability as opposed to black box models. We, hereby, present structural breaks/cut-off dates and coefficients of independent factors within each structural break in Table 4 and 5 for the models where the number of structural breaks is given as 3 and 4. Each cell in the table represents coefficient, [standard error] and (t-values) respectively for the constant and the independent factors. The significance levels of the factors are denoted by single, double and triple star sign at different $\alpha$ levels that are 10%, 5% and 1%.

In no break case, all factors except oil prices are found to be statistically significant in the estimation model of clean index. Index and gas have positive impact with coefficients 1.01641 and 0.3893 respectively, where time index, carbon and coal prices are negatively related to clean index with coefficients -0.2121, -1.8848 and -0.2294 respectively. Explanatory power of the model is also reported to be around 83%.

When the number of structural breaks is given as three, the cut off dates are determined as 08/03/2022 and 12/04/2023. The general trend with respect to time is found to be positive in the first break and negative in the last two breaks, with time index coefficients of 0.6929, -0.6505 and -1.0864. The relationship between clean index and stock market index is found to be statistically significant and positive in entire timeline with the coefficients 0.8760, 1.6069, 1.1382. Clean index, however, deviates inversely proportional to carbon price, such that it displays a negative relationship between dates 01/01/2021-08/03/2022 with coefficient -4.9870, but its effect on clean index is found to be insignificant between the dates 09/03/2022-12/04/2023 and 13/04/2023-31/07/2023. Similar to carbon prices, oil prices are also inversely proportional to clean index and it is found to be significant with coefficient values of -6.8967 and -3.9494 between dates 01/01/2021-08/03/2022 and 13/04/2023-31/07/2023. Gas prices, on the other hand, reveals an alternating effect on clean index and are found to be significant in all structural breaks with coefficients of 0.8618, 0.4607, -2.5001. When it comes to the effect of coal, we again observe a directional change in the behaviour, such that it is positive between 09/03/2022-12/04/2023 and changes to negative between the dates 13/04/2023-31/07/2023 with coefficients 0.0513 and -0.4901, where its impact is found to be insignificant in the first structural break until 08/03/2022. Also note that its positive effect in the second structural break is found to be significant, but at a significance level of 10% only.

*Table 3 – Empirical Findings (No breaks)*

| Variable | Coefficient | [Standard Error] | (T-Value) |
|---|---|---|---|
| $c$ | 830.3239*** | [43.6379] | (19.0276) |
| $\beta_{time\ index}$ | -0.2121*** | [0.0190] | (-11.1646) |
| $\beta_{index}$ | 1.01641*** | [0.0441] | (22,9993) |
| $\beta_{carbon}$ | -1.8848*** | [0.2699] | (-6,9829) |
| $\beta_{oil}$ | -0.17046 | [0.2395] | (-0,7116) |
| $\beta_{gas}$ | 0.3893*** | [0.0583] | (6,67203) |
| $\beta_{coal}$ | -0.2294*** | [0.0441] | (-5,2007) |
| $R^2$ | 0.8366 | | |
| $Adj.R^2$ | 0.8351 | | |

*, **, *** denote the significance at the level %10, %5 and %1 respectively

*Table 4 – Empirical Findings (Number of breaks: 3)*

| | Cut-off Dates | | |
|---|---|---|---|
| **Variable** | **01/01/2021-08/03/2022** | **09/03/2022-12/04/2023** | **13/04/2023-31/07/2023** |
| $c$ | 1379.0962***<br>[112.374]<br>(12.272) | 216.4980***<br>[55.042]<br>(3.933) | 1389.828***<br>[168.4131]<br>(8.253) |
| $\beta_{time\ index}$ | 0.6929***<br>[0.227]<br>(3.050) | -0.6505***<br>[0.028]<br>(-23.371) | -1.0864***<br>[0.1909]<br>(-5.6887) |
| $\beta_{index}$ | 0.8760***<br>[0.090]<br>(9.733) | 1.6069***<br>[0.040]<br>(40.490) | 1.1382***<br>[0.1745]<br>(6.5228) |
| $\beta_{carbon}$ | -4.9870***<br>[0.597]<br>(-8.358) | 0.0847<br>[0.200]<br>(0.424) | 1.2297<br>[0.7841]<br>(1.5683) |
| $\beta_{oil}$ | -6.8967***<br>[0.653]<br>(-10.562) | -0.3294<br>[0.206]<br>(-1.597) | -3.9494***<br>[0.7537]<br>(-5.2396) |
| $\beta_{gas}$ | 0.8618***<br>[0.149]<br>(5.794) | 0.4607***<br>[0.030]<br>(15.201) | -2.5001***<br>[0.5983]<br>(-4.1787) |
| $\beta_{coal}$ | 0.0123<br>[0.140]<br>(0.088) | 0.0513*<br>[0.027]<br>(1.891) | -0.4901**<br>[0.2178]<br>(-2.2502) |
| $R^2$ | 0.725 | 0.939 | 0.558 |
| $Adj. R^2$ | 0.720 | 0.938 | 0.52 |

*, **, *** denote the significance at the level %10, %5 and %1 respectively

When the number of structural breaks is forced to be 4, the cut-off dates are determined as 05/07/2021, 04/02/2022 and 07/04/2022. Time index is found to be negatively related to clean index at the first, and the last breaks (i.e. 01/01/2021-05/07/2021 and 08/04/2022-31/07/2023) with coefficients -1.8712 and -0.5734. It is effect on clean index is demonstrated to be insignificant during the period 06/07/2021-04/02/2022 and statistically significant and positive during 07/02/2022-07/04/2022 with a coefficient of 4.4487. Index has a positive effect all through the timeline with coefficients 1.9469, 2.0597, 0.7165, 1.6019 for each break respectively. Carbon price, on the other hand, has a negative impact all through the timeline except the period between 07/02/2022-07/04/2022, where it is found to be insignificant. The corresponding coefficients for those breaks that it is found to be significant have been reported as -5.5038, -1.4163, -1.0358. Oil price also displays a negative impact on clean index for the first two breaks with coefficients of -4.4269 and -7.3147 respectively, and it is found to be insignificant afterwards. Clean index is found to be directly proportional to gas price during 01/01/2021-05/07/2021 and 08/04/2022-31/07/2023 with coefficients 9.7644 and 0.5663. Lastly, the effect of coal price changes direction among breaks, such that, it is coefficient is found to be -1.2400 between 01/01/2021-05/07/2021, 0.5795 between 07/02/2022-07/04/2022 and -0.1964 between 08/04/2022-31/07/2023. Its impact is found to be insignificant between 06/07/2021-04/02/2022.

*Table 5 – Empirical Findings (Number of breaks: 4)*

| | ***Cut-off Dates*** | | | |
|---|---|---|---|---|
| ***Variable*** | **01/01/2021-05/07/2021** | **06/07/2021-04/02/2022** | **07/02/2022-07/04/2022** | **08/04/2022-31/07/2023** |
| $\boldsymbol{c}$ | 299.2693<br>[194.074]<br>(1.542) | 145.3533<br>[115.965]<br>(1.253) | -459.5278<br>[452.963]<br>(-1.014) | 319.8922***<br>[69.1897]<br>(4.623) |
| $\boldsymbol{\beta_{time\ index}}$ | -1.8712***<br>[0.444]<br>(-4.210) | -0.0917<br>[0.197]<br>(-0.466) | 4.4487***<br>[0.644]<br>(6.904) | -0.5734***<br>[0.040]<br>(-14.252) |
| $\boldsymbol{\beta_{index}}$ | 1.9469***<br>[0.195]<br>(9.959) | 2.0597***<br>[0.103]<br>(19.923) | 0.7165**<br>[0.266]<br>(2.689) | 1.6019***<br>[0.049]<br>(32.111) |
| $\boldsymbol{\beta_{carbon}}$ | -5.5038***<br>[1.596]<br>(-3.449) | -1.4163***<br>[0.474]<br>(-2.990) | -0.6170<br>[1.508]<br>(-0.409) | -1.0358***<br>[0.256]<br>(-4.045) |
| $\boldsymbol{\beta_{oil}}$ | -4.4269***<br>[1.115]<br>(-3.971) | -7.3147***<br>[0.617]<br>(-11.857) | -1.5685<br>[1.100]<br>(-1.426) | 0.0506<br>[0.252]<br>(0.200) |
| $\boldsymbol{\beta_{gas}}$ | 9.7644***<br>[1.431]<br>(6.825) | 0.1467<br>[0.105]<br>(1.395) | -0.1107<br>[0.354]<br>(-0.313) | 0.5663***<br>[0.038]<br>(14.703) |
| $\boldsymbol{\beta_{coal}}$ | -1.2400*<br>[0.669]<br>(-1.852) | -0.0523<br>[0.101]<br>(-0.518) | 0.5795***<br>[0.183]<br>(3.167) | -0.1964***<br>[0.032]<br>(-5.989) |
| $\boldsymbol{R^2}$ | 0.695 | 0.898 | 0.762 | 0.957 |
| $\boldsymbol{Adj.\,R^2}$ | 0.680 | 0.894 | 0.723 | 0.916 |

*, **, *** denote the significance at the level %10, %5 and %1 respectively

After reporting the empirical findings, we further scrutinize the structural behaviour mechanism by predictor importance graphs that are plotted in SPSS Software package for each linear regression model of a particular break. At this stage, we also checked on the residuals and ensured that we comply with the principal assumptions that the errors are independently and normally distributed with mean 0 and standard deviation 1. Predictor importance graphs are utilized to visualize the relative impact of independent factors within each structural break. The importance measure is given within a continuum between [0,1]; 0 representing the least important and 1 representing the most important. Figure 2 showcases the predictor importance graph of the model where no structural break is imposed. In that model, although most independent variables are found to be statistically significant, they display a very low importance, but the main driver of estimation is found to be the conventional market performance. As expected, this simplistic approach of multiple linear regression does not provide much explanation about the relationship between the performance of renewable energy companies or energy related commodity prices.

*Figure 2 – Predictor importance graph (No Break)*

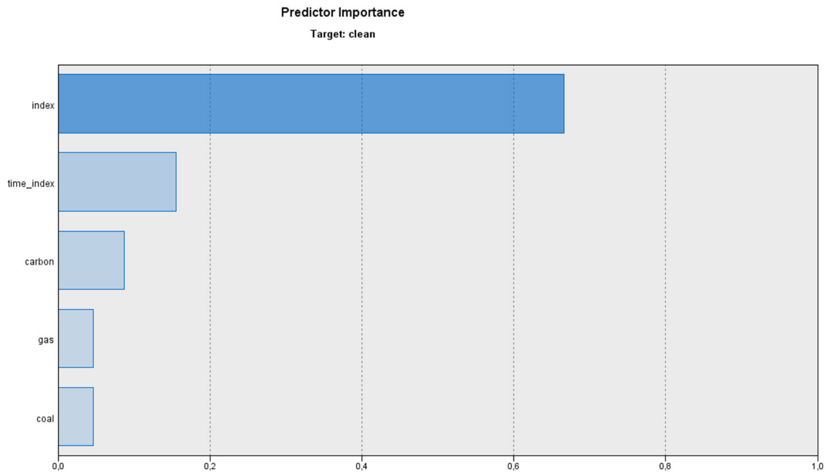



Figure 3 explores the predictor importance when the number of breaks is set to 3. In that case, index is still listed among the key influencing factors, however, we can also observe the effect of energy commodity prices, especially in the first break, oil being the key driver that is followed by carbon and gas. Moreover, the time index is also included in the bundle with relatively high importance in the second and third breaks. In the third break, the importance of index and time index recede, while the energy commodity prices gain an impact on the clean index estimation with a descending order of oil, gas, coal and carbon. Figure 4, on the other hand, reveals a different picture. In the first break driver force of estimation is found to be index followed by gas, oil, time index, carbon, coal with a descending order. In the second break the bundle of significant factors shrinks mainly to conventional market index and oil prices supported with slight impacts of carbon and gas. Clean index estimation function in the third break is dominated by time index, further enhanced by the contribution of coal, index and oil price. In the last break, the clean index is mainly derived by index, time index and gas.

These results assert that there does not appear to be a single bundle of factors that will fit into a one single recipe for clean index estimation. As expected, the relationships are dynamic, non-stationary and non-linear. Nevertheless, the outputs indicate that a piece-wise linear regression approach works well in terms of catching up the ripples in the real data along with the feature of interpretability and it provides some generalizable insights that we can list. Index is the robust estimator for clean index with positive influences in any circumstances. Carbon and oil prices, on the other hand, are the determinant factors that are found to be significant/insignificant depending on the time period that they are analysed. Those are the factors that explain the structural changes along with the alternating time trends during structural breaks. Furthermore, they demonstrate consistent behaviours as explanatory variables. Namely, they always display a negative impact in those cases that they are deemed to be statistically significant. On the contrary, gas and coal prices demonstrate a directional shift in the relationship with the clean index. Last but not the least, when energy commodity prices are not listed among the influencing factors or listed there with a relatively low importance, then the behaviour of the clean index is explained mainly by conventional market index and the time index only.

*Figure 3 – Predictor importance graph (3 Breaks) (impact rate the more the darker)*

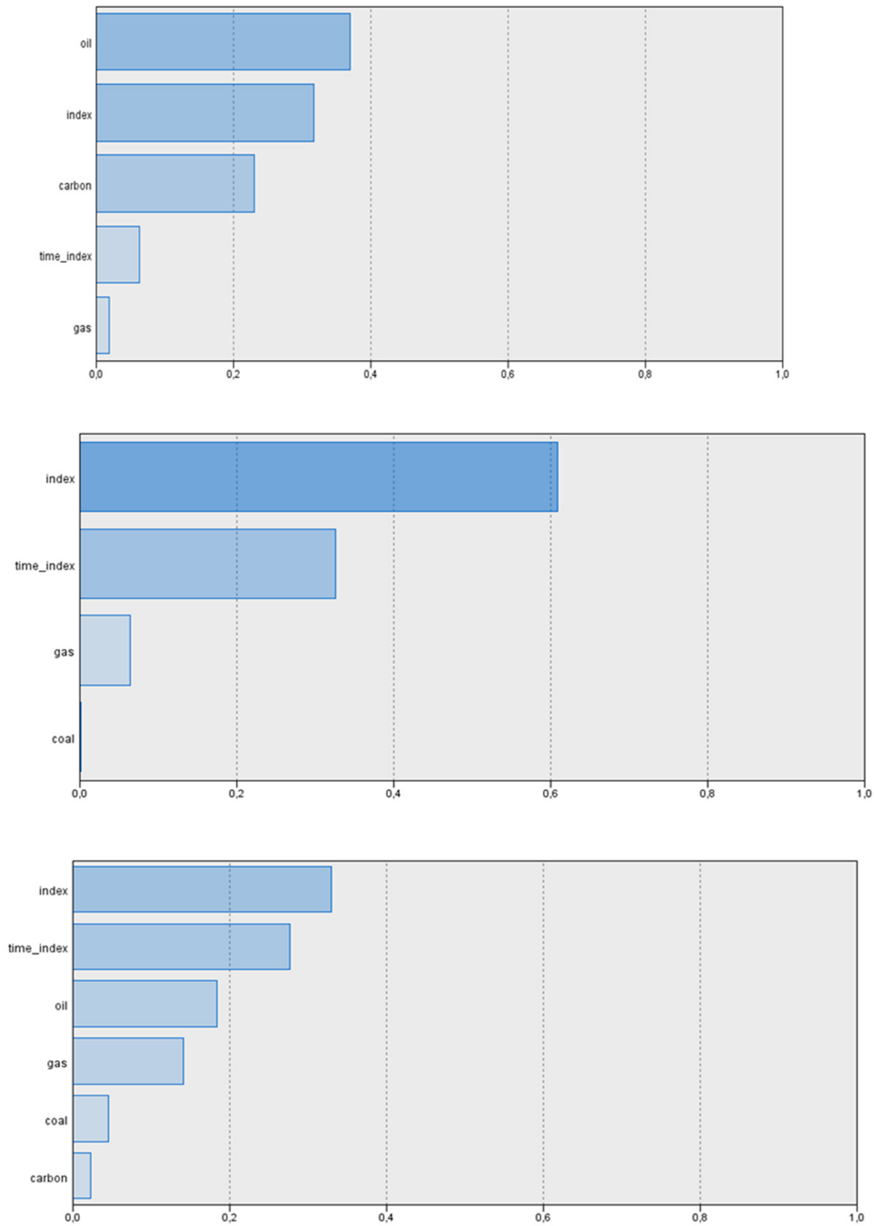
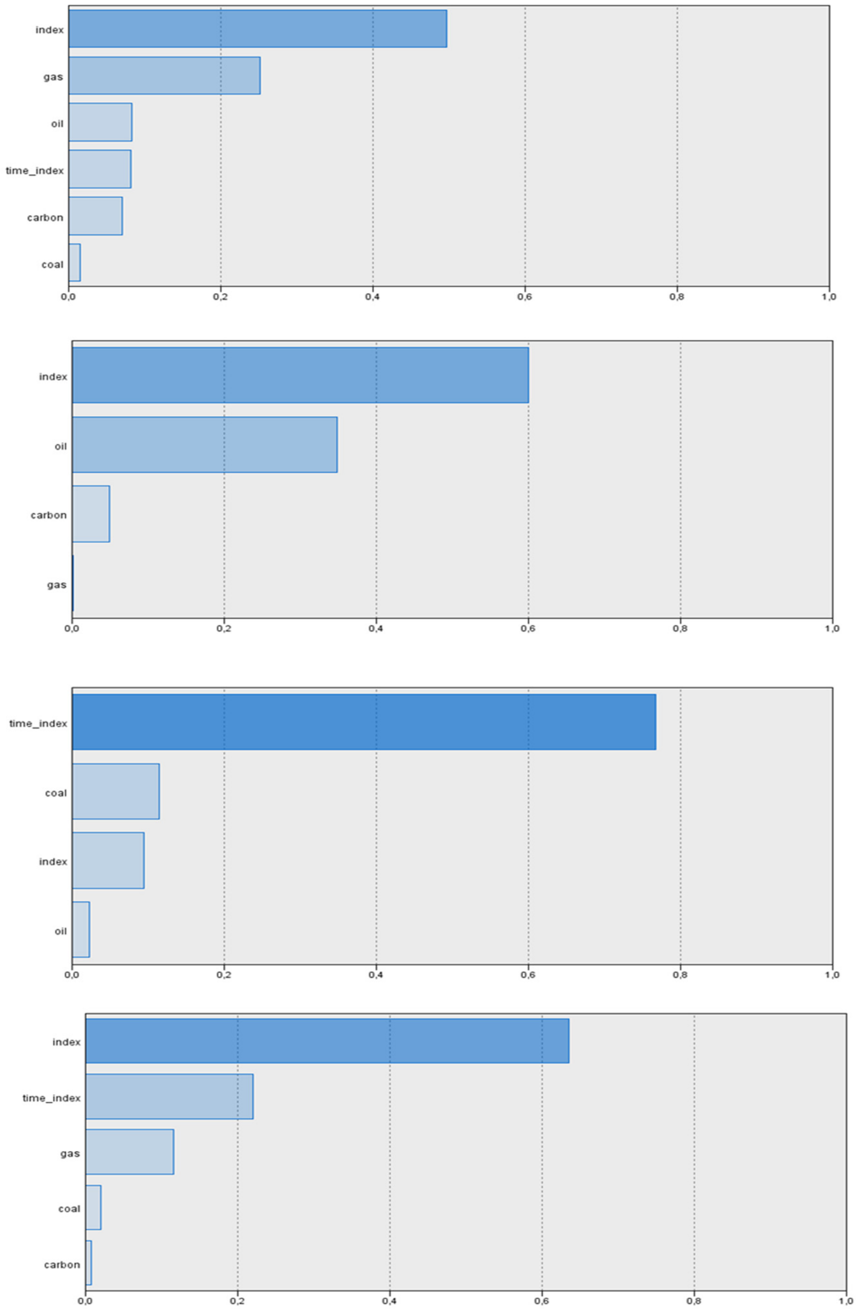


*Figure 4 – Predictor importance graph (4 Breaks)*



## 6. Discussion

The NASDAQ EURO 50 index has consistently exhibited positive trends during all identified structural break periods, serving as an indicative validation of the model's accuracy, given the anticipated positive impact of the NASDAQ EURO 50 on the NASDAQ OMX Clean Energy Europe index (Sharpe, 1963).

In instances denoted as structural break periods 3 within the model, a negative effect of carbon prices on the clean energy index was observed at the onset of the periods. Similarly, in situations designated as structural break periods 4, the negative impact of carbon prices was observed at both the conclusion and commencement of the periods. No discernible relationship between carbon prices and clean energy prices was identified between the dates of 09/03/2022-31/07/2023 in the first model and 07/02/2022-07/04/2022 in the second model. This finding aligns with the conclusions reached in studies conducted by Kumar et al. (2012), Ahmad et al. (2018), and Dutta et al. (2018). However, despite the general expectation that increasing carbon prices would positively influence clean energy stocks due to the lesser dependency of clean energy firms on carbon fuels and the absence of carbon allowance costs compared to traditional energy firms, the results contradict these expectations. Possible explanations for this phenomenon may include the potential inefficiency of the Market Stability Mechanism system and failed efforts for imposition of a substantial cost burden associated with carbon allowances on traditional energy firms. Due to the insufficient pressure of carbon costs on fossil energy firms, the anticipated relationship between carbon prices and clean energy stocks does not materialize. However, the anticipation of a recession in Europe due to the Russia-Ukraine tension has collectively impacted all markets, including clean energy firms, resulting in a depreciation of renewable energy stocks in the face of rising carbon prices. As a result, a negative relation is observed between carbon allowances and clean energy stocks.

The relationship between oil prices and the stocks of clean energy firms was modeled, and no statistically significant relationship was observed between 09/03/2022 and 12/04/2023 dates in the first model and between 07/02/2022 and 31/07/2023 in the second model, except for negative associations during other structural breaks. Regarding the negative relationship between clean energy stocks and oil prices, the results contradict with the studies conducted by Managi and Okimoto (2013), Bibi et al. (2022), Reboredo (2015) and confirms Fu et al. (2022) under bullish market conditions, and consistent with the findings of Kocaarslan and Soytas (2019) in the long term, as well as those reported by Ahmad (2017). The escalating impact of rising oil prices, resulting in negative effects on firms' production costs and household income levels, results in a negative economic outlook and thus oil prices adversely influences the stock performance of clean energy companies (Kocaarslan and Soytas, 2019). Examination of temporal characteristics is necessary to understand the observed negative relationship between oil prices and clean energy firm stocks, particularly during the fourth phase of the EU Emission Trading System (EU ETS). The period encompassing the onset of the COVID-19 pandemic witnessed record-low levels of oil prices, which subsequently exhibited a substantial surge during the normalization phase that commenced in 2021. However, economic recovery during the same period did not proceed at an equivalent pace, leading European economies to suddenly confront the looming threat of escalating inflation. Despite the fact that the increase in oil prices in response to growing demand (Kilian, 2009) have positive impact on the stock markets, the overall negative impact of the rising oil prices on the economy has been more pronounced. Additionally, due to inflationary pressures, clean energy stocks have not gained sufficient value in tandem with the general market outlook.

The impact of natural gas prices is found to be positive between 01/01/2021-12/04/2023 in the first model and between the dates 01/01/2021-05/07/2021 and 08/04/2022-31/07/2023 in the second model. Given that the general trend is positive, the results are in line with the study of Fu et al. (2022) in bearish market conditions. In general, rising natural gas prices have positive impact on the stock market performance of clean energy companies and this is in line with the expectations. Investors turn their eye to renewables in the EU when natural gas prices are rising. Especially after the invasion of Ukraine, both models (i.e. number of structural break 3 and 4) give the same result that the rise in natural gas prices affected the clean energy companies positively. The impact of coal prices is negative in the final period of both models and positive between 09/03/2022 and 12/04/2023 in the first model 07/02/2022 and 07/04/2022 and this is in line with the study of Bibi et al. (2022). Examination of the results suggests that the influence of coal has only begun to be discernible in recent years. As indicated by Sun et al. (2019), for a long time, clean energy firms were primarily associated with technology companies. In a manner akin to the findings of the study by Song et al. (2019), this investigation also indicates that in recent years, investors have commenced establishing connections between fossil fuels such as coal and clean energy firms, with the impact of coal becoming increasingly apparent.

## 7. Conclusion and policy implications

This study aims to investigate the effect of fossil fuels including oil, gas and coal; carbon prices as well as stock market index on the European clean energy market, using the time series data between 01/01/2021-31/07/2023 covering the 4$^{th}$ phase of EU ETS. Besides the practical contribution of the study, we have utilized a computationally efficient piece-wise linear regression approach. This methodology accounts for the structural shifts in a non-stationary data with a predetermined number of possible structural breaks. The timing of the shifts, nonetheless, is determined endogenously. The results highlight that stock market index has a positive effect and that is in line with expectations. On the other hand, gas has generally positive effect, where carbon and oil reveal a negative effect. We should remark that the effects of carbon, oil, gas, and coal alternate between significant and insignificant based on the structural shifts. Yet, only the effects of gas and coal change direction from positive to negative in some structural breaks.

The results of the study lead us for the discussion of policy implications in the field of renewable energy studies. The EU should employ the Market Stability Reserve more effectively to proactively address abrupt and significant declines in carbon prices. To achieve this objective, it must actively monitor the carbon market and restore market equilibrium and stability through the reacquisition of allowances. In doing so, sectors with a low carbon footprint, such as the renewable energy sector, should derive advantages from rising carbon prices, and the stocks of renewable energy companies should continue to appreciate in the face of increasing carbon prices.

Our study, in general, has elucidated the impact of market portfolio, carbon, oil, natural gas, and coal prices on the stock performance of renewable energy companies in Europe during the fourth phase of the EU Emissions Trading System (EU ETS). The findings have significant implications for understanding how EU will shape the EU carbon market and formulate policies in the energy market in the future.

## Statements and declarations

**Competing Interests:** The authors declare that they have no known conflict of interest.

### Data Availability Statement

All data is compiled from Investing.com. Below links provide each time series data

Investing.com (2023). NASDAQ OMX Clean Energy Europe (GRNFOCEUR). -- https://www.investing.com/indices/nasdaq-omx-clean-energy-europe.

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