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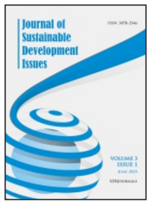

The Impact of Carbon Allowance and Oil Prices on Low-Carbon Footprint Stocks: Evidence from RALS Cointegration Analysis

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ABSTRACT

This study analyzes the long-run relationships among the STOXX Low Carbon Footprint Price Index, oil prices, carbon allowance prices under the EU Emissions Trading System (EU ETS), and the STOXX 600 Technology Index over the period from February 9, 2016, to March 31, 2025. The aim is to understand how climate policy instruments and sectoral developments, particularly in technology and energy markets, influence low-carbon financial assets. The analysis applies the Residual Augmented Least Squares (RALS) cointegration method, which accounts for non-normal error distributions and higher-order moment conditions, offering advantages over traditional techniques. Unlike the Engle-Granger approach, which fails to detect a cointegrating relationship, RALS identifies a statistically significant long-term connection among the variables. Long-run coefficients are estimated using FMOLS, DOLS, and CCR methods, all of which reveal consistent and significant positive effects of the technology index, carbon allowance prices, and oil prices on the low-carbon footprint stock. Notably, the STOXX 600 Technology Index shows a stable coefficient of around 0.81, underscoring the sector's critical role in advancing low-carbon investments. The positive impact of carbon prices aligns with expectations about the incentivizing role of emissions trading, while higher oil prices appear to enhance the appeal of low-carbon assets, possibly due to substitution effects. These findings offer new empirical insights into the financial implications of climate policy and market dynamics, contributing to the literature and informing investors and policymakers focused on sustainable economic transition.

Keywords: Low Carbon Footprint Stocks, Carbon Allowance, STOXX indices, Oil Prices, STOXX 600 Technology sector index, Rals Cointegration.

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1. INTRODUCTION

In recent years, growing concerns over climate change, increasing energy security challenges, rapid technological advancements, and heightened environmental awareness among consumers have significantly accelerated global investment in renewable energy (Sadorsky, 2012; Çelik vd., 2022). These dynamics have positioned the renewable energy sector as one of the fastest-growing areas within the global energy industry. Although initial investment costs for clean energy technologies remain relatively high, efforts to achieve environmental sustainability and build resilience against the climate crisis have driven these investments (Fazlollahi and Ebrahimijam, 2017). According to the Renewables 2024 Global Status Report, approximately USD 1.3 trillion in climate finance was allocated annually during the 2021-2022 period, nearly double that of the previous biennium. A substantial portion of this funding was directed toward carbon emission reduction initiatives, with investments in renewable energy sources such as solar and wind, as well as low-carbon transportation infrastructure, taking precedence. During this period, low-carbon transport projects accounted for 29% of total mitigation finance, while renewable energy investments represented 43%. These underscore that investments in clean energy are motivated not only by environmental concerns but also by economic transformation objectives. Furthermore, macroeconomic factors such as fluctuations in oil prices and carbon pricing mechanisms serve as significant policy tools influencing investments in alternative energy. Therefore, a comprehensive understanding of the financial mechanisms underpinning clean energy is critical for achieving sustainable growth and the success of energy transition policies.

Jones and Kaul (1996) explain the mechanism between oil prices and stock prices primarily within the framework of the cash flow and discount rate-based valuation model developed by Campbell and Shiller (1988). According to this model, an increase in oil prices generally raises production costs, thereby reducing firms' profitability and expected cash flows, which in turn leads to a decline in stock prices. For instance, rising oil prices can exert cost pressures particularly on energy-intensive sectors, negatively impacting corporate earnings. Furthermore, increases in oil prices can elevate inflation and interest rates, resulting in higher discount rates that reduce the present value of future cash flows and negatively affect stock prices. Numerous studies support this negative relationship between oil prices and stock returns (Papapetrou, 2001; Oberndorfer, 2009; Miller and Ratti, 2009; Filis, 2010; Ready, 2018; Sharma et al., 2018).

Although increases in oil prices generally exert negative pressure on overall stock markets, certain sectors may actually benefit from such developments. One such sector is clean energy, which has gained attention as part of global efforts to reduce carbon emissions through the adoption of alternative energy sources. In this regard, a notable substitution relationship exists between fossil fuel markets and clean energy stock markets, particularly on the demand side. As fossil fuel prices rise, demand for these traditional energy sources tends to decline, thereby fostering greater investment in clean energy technologies and contributing to upward movements in clean energy stock prices. Moreover, on the supply side, the expansion of renewable energy depends heavily on technological innovation, as the industry is characterized by high R&D intensity and structural complexities features similar to those found in the semiconductor segment of the photovoltaic sector (Song et al., 2019).

One of the key mechanisms that promote investment in clean energy is the European Union Emissions Trading System (EU ETS). This system imposes a cap on the amount of carbon dioxide that firms can emit by allocating tradable emission permits. By placing a binding limit on greenhouse gas emissions, the EU ETS increases the cost of energy production from carbon-intensive sources such as coal, making renewable energy alternatives more economically viable and competitive (Hanif et al., 2021). Within this framework, Welfens and Celebi (2020) examine the relationship between carbon prices and stock valuations from a market-based perspective. Firms holding a surplus of emission permits are required to record them as assets on their balance sheets. As the market price of these permits rises, the total valuation of such firms increases, which positively affects their stock prices. Conversely, a decline in carbon prices may reduce expected profitability and lead to a decrease in stock values. Since the EU ETS covers approximately 45 percent of the EU's total value-added, including the industrial and energy sectors, large-scale firms operating in these areas are particularly sensitive to fluctuations in carbon permit prices. Moreover, firms that develop innovative and carbon-reducing technologies tend to gain competitive advantages within this market structure, which translates into higher profitability and elevated stock performance. Higher carbon permit prices also stimulate investment in the alternative energy sector and support its expansion and market development (Kumar et al., 2012). Empirical research provides further evidence of a positive relationship between carbon permit prices and the stock prices of clean energy firms (Hu et al., 2019; Welfens and Celebi, 2020; Chun, 2022; Hanif et al., 2021).

This study contributes to the existing literature by employing the Residual Augmented Least Squares (RALS) cointegration methodology to analyze the long-run interdependencies among the STOXX Low Carbon Footprint Price Index, oil prices, carbon allowance prices under the EU Emissions Trading System (EU ETS), and STOXX 600 Technology Index for the period from February 9, 2016, to March 31, 2025. Unlike traditional cointegration methods, the RALS framework incorporates higher-order moment conditions and accounts for non-normal error distributions, thus offering more robust inferences in leptokurtic data common features in financial time series. By integrating both environmental regulatory variables (e.g., carbon permit prices) and sectoral indices representing clean energy and technological innovation, this research provides a holistic understanding of how climate policy instruments interact with financial markets. The inclusion of technology stocks recognizes the critical role of innovation in scaling clean energy solutions, especially under supply-side dynamics that demand significant research and development investment. The findings yield new empirical insights into the nexus between carbon pricing, oil prices, and the market valuation of low-carbon and technology-oriented assets. This offers valuable implications for investors seeking climate-aligned strategies and for policymakers aiming to design effective mechanisms that foster sustainable economic transitions while enhancing market resilience amid in the context of ongoing climate change challenges.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the data, econometric methodology, and the empirical design of the study. Section 4 presents and discusses the empirical findings in detail. Finally, the conclusion section summarizes the main results, discusses the policy implications.

2. LITERATURE REVIEW

The dynamic interaction between oil prices and clean energy stock prices has been widely investigated in the literature, yielding diverse findings depending on the period and methodology employed. Henriques and Sadorsky (2008) utilized a Vector Autoregressive (VAR) model on daily data from January 3, 2001, to May 30, 2007, and concluded that oil prices had only a minimal impact on the stock prices of alternative energy companies. This finding was later supported by Sadorsky (2012), who applied multivariate GARCH models to an extended period (January 1, 2001 – December 31, 2010), reaching similar conclusions regarding the limited influence of oil prices.

Contrary to these results, Kumar et al. (2012) examined the relationship over a different sample period (April 22, 2005 – November 26, 2008) using a comparable econometric framework. They found that oil prices had a statistically significant and positive effect on clean energy stock returns, while carbon allowance prices had no significant impact.

More recent studies have employed frequency-domain and nonlinear methods to uncover time-varying relationships. For instance, Reboredo et al. (2017), using linear and nonlinear causality techniques in the time-frequency domain along with wavelet coherence analysis over the period January 1, 2006 – March 16, 2015, found a weak short-run relationship between oil and clean energy stocks, which strengthened in the long run. Similarly, Song et al. (2019) employed the connectedness framework developed by Diebold and Yılmaz (2014) to analyze the interconnectedness between oil, natural gas, coal, and clean energy stock markets from June 15, 2009, to October 26, 2018. Their findings suggest that oil prices exert a particularly strong influence on clean energy stock prices during this period.

Beyond price levels, several studies have explored the role of oil price uncertainty in affecting clean energy stocks. Dutta (2017), analyzing data from May 10, 2007, to June 30, 2016, reported that oil price uncertainty had a more pronounced effect on clean energy stock volatility than oil price levels themselves. According to the study, increasing uncertainty led to heightened volatility in clean energy markets.

Using the same time span, Fazlollahi and Ebrahimijam (2017) applied the ARDL cointegration approach and found no significant short-term impact of oil price volatility on clean energy stocks. However, in the long run, both oil prices and oil price uncertainty positively influenced clean energy stock prices, with the magnitude of the oil price effect being stronger.

More nuanced evidence is provided by Çelik et al. (2022), who used an asymmetric DCC-GARCH model and revealed that the conditional correlation between clean energy stocks and oil price uncertainty is negative. Furthermore, Arfaoui et al. (2025) investigated sector-specific effects using the Wavelet Quantile Correlation method for the period from February 22, 2022, to July 15, 2024. Their findings highlight sectoral heterogeneity: while solar energy firms were found to be both positively and negatively affected by oil uncertainty in the short run, renewable fuel firms experienced positive impacts in both the short and medium run. Nevertheless, all sectors were negatively affected by oil uncertainty in the long term.

The literature on the interaction between carbon prices and clean energy stock returns generally suggests a limited direct relationship. Kumar et al. (2012) found no significant link between carbon emissions and clean energy stock performance. These findings are corroborated by Dutta (2017) and Dutta et al. (2018), who concluded that carbon emission allowance prices do not exert a consistent effect on renewable energy stock prices.

However, Dutta et al. (2018), employing a VAR-GARCH model, emphasized that while there is no general impact of European carbon allowance prices on renewable energy stocks, there exists a volatility spillover effect, which varies across regions. Building on this, Hanif et al. (2021) extended the analysis using time-domain and time-frequency spillover methods, showing that short-term volatility spillovers were more dominant than long-term ones. Additionally, a dynamic copula analysis indicated a positive dependence between carbon emission prices and clean energy stock returns.

3. METODOLOGY AND DATA

3.1. RALS ADF

The Residual Augmented Least Squares - Augmented Dickey-Fuller (RALS-ADF) unit root test introduced by Im et al. (2014) represents a significant methodological advancement by utilizing higher-order moment information from non-normal error distributions, which are often neglected in traditional unit root testing frameworks. Unlike existing approaches that require specific distributional assumptions or complex non-linear estimation techniques, the RALS methodology achieves power gains through a computationally simple, two-step least squares procedure. This makes it particularly valuable in empirical applications involving financial or macroeconomic time series, where non-normality and structural complexities are common.

The RALS-ADF unit root test begins with the estimation of standard ADF regressions, both with a constant (Equation 1) and with a constant & trend (Equation 2), using ordinary least squares (OLS). From these estimations, residual series are obtained:

$$\Delta y_t = \alpha + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \quad (1)$$

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \quad (2)$$

In the second stage of the procedure, the non-normality of the residuals is explicitly accounted for. The second and third moments of the residuals, denoted as $s_2 = T^{-1}(\sum_{t=1}^{T} \hat{\varepsilon}_t^2)$ and $s_3 = T^{-1}(\sum_{t=1}^{T} \hat{\varepsilon}_t^3)$ are computed. Using these, two new variables are constructed to capture the deviation from normality:

$$\hat{z}_{2t} = \hat{\varepsilon}_t^2 - s_2 \quad (3)$$

$$\hat{z}_{3t} = \hat{\varepsilon}_t^3 - s_3 - 3s_2\hat{\varepsilon}_t \quad (4)$$

These transformed residual terms are then incorporated into the original ADF equations, resulting in the modified RALS-ADF regression models:

$$\Delta y_t = \alpha + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \lambda_2 \hat{z}_{2t} + \lambda_3 \hat{z}_{3t} + u_t \quad (5)$$

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \lambda_2 \hat{z}_{2t} + \lambda_3 \hat{z}_{3t} + u_t \quad (6)$$

In this extended formulation, λ_2 and λ_3 measure the contribution of the second and third moment deviations. The test statistic will be $\tau^* = \rho\tau_{ADF} + \sqrt{1-\rho^2}Z$ where $\rho^2$is estimated as $\hat{\rho}^2 = \hat{\sigma}_u^2/\hat{\sigma}_\varepsilon^2$.

3.2. RALS Cointegration

The two-step cointegration test introduced by Engle and Granger (1987) is widely used in the literature due to its simplicity. In the first step, a regression is estimated using the OLS method between two series that are integrated at the same order (Yılancı and Aydın, 2018).

$$y_t = \delta x_t + u_t \quad (7)$$

In the second step, the stationarity of the residuals $\hat{u}_t$ obtained from Equation (7) is tested using an ADF-type regression:

$$\Delta \hat{u}_t = \Theta_0 + \delta \hat{u}_{t-1} + \sum_{i=1}^{k} \Theta_i \Delta \hat{u}_{t-i} + v_t \quad (8)$$

To account for non-normality in the error term v_t, we follow the RALS approach. For this purpose, the higher moments of the residuals are used to construct additional variables:

$$\widehat{w}_t = h(\hat{v}_t) - \widehat{K} - \hat{v}_t \widehat{D}_t, \qquad t = 1, 2, .., T \quad (9)$$

where $h(\hat{v}_t) = (\hat{v}_t^2, \hat{v}_t^3)'$, $\widehat{K} = T^{-1}\sum_{t=1}^{T} h(\hat{v}_t)$ and, $\widehat{D}_t = T^{-1}\sum_{t=1}^{T} h'(\hat{v}_t)$

$$\widehat{w}_t = (\hat{v}_t^2 - m_2, \hat{v}_t^3 - m_3 - 3m_2\hat{v}_t)' \quad (10)$$

where $m_j = \frac{1}{T}\sum_{t=1}^{T} \hat{v}_t^j$. The initial component of $\widehat{w}_t$ is derived from the moment restriction $E(v_t^2 - \sigma_t^2) = 0$ for orders $j = 2, 3,$ which holds under the assumption of homoskedasticity. Provided that the error terms exhibit asymmetry, this moment condition contributes to efficiency improvements. The second component of $\widehat{w}_t$ stems from the redundancy restriction $\mu_4 = 3\sigma^4$, where $\mu_j = E(v_t^j)$, a condition that exclusively holds under normality. For all non-normal distributions, the condition generates a significant stationary term, which, when incorporated into the cointegration regression, improves test performance. Thus, RALS cointegration regressions are formulated by augmenting the standard specification with $\widehat{w}_t$.

$$\Delta \hat{u}_t = \Theta_0 + \delta \hat{u}_{t-1} + \sum_{i=1}^{k} \Theta_i \Delta \hat{u}_{t-i} + \widehat{w}_t'\gamma + e_t \quad (11)$$

The null hypothesis of no long-run relationship ($\delta = 0$) can be tested using the standard t-statistic.

$$t^* \to p.t + \sqrt{1-p^2}.Z \quad (12)$$

where Z is a standard normal random variable and p is the long-run correlation between v_t in Equation (8) and e_t in Equation (11).

The findings indicate that the asymptotic distributions of the RALS cointegration tests are influenced by the nuisance parameter p^2. However, as noted by Lee et al. (2015), this parameter can be computed using the nonparametric estimation techniques proposed by Hansen et al. (1995).

3.3. Data

This study employs a comprehensive dataset spanning from February 9, 2016, to March 31, 2025, obtained from the Datastream database. The variables analyzed include the STX Global Low Carbon Footprint Index (STOXXLCF), the European Union Allowance (EUA) prices from the EEX market the STOXX 600 Technology sector index (STOXX600T), and West Texas Intermediate crude oil prices (WTI). The purpose of the analysis is to investigate the influence of EUA prices, technology sector performance, and oil prices on the low carbon footprint stock price index, modeled as:

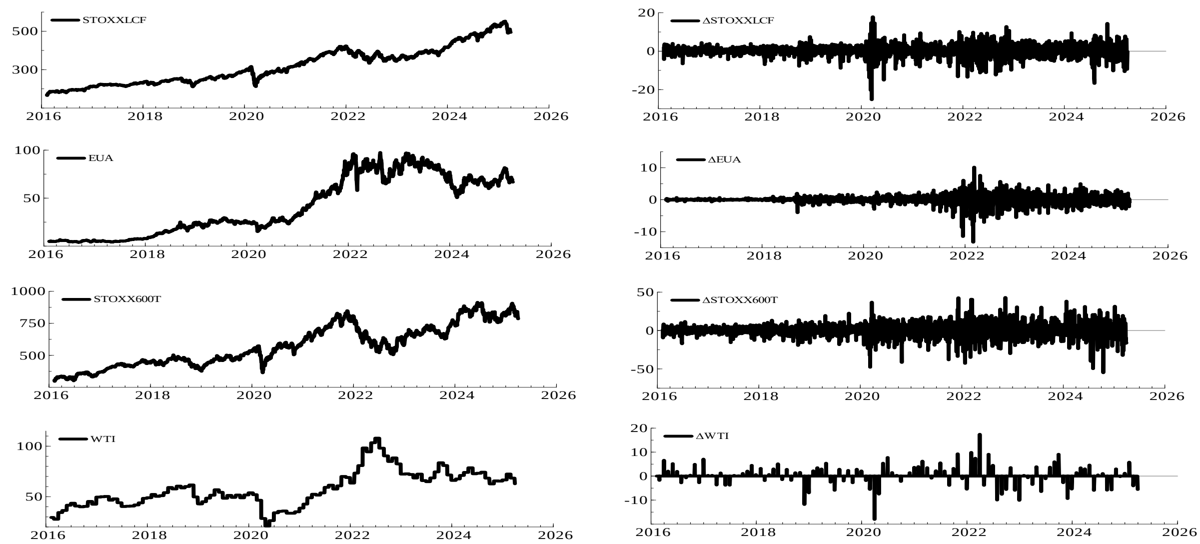
$$STOXXLCF_t = f(EUA_t, STOXX600T_t, WTI_t) \tag{13}$$

where $STOXXLCF_t$ is the low carbon footprint stock price index; EUA_t represents EUA prices; $STOXX600T_t$ is the technology sector index, and WTI_t the oil price. The coefficients β_1, β_2, and β_3 capture the effects of the independent variables, while β_0 denotes the intercept and ε_t the error term.

$$STOXXLCF_t = \beta_0 + \beta_1 EUA_t + \beta_2 STOXX600T_t + \beta_3 WTI_t + \varepsilon_t \tag{14}$$

Figure 1 illustrates the evolution of daily prices (left panels) and daily first differences (right panels) for the STOXXLCF, EUA, STOXX600T, and WTI indices over the period from 2016 to 2025. As depicted in the left-hand panels, the price series for all four indices generally exhibit a notable upward trend from 2016 through approximately 2022. In particular, the technology sector and carbon allowance markets demonstrated strong growth during this period. Following a peak in 2022, the price paths of these indices exhibit either a modest decline through 2024, albeit at relatively high levels. The WTI crude oil index, in contrast, shows more pronounced fluctuations and a sideways movement throughout the same period, reflecting a more volatile pattern relative to the other indices. The right-hand panels of Figure 1 display the daily first differences calculated as the changes in daily prices fluctuating around zero. These first difference series show periods of increased volatility, with notable positive and negative changes, especially around early 2020 at the start of the COVID-19 pandemic and in 2022, likely due to geopolitical and economic shocks. These pronounced fluctuations indicate significant market reactions to external shocks, underlining the dynamic and volatile nature of these asset classes.

Figure 1: Daily Prices and Differences of Selected Indices



As shown in Table 1, the descriptive statistics indicate that the STOXXLCF index exhibits the highest average price level and volatility among the series. All indices display positive skewness, suggesting a tendency toward more frequent extreme positive price movements. While the kurtosis values generally approximate or fall below those of a normal distribution, the Jarque-Bera (J-B) tests reject the normality assumption for all series, implying deviations from normal distribution in the price dynamics.

Table 1: Descriptive Statistics

	STOXXLCF	STOXX600T	EUA	WTI
Mean	307.61	136.06	39.67	56.93
Maximum	503.306	349.97	97.58	107.93
Minimum	165.586	48.02	3.91	20.92
Skewness	0.351	0.566	0.391	0.597
Kurtosis	1.984	2.293	1.612	3.016
Jarque-Bera	143.99***	167.9***	239.35***	134.69***

Note: *** indicates significance at the 1% level

4. EMPIRICAL RESULTS AND DISCUSSION

Before conducting the cointegration analysis, it is essential to examine the time series properties of the variables. This section applies both the traditional ADF test and the more robust RALS-ADF test to determine the order of integration of the series. While the ADF test assumes normally distributed residuals, the RALS-ADF test accounts for non-normality and higher-order moments, providing more reliable inference when analyzing financial time series, which are often characterized by leptokurtosis and skewness.

To assess the stationarity of the series, both tests were applied under constant and constant & trend model. As shown in Table 2, all level series fail to reject the null hypothesis of a unit root at the 5% significance level in both model, indicating that the variables are non-stationary in levels. This is further supported by extremely high J-B test statistics in the ADF test results, particularly for oil prices (J-B = 2,836,739), STOXXLCF (J-B = 21,263.4), and other variables, which reveal substantial deviations from normality.

In contrast, both the ADF and RALS-ADF tests under the constant specification indicate that all first-differenced series are stationary at the 1% significance level. For example, the RALS-ADF statistics for the differenced series are highly significant (e.g., -52.491 for $\Delta STOXXLCF$, -54.869 for ΔEUA), confirming the I(1) nature of the variables. However, when applying the RALS-ADF test under the constant and trend model, the presence of unit roots persists, indicating possible limitations in detecting stationarity when trend components are included. Nevertheless, as illustrated in Figure 1, the trend components observed in the level series disappear after first differencing. Therefore, it is more appropriate to rely on the results of the constant model.

Table 2: Unit Root Test Results

	ADF				RALS ADF			
	Constant		Constant & trend		Constant		Constant & trend	
	Test Stat	J-B	Test Stat	J-B	Test Stat	ρ^2	Test Stat	ρ^2
$STOXXLCF$	-0.980	21263.4***	-3.385*	22654.9***	-1.217	0.919	4.391	0.909
$STOXX600T$	-1.794	2104.1***	-3.406*	2167.9***	-1.914	0.935	3.618	0.916
EUA	-1.466	1758.9***	-1.354	1658.7***	-1.132	0.931	0.047	0.932
WTI	-2.352	2836739.9***	-2.244	2841723.0***	-2.415	0.726	0.484	0.726
$\Delta STOXXLCF$	-52.787***	21027.05***	-52.779***	21040.6***	-52.491***	0.919	-0.269	0.907
$\Delta STOXX600T$	-49.188***	2080.6***	-49.187***	2079.9***	-52.787***	0.934	-0.514	0.935
ΔEUA	-50.649***	1756.0***	-50.664***	1768.7***	-54.869***	0.931	-1.084	0.931
ΔWTI	-48.664***	2792758***	-48.647***	2796382***	-10.935***	0.723	-0.768	0.723

Note: *** and * indicates significance at the 1% and 10% level, respectively.

As shown in Table 3, the standard Engle-Granger (EG) cointegration test fails to provide sufficient evidence for a long-run relationship among the variables. Furthermore, the high J-B statistic (1419.9) indicates a strong deviation from normality in the residuals. This supports concerns raised in the literature about the sensitivity of the EG test to non-normal error distributions, particularly in financial time series, which often exhibit leptokurtosis and skewness.

In contrast, the RALS version of the Engle-Granger test (RALS-EG) yields a statistically significant test statistic of -4.069, surpassing the critical value at the 1% level, thereby confirming the existence of a long-run cointegrating relationship. The improvement in inference under the RALS framework can be attributed to its ability to account for higher-order moment conditions and non-normal error structures, aligning with theoretical expectations and enhancing the robustness of the long-run analysis.

Table 3: Cointegration Results

EG		RALS-EG	
Test Stat	J-B	Test Stat	ρ^2
-2.974	1419.9***	-4.069***	0.343

Note: *** indicates significance at the 1% level. Critical values with constant are taken from Yılancı and Aydın (2018) for RALS-EG.

As shown in Table 4, the long-run estimation results obtained through FMOLS, DOLS, and CCR methods consistently demonstrate that the STOXX 600 Technology index, carbon allowance index, and oil prices have statistically significant and positive effects on the STOXX Low Carbon Footprint index. Across all three estimation techniques, the coefficient of STOXX600T is consistently estimated at approximately 0.81, indicating a strong and stable positive association between the performance of the technology sector and low-carbon investments. Similarly, the EUA variable exhibits positive and highly significant coefficients, suggesting that rising carbon prices are conducive to increased investment in low-carbon assets, consistent with theoretical expectations regarding the incentivizing role of emissions pricing. The positive coefficients on oil prices across models imply that higher oil prices may enhance the appeal of low-carbon investments, potentially due to cost-driven substitution effects. The robustness and consistency of these findings across different estimators highlight the structural link between technology sector dynamics, energy markets, environmental pricing mechanisms, and the performance of low-carbon financial assets.

Table 4: Long Run Estimation Results

Variables	*FMOLS*	*DOLS*	*CCR*
$STOXX600T$	0.821 (0.000)	0.8130 (0.000)	0.8218 (0.000)
EUA	0.0441 (0.000)	0.0464 (0.000)	0.0441 (0.000)
WTI	0.0945 (0.000)	0.0950 (0.000)	0.0949 (0.000)

5. CONCLUSION

This study investigates the long-run relationships among the STOXX Low Carbon Footprint Price Index, oil prices, carbon allowance prices under the EU Emissions Trading System (EU ETS), and the STOXX 600 Technology Index during the period from February 9, 2016, to March 31, 2025. Using the Residual Augmented Least Squares (RALS) cointegration methodology, which is robust to non-normal distributions and higher-order moment conditions frequently observed in financial time series, the study identifies a statistically significant long-run cointegrating relationship that could not be detected using the traditional Engle-Granger test.

The long-run estimations via FMOLS, DOLS, and CCR methods consistently demonstrate that technology sector performance, carbon allowance prices, and oil prices have positive and statistically significant effects on low-carbon equity prices. In particular, the stable and strong coefficient of the STOXX Europe 600 Technology Index confirms the vital role of technological innovation in driving low-carbon investment, in line with prior studies emphasizing the R&D-intensive and innovation-driven nature of the clean energy sector (Song et al., 2019; Çelik et al., 2022). The positive effect of carbon allowance prices is also consistent with market-based regulatory mechanisms as highlighted by Welfens and Celebi (2020) and Hanif et al. (2021), indicating that higher emissions prices incentivize cleaner investments and improve firm-level valuation through regulatory alignment. Moreover, the positive impact of oil prices suggests a demand-side substitution effect, where rising fossil fuel costs enhance the relative attractiveness of clean energy, supporting findings from Kumar et al. (2012) and Fazlollahi and Ebrahimijam (2017).

These results confirm the hypotheses presented in the introduction, particularly the expected positive linkage between low-carbon investment performance and both environmental regulation and technology sector dynamics. Unlike some earlier studies that report limited or inconsistent relationships (Henriques and Sadorsky, 2008; Sadorsky, 2012), this study's use of a more robust cointegration framework provides clearer evidence of structural long-run interactions among the variables.

From a policy standpoint, the findings highlight the importance of maintaining a credible and stable carbon pricing regime, as well as supporting technology development through targeted innovation policies. Investors and portfolio managers should consider carbon markets and technology sector indicators when designing climate-aligned investment strategies. As clean energy transitions increasingly shape global financial markets, aligning regulatory tools with innovation-driven sectors can enhance both sustainability outcomes and financial resilience.

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