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THE INTERRELATION BETWEEN THE CARBON TRADING SYSTEMS AND ENERGY MARKETS AND ECONOMIC OUTLOOK: A COMPARATIVE ANALYSIS USING VECM AND ARDL[2]

This study examines the mutual relationship between carbon markets, energy markets, power markets, and the economic outlook. The analysis utilizes daily data from 2008 to 2023, encompassing all phases of the European Emissions Trading System. The relationship between the variables is examined through comparative analysis in both the long and short term, employing VECM (Vector Error Correction Model) and ARDL (Autoregressive Distributed Lag) analyses. The study findings indicate a persistent and mutual relationship between carbon markets, energy markets, power markets, and economic outlook over the long term. Short-term fluctuations decrease in order to reach long-term equilibrium. Both the energy and power markets, as well as the economic outlook, have an impact on carbon prices, and there is a positive relationship between them..Carbon markets have a minor and temporary impact on power and energy markets and the economic outlook. Companies choose cheaper and ecologically harmful fuels in response to an increase in fossil fuel costs. As the economic forecast improves and companies experience improved financial conditions, they are inclined to boost their industrial production, thus leading to higher levels of emissions. The rise in carbon costs results in a minimal and temporary decline in corporations' demand for fossil fuels.

Keywords: Carbon Markets; Carbon Trading Systems; Carbon Pricing; Vector Error Correction Model; Autoregressive Distributed Lag
JEL: Q01; Q43; Q48; Q54; Q56

1. Introduction

Global warming is the long-term heating of the Earth's surface observed since the pre-industrial period due to human activities, primarily fossil fuel burning, which increases heat-trapping greenhouse gas levels in Earth's atmosphere (NASA, 2020). According to the most recent statistics from the United Nations Environment Programme, surface temperatures have surpassed the threshold of 1.5 degrees. It is advised to implement measures to prevent the

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rise to a maximum of 2 degrees (UNFCC, 2015). Numerous agreements and protocols have been established in pursuit of this objective such as the Kyoto Protocol, the Paris Agreement, United Nations Framework Convention on Climate Change, Conference of the Parties and carbon trading systems.

Researchers conducted studies to analyze the impact of these arrangements on economic indicators, macroeconomic data, the stock market, and the energy market. The carbon trading system, also known as emission trading, is the most influential framework for economies such as those in Europe, China, New Zealand and North Korea. Emissions trading is an economic approach that tries to control pollution by providing financial incentives for achieving reductions in emission levels. Under this system, a central authority sets a limit or restriction on the amount of a pollutant that can be released. Subsequently, the limit is divided into allocations, with each allocation representing the allowed quantity of the emission released by the individual or entity. As required, organizations that are subject to the cap have the option to buy or sell these permits. To put it simply, organizations can exchange the emission permits they get under the cap-and-trade system on carbon trading markets.

One of the pioneering and most important emission trading systems is the EU Emission Trading System (EU ETS). The Kyoto Protocol is one of the cornerstones of the EU ETS's establishment. The Kyoto Protocol to the UN Framework Convention for Climate Change (UNFCCC) was agreed upon in 1997; legally binding GHG reduction targets, or caps, were set for industrialized countries under the agreement. This led to the need for policy instruments to meet the Kyoto commitments (European Commission, 2015). The EU ETS is one of the policy instruments designed to address this need.

The EU ETS, launched at the start of 2005, is the world's first international company-level 'cap-and-trade' system of allowances for emitting carbon dioxide (CO2) and other greenhouse gases. (European Commission, 2016). The EU ETS is the cornerstone of the European Union's drive to reduce its emissions of human-caused greenhouse gases, which are largely responsible for warming the planet and causing climate change. EU ETS refers to the "cap-and-trade" structure of the EU Emissions Trading System. As the first and largest emissions trading system for reducing greenhouse gas(GHG) emissions, The EU ETS covers more than 10,000 installations in the energy sector and manufacturing industry, as well as aircraft operators flying within the EU and departing to Switzerland and the United Kingdom. It applies to all EU Member States and the European Free Trade Association countries (Iceland, Liechtenstein, and Norway) (Scope of the EU Emissions Trading System, n.d.). Over time, the system's implementation has been segmented into separate trading periods referred to as phases. These phases are phase I (2005-2007), phase II (2008-2012), phase III (2013-2020), and phase IV (2021-2030).

The EU ETS affects the production levels and financial situations of companies by restricting their emissions; therefore, the carbon market affects companies, prices, and the economy. Many studies have been conducted to investigate this effect. Some studies have examined the relationship between the carbon market and the energy markets, including power and fuel prices. (Chevallier, 2011b; Zeng et al., 2017; Bunn, Fezzi, 2009; Kim, Koo, 2010)

Several studies have examined the relationship between the carbon market and macroeconomic indicators. (Shahbaz et al., 2017; Chevallier, 2011a; Fan et al., 2016; Li et

al., 2014). Scholarly research has investigated a connection between the carbon market and the stock market. (Bouri et al., 2017; Hu et al., 2017; Moreno, Da Silva, 2016). Researchers also analyze the variables that drive carbon prices. (Alberola et al., 2008; Benz, Trück, 2009; Hintermann, 2010)

In this study, with respect and contribution to the literature, the relationship between the carbon market and the energy market, power market and economic outlook was evaluated throughout the II, II, and IV phases of EU ETS in the European Union. Phase I was a pilot phase, during which the European Commission determined the pricing rather than relying on the natural market forces of supply and demand. The establishment of the carbon market was not influenced by other markets. Therefore, phase I is excluded from the research. The Vector Error Correction Model (VECM) and Autoregressive Distributed Lag (ARDL) approaches were utilized to identify the relationship and conduct a comparative analysis of the findings.

This study differs from the existing literature and makes a valuable contribution to it for three reasons: The study includes all phases of the EU Emissions Trading System, the relationship between the carbon market and the energy market, the power market, the economic outlook was investigated all together and mutually, the results were strengthened and compared through the implementation of two analyses, namely VECM and ARDL.

2. Literature

Extensive literature has been generated in order to determine the impact of carbon markets. The comprehensive literature provides the dynamic relationship between the carbon market and industries, investments, and the overall economy. Some studies focus on the impact of the carbon market on economic indicators, while others concentrate on energy prices. Researchers also examined and observed the mechanism of carbon pricing.

Fell (2010) analyzed the relationship between carbon prices and wholesale electricity prices with the CVAR method between 2005-2008. He found that electricity prices respond strongly to a shock (1€ price jump) in carbon prices. Freitas, et al. (2015) examined the relationship between carbon prices and electricity prices with the VECM method between 2008-2013. They also included fuel prices in the study. In their study, they found that there is a long-run positive relationship (cointegration) between carbon prices, electricity prices, and fuel prices.

Wolff, G., and others (2019) examined the relationship between carbon prices and electricity prices in phase 3 of EU ETS and found a negative relationship between the variables. Ahamada and Kirat (2015) examined the relationship between carbon prices and electricity prices between 2008-2012. They found that there was no relationship between the variables for the first ten months, because of the 2008 financial crisis structural break, but then carbon prices affected electricity prices.

Chevallier et al. (2019) examine the relationship between carbon certificates and energy prices with the vine copula model. They found that carbon prices co-move with energy prices for only one week, and the relationship with oil and gas prices is negative. Chevallier (2011a) analyzed the relationship between carbon prices and the macroeconomy (industrial production index) with the Markov switching var model between 2005-2010. He found that

macroeconomic activities affect carbon prices. S. Zeng et al. (2017) analyzed the relationship between carbon prices and economic development and energy prices with structural variables. They found a negative relationship between carbon prices and coal prices and a negative relationship between carbon prices and energy prices and economic development.

Fezzi et al. (2009) analyzed the relationship between carbon prices and energy prices with the VECM model. They found that gas prices affect carbon prices, and there is a positive relationship between carbon prices and electricity prices. Chen et al. (2019) examined the relationship between carbon prices and energy prices with the asymmetric BEKK model. They found a positive relationship between carbon prices and oil and natural gas prices and a weak negative relationship between carbon prices and coal prices.

Shi et al. (2022) examined the relationship between carbon prices and energy prices, macroeconomic levels, and weather using a structural variance model. They found that carbon prices are affected by their own past values; there is a positive relationship between carbon prices and oil and natural gas prices, a negative relationship between carbon prices and coal prices, and insignificant relationships between carbon prices and macroeconomic level and weather.

Luo et al. (2022) examined the relationship between carbon prices and oil and natural gas prices using the wavelet analysis method. They found a negative relationship between carbon prices and natural gas prices and an unstable dependency relationship between carbon prices and oil prices. Xu et al. (2020) examined the relationship between carbon and the energy market with the Multiplex Recurrence Network Approach and found that there is a mutually leading relationship between carbon and the energy market.

Zhang et al. (2016) investigated the relationship between carbon prices, economic growth, energy prices, and temperature. They found that economic growth leads to a fall in carbon prices, oil prices have a positive impact on carbon prices, and there is a long-term negative relationship between coal and carbon prices.

Boersen et al. (2014) attempted to determine the factors influencing carbon prices by considering their relationship with electricity markets. They found that natural gas, oil prices, and changes in electricity generation are important determinants of carbon prices. Benz et al. (2009) modelled the price dynamics of carbon prices using Markov switching and AR-GARCH models and found that the models used were able to capture the characteristics of the carbon market. Conrad et al. (2012) studied carbon price dynamics with the GARCH model at high-frequency fractionally integrated asymmetric power. They have been able to capture the dynamics of the carbon market with their model. Aatola et al. (2013a) researched the price dynamics of carbon allocation certificates. They found that carbon future prices depend on electricity, gas, and coal prices. Lutz et al. (2013) studied the carbon price fundamentals with the Markov regime-switching model. They found that the most important carbon price drivers are stock market and energy prices, and coal and oil prices have a long and positive effect.

When the measures taken against global warming and the literature are analyzed, it is seen that carbon markets are still a developing concept in line with these measures. Carbon trading systems are both influenced by and have an impact on energy costs, power prices, air

pollution, the economic climate, CO2 emission levels, natural disasters, and stock market fluctuations. Policymakers should consider all these together when making decisions against global warming and should understand the relationship between these variables well.

3. Data and Methodology

This analysis utilizes daily data covering the period from 2008 to 2023, encompassing the three periods of the carbon trading system. The objective of the study is to analyse the dynamic relationship between the carbon market, energy market, power market, and economic outlook in the European Union. Carbon allowance certificate prices in the European Union Emissions Trading System are considered an indicator of the carbon market. The most widely used oil types which are Brent oil, crude oil, gasoil, gasoline RBOB, heating oil, and natural gas prices are considered indicators of the energy market. The electricity price variable is referred to as the power market, as it is intended to be kept separate from the oil variables within the energy market. The MSCI Europe Index and the EURO STOXX 600 Index, which are large indices covering companies in the European Union, are used to account for the economic outlook of the entire European Union. The study's data was obtained from the Bloomberg Database, and the analysis was conducted using the E-Views 10 software.

The study examines the relationship between variables through the utilization of VECM and ARDL methodologies. Both techniques enable the examination of the short- and long-term relationship between the variables and the determination of a mutual causal relationship. Therefore, the obtained findings can be evaluated in a comparable way, which will corroborate and strengthen the conclusions of both models.

Table 1. Variables

Market	Variable	Representation
Carbon Market	European Union Emissions Trading System Carbon Allowance Certificate Price	CP
Power Market	Electricity Price	ELEC
Energy Market	Brent Oil Price	BROIL
	Crude Oil Price	CROIL
	Gasoil Price	GASOIL
	Gasoline RBOB Price	RBOIL
	Heating Oil Price	HTOIL
	Natural Gas Price	NGAS
Economic Outlook	MSCI Europe Index	MSCI
	EURO STOXX 600 Index	STOXX

3.1. Vector Autoregressive Models(VAR), The Vector Error Correction Model (VECM)

Econometric modelling involves the use of two variables: a dependent variable and an independent variable. The movements of the dependent variable are explained by the independent variables. However, in economic and financial time series, variables are influenced by both their present and previous values, as well as the present and previous values of other variables. Given the circumstances and criticism of the fundamental

modelling logic, Sims (1980) proposed vector autoregressive models (VAR). VAR models incorporate the present and previous values of all variables, using the specified lag length "p." VAR modelling involves the use of multiple equations, where a model with "p" previous values is represented as VAR(p).

The VAR model with two variables (yt, xt) and a lag length of 1 is presented below:

$$y_t = \alpha_1 + \beta_{11} y_{t-1} + \beta_{12} x_{t-1} + u_{1t} \quad (1)$$

$$x_t = \alpha_2 + \beta_{21} y_{t-1} + \beta_{22} x_{t-1} + u_{2t} \quad (2)$$

yt and xt = variables investigated in relation to each other, $\alpha 1$ and $\alpha 2$ = constants, u1t and u2t = error terms, $\beta 11$, $\beta 12$, $\beta 21$, $\beta 22$. = The coefficients in the main matrix.

Matrix Representation;

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \quad (3)$$

Although VAR allows us to model endogenous and exogenous variables as a whole, especially in economic and financial time series, it only allows the modelling of stationary variables. In order to ensure that the series are stationary, it is usually necessary to take first-order differences, but this will cause the series to move away from their original values, and therefore the short-run and long-run effects of the series will disappear. (Sarıkovalık et al., 2020). The problem is effectively solved by cointegration tests. Engle and Granger developed the Vector Error Correction Model (VECM), which enables the simultaneous utilization of cointegration and error correction models by including cointegration testing. (Engle et al., 1987).

The VECM incorporates an error-correcting approach that takes into account the cointegration relationship between the variables. This process assumes that short-term fluctuations in the series will result in a corrective movement towards long-term equilibrium. It investigates long-term relationships between variables, and if there is a long-term equilibrium relationship between the series and this equilibrium is broken, the VECM model includes a mechanism to restore this equilibrium.

VECM formulation is as follows.

$$\Delta y_t = \alpha \beta' y_{t-1} + \Gamma_1 \Delta_{y_{t-1}} + \Gamma_2 \Delta_{y_{t-2}} + \cdots + \Gamma_p \Delta_{y_{t-p}} + u_t \quad (4)$$

We can also specify as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta y_{t-1} + u_t \quad (5)$$

yt = the state of the time series at time t, Δy_t = first difference of the y, p = lag length, β' = coefficients of long-run dynamics, Π = coefficient matrix of cointegration vector, Γ = coefficient matrix of error correction mechanism.

In summary, both short-term and long-term relationships between variables can be identified with the VECM. Considering that carbon trading systems are a relatively new market, the VECM is a very important tool in examining the relationship between carbon markets and other markets and the economic situation. Furthermore, since the VECM simulates the

correction of short-term imbalances in the face of instantaneous shocks to reach long-term equilibrium, it is very effective in capturing the dynamic relationship between carbon markets and other commodity markets.

3.2. The Autoregressive Distributed Lag (ARDL)

The autoregressive distributed lag (ARDL) model, proposed by Paseran (2001), is a model that does not need the stationarization of the series and is capable of analyzing both short-term and long-term connections. The model includes two components: autoregressive (AR) components that capture short-term dynamics and distributed lag (DL) components that capture long-term dynamics. ARDL is a useful method for examining economic and financial time series data, as it allows for the presence of non-stationary components. The model is composed of three steps. The first step involves assessing the presence of a long-term relationship. The second step employs the calculation of the long-run relationship. The third and final step is to estimate the short-run relationship. (Pesaran, 2001)

General formulation of the ARDL model:

$$\Delta y_t = \alpha + \sum_{i=1}^{p} \beta_1 \Delta y_{t-i} + \sum_{i=1}^{p} \beta_2 \Delta x_{t-i} + \beta_3 \Delta y_{t-1} + \beta_4 \Delta x_{t-1} + u_t \quad (6)$$

Firstly, the hypothesis " β3 = β4 = 0 " is tested with this formulation and if the test result confirms the existence of a long-term relationship, the analysis continues to calculate the long-term relationship.

Long-term relationship:

$$y_t = \alpha + \sum_{i=1}^{p} \beta_1 \Delta y_{t-i} + \sum_{i=1}^{p} \beta_2 x + e_t \quad (7)$$

After analyzing the long-term relationship to estimate the short-term relationship, one lagged value of the error term (et) from the long-run relationship is utilized in the following equation:

Short-term relationship:

$$\Delta y_t = \alpha + \sum_{i=1}^{p} \beta_1 \Delta y_{t-i} + \sum_{i=1}^{p} \beta_2 \Delta x_{t-i} + \beta_3 e_{t-1} + u_t \quad (8)$$

et = the error term derived from the equation for the long-run relationship.

Using the previous formulation (8), we can determine the extent to which the short-term imbalance will be resolved in the long term. If the coefficient of a lagged value of the error term from the long-term relationship is both statistically significant and negative, it may be inferred that the short-term imbalance is eradicated in the long run.

ARDL is a popular approach in economic and financial time series analysis because it allows us to work with both stationary and non-stationary data. The ARDL methodology is an important tool in studying the structure of the carbon market because it is necessary to capture short- and long-term dynamics in the evaluation of carbon trading systems. It is also especially effective at capturing the impact of the complicated relationship between carbon and other markets.

4. Results

When beginning the analysis, the stationarity of the variables used in the model should first be checked, that is, whether they contain unit roots. There are several ways to determine stationarity. The Augmented Dickey-Fuller Test (ADF), a commonly utilized approach, will be employed in this investigation. The ADF test's null hypothesis is "the series contains a unit root," and if the test statistic is less than the critical value at the stated significance level, the null hypothesis is rejected, and the series is stationary. To establish the level of integration of non-stationary datasets, the first or next differences can be used to determine the level at which they are stationary.

The following Table 2 shows the results of the ADF unit root tests. The stationarity of the variables is assessed using the ADF test with a constant and trend model at a significance level of 5%. The test was conducted initially at the level(in raw form) and then at the first difference. According to the results, we are unable to reject the null hypothesis at a 5% significance level for all variables at the level since the probability values for all variables exceed the crucial threshold of 0.05. That is, all variables are non-stationary when measured at their original level. Applying the ADF test by calculating the first differences between the variables reveals that the probability values for all variables are below the critical value of 0.05. Consequently, we reject the null hypothesis and conclude that the variables are stationary. Based on the results, it is evident that all variables have an integration level of 1, I (1). This indicates that we have satisfied the prerequisites for utilizing Johansen's co-integration model.

The Johansen cointegration test, a widely utilized method, was employed to find out the long-term relationship between the variables. Cointegration indicates the presence of enduring equilibrium connections between variables, and for a long-term relationship to exist, there must be at least one cointegration equation. The Johansen cointegration test employs two likelihood ratio test statistics, namely the maximum eigenvalue and trace, to ascertain the quantity of cointegration vectors. The null hypothesis of the test is "there is no cointegration between variables." If the test statistic value is lower than the critical value of 0.05, the null hypothesis is rejected, and the cointegration equation is determined.

To apply Johansen's co-integration test with the VECM, the appropriate lag length must be determined. The lag length defines how many prior time periods will be used to generate the current values. Various information criteria, such as the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SC), the Hannan-Quinn Information Criterion (HQ), and the Final Prediction Error (FPE), are widely used to determine the lag order. (Liu & Lee, 2020). The VAR Lag Order Selection Criteria were applied in this study to determine the optimal lag. The following table 3 provides the results for the lag length. Based on the findings of the information criteria, the lag length of our model is determined to be "3".

Tablo 2. Unit Root Test Results

Variable	ADF test in	Model	t-Statistics	Prob.	Result
Brent	Level	CT	-2.166418	0.5077	Non-stationary
Crude	Level	CT	-2.377654	0.3913	Non-stationary
Electricity	Level	CT	-2.169579	0.1650	Non-stationary
ETS	Level	CT	-1.011252	0.9409	Non-stationary
Gasoline RBOB	Level	CT	-2.424154	0.3668	Non-stationary
Natural Gas	Level	CT	-2.780045	0.2048	Non-stationary
Heating Oil	Level	CT	-2.270758	0.4494	Non-stationary
Gas Oil	Level	CT	-2.348088	0.4071	Non-stationary
MSCI	Level	CT	-2.247915	0.4621	Non-stationary
STOXX	Level	CT	-3.261603	0.0729	Non-stationary
Brent	1st difference	CT	-64.97121	0.0000	Stationary
Crude	1st difference	CT	-51.83679	0.0000	Stationary
Electricity	1st difference	CT	-63.64281	0.0000	Stationary
ETS	1st difference	CT	-30.23236	0.0000	Stationary
Gasoline RBOB	1st difference	CT	-64.51717	0.0000	Stationary
Natural Gas	1st difference	CT	-70.48760	0.0000	Stationary
Heating Oil	1st difference	CT	-30.03809	0.0000	Stationary
Gas Oil	1st difference	CT	-34.67129	0.0000	Stationary
MSCI	1st difference	CT	-63.59147	0.0000	Stationary
STOXX	1st difference	CT	-63.45682	0.0000	Stationary

CT: Constant and Trend

Table 3. Lag Length Determination

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-154568.0	NA	8.75e+20	76.59962	76.61524	76.60516
1	-70412.14	167853.1	711.7890	34.94655	35.11834	35.00742
2	-69838.73	1140.854	562.9487	34.71196	34.55026	34.82816
3	-69444.47	782.4754	486.5647	34.46614*	34.48939*	34.73767*
4	-69310.20	265.8038	478.3744	34.49316	34.49205	34.77602
5	-69164.87	286.9773	467.7528	34.50670	34.50213	34.80889

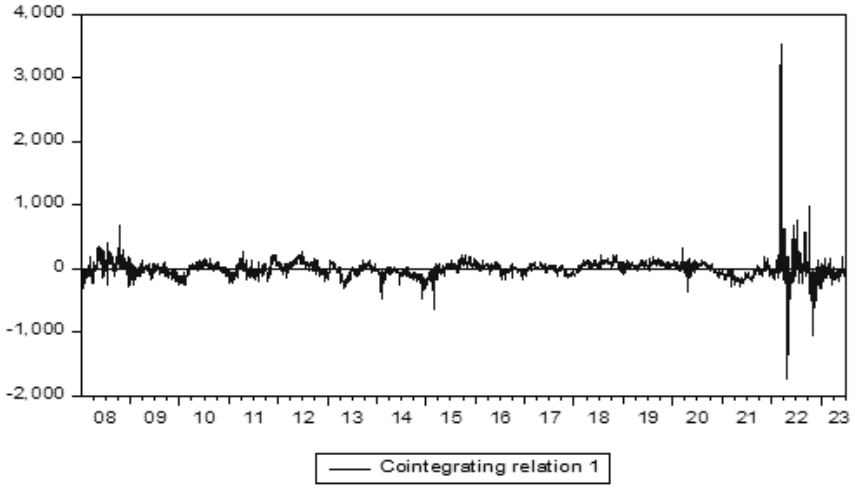
The following Table 4 shows the results of the Johansen cointegration test, utilizing the following methods: maximum eigenvalue and trace. Both the maximum eigenvalue and trace point to the presence of a three-cointegration equation. The existence of a cointegration equation indicates the presence of a long-run relationship between the variables. If a long-term relationship exists, a short-term correlation also exists; however, there are fluctuations between the short-term and long-term. The presence of a cointegration equation demonstrates that these fluctuations will eventually reach a long-term equilibrium. The VECM analysis findings indicate the duration required.

Figure 1 shows the cointegration graph. There are anomalies in the graph for 2022. The cause of this situation is the ongoing war between Russia and Ukraine. The war led to an energy crisis due to an interruption of natural gas supply from Russia. This issue has had significant effects on both the energy market and the carbon market.

Table 4. Cointegration Test

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.064219	564.1393	251.2650	0.0000
At most 1 *	0.022589	295.9880	208.4374	0.0000
At most 2 *	0.017500	203.6837	169.5991	0.0002
At most 3	0.010810	132.3581	134.6780	0.0679
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.064219	268.1513	65.30016	0.0001
At most 1 *	0.022589	92.30429	59.24000	0.0000
At most 2 *	0.017500	71.32556	53.18784	0.0003
At most 3	0.010810	43.91175	47.07897	0.1050

Figure 1. Cointegration Graph



After the confirmation of a long-term relationship by the cointegration test, the VECM was conducted to examine the relationship between the variables. The results of the VECM are presented in Table 5. The results comprise three different parts. Part I contains the analysis of the long-term relationship; part II focuses on the short-term relationship; and part III presents the descriptive findings of the model.

For the purpose of determining the long-term relationship between the variables, the cointegration equation in Part I was initially analyzed. All variables exhibit statistical significance. The value of tstat is greater than the value of t-table for all variables. Hence, it is evident that the model is both accurate and significant. The model output consists of variable coefficients, a standard error, and a t-statistic value. The model provides the coefficients for all variables as one-sided, and the long-run cointegration equation, obtained by making appropriate adjustments, is presented as follows:

$$CP(1)=271.47+13.88*BROIL(1)+7.40*CROIL(1)+0.78*ELEC(1)+4.65*RBOIL(1)+16.91*HTOIL(1)+3.72*NGAS(-1)+6.47*GASOIL(-1)+70.59*MSCI(-1)+64.10*STOXX(-1) \quad (9)$$

In the long-run, there is a positive relationship between carbon price, Brent oil, crude oil, electricity price, gasoline rbob, heating oil, natural gas, gasoil, msci and stoxx. For instance, an increase of 1% in Brent oil prices results in a 13.88% increase in the ETS price. Likewise, increases in the cost of crude oil, gasoline, the most common sort of oil in the USA, and gasoil, an oil variant utilized in industrial manufacturing, and an increase in the price of heating oil, which is produced from oil and used for heating, result in a rise in the price of carbon. The results align with both the anticipated outcomes and the established theoretical framework and past literature (Similar to Zhang et al., 2021; Luo et al., 2022; Shi et al., 2022; Wei et al., 2020; Ma et al., 2021; Xu et al., 2020; 2014; Zou, 2018). Rises in any oil derivative result in an increase in costs for companies. Companies switch to coal, a more cost-effective energy source, in order to lower their expenses. This will result in a rise in the carbon emissions of firms, encouraging them to participate in the carbon market in order to purchase carbon certificates. As demand grows, the price of carbon will also rise.

An increase of 1% in the cost of natural gas results in a corresponding 3.75% increase in carbon prices (Similar to Aslam et al., 2022; Nazifi & Milunovich, 2010; Wang et al., 2022; Cretì et al., 2012; 2014; Nie et al., 2021; Weng, 2017). Consistently, the rise in natural gas prices pushes companies to seek more affordable energy alternatives. The utilization of more affordable energy sources leads to a rise in carbon emissions, therefore increasing the demand for carbon certificates.

An electricity price rise of 1% results in a corresponding price increase of 0.78% for carbon (Similar to Freitas, Silva, 2015; Li, 2021; Sijm et al., 2012; Thoenes, 2014; Giduck, Jeong, 2011; 2014; Aatola et al., 2013b; Scholtens, Boersen, 2014; Bonacina, Gullì, 2007; Fezzi, Bunn, 2009). Indeed, the influence is rather minor; nevertheless, the majority of fossil fuels in electricity production increase carbon emissions and hence raise the carbon price. As a result of this indirect influence, the consequences might be minimal.

A 1% rise in the MSCI Europe index corresponds to a 70.59% increase in carbon prices, whereas a 1% increase in the Euro Stoxx 600 index corresponds to a 64.10% increase in carbon prices (Similar to Shi et al., 2022; Chevallier, 2011a; Zou, 2018; Alberola et al., 2009; Zhang et al., 2020). The rise in the indices is driven by economic expansion and the enhanced performance of companies. This growth will result in a rise in the industrial operations of companies, thus leading to an increase in carbon emissions. Additionally, the growing need for carbon certificates will cause the price of carbon to rise significantly.

The second part of the table illustrates the equilibrium relationship in the short run. In the short-run cointegration equation, all variables exhibit statistical significance, with t-statistics above the critical t-table value. Nevertheless, the coefficients in this equation must be negative as they indicate that short-term volatility will eventually converge to long-term equilibrium. All variables in the results have negative coefficients, indicating that they will eventually reach equilibrium over time.

The accuracy indicators of the VECM are listed in Part III of the table. The model's predictive ability is 51%. This finding is highly applicable in comparison to other studies on similar

subject matter. Furthermore, the Akaike information criterion and Schwarz criteria have quite low values, indicating the robustness of the employed model.

Tablo 5. Vector Error Correction Estimates

PART I

Cointegrating Eq:	CointEq1		
CP(-1)	1.000000		
BROIL(-1)	-13.88438	*(2.40647)*	*[-5.76961]*
CROIL(-1)	-7.405903	*(2.11838)*	*[3.49601]*
ELEC(-1)	-0.780270	*(0.18057)*	*[-4.32114]*
RBOIL(-1)	-4.650073	*(0.69504)*	*[-6.69033]*
HTOIL(-1)	-16.91936	*(1.07230)*	*[-15.7786]*
NGAS(-1)	-3.75215	*(11.6309)*	*[-2.04216]*
GASOIL(-1)	-6.479259	*(0.39050)*	*[16.5922]*
MSCI(-1)	-70.59400	*(11.3583)*	*[-6.21521]*
STOXX(-1)	- 64.10547	*(3.74294)*	*[6.44024]*
C	271.4767	*(79.9213)*	*[3.39680]*

PART II

Error Correction:	D(CP)	D(BROIL)	D(CROIL)	D(ELEC)	D(RBOIL)	D(HTOIL)	D(NGAS)	D(GASOIL)	D(MSCI)	D(STOXX)
CointEq1	-0.002791	-0.004035	-0.006031	-0.004051	-0.001473	-0.002501	-0.002089	-0.023460	-0.001093	-0.003227
	(0.00099)	(0.00021)	(0.00025)	(0.00115)	(0.00065)	(0.00150)	(0.00017)	(0.00197)	(0.00030)	(0.00088)
	[-2.81234]	[-2.09345]	[-2.51777]	[3.52450]	[-2.26991]	[-2.08795]	[-2.79827]	[-11.9161]	[3.65787]	[3.65979]

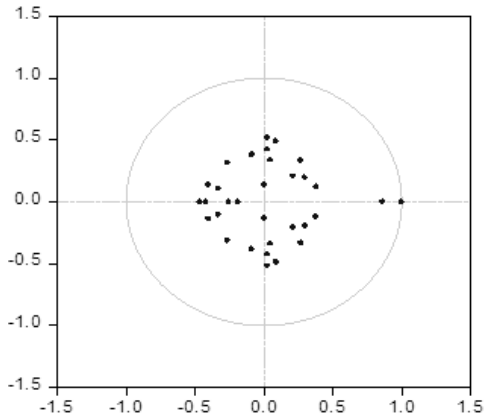
Standard errors in ( ) & t-statistics in [ ]

PART III

	D(CP)	D(BROIL)	D(CROIL)	D(ELEC)	D(RBOIL)	D(HTOIL)	D(NGAS)	D(GASOIL)	D(MSCI)	D(STOXX)
R-squared	0.537112	0.367179	0.387012	0.327474	0.346092	0.472454	0.448023	0.579234	0.312751	0.314755
Akaike information criterion	33.90140									
Schwarz criterion	49.04858									
Number of coefficients	321									

The inverse root of the AR characteristic polynomial can be employed to assess the stationarity of the VECM. Figure 2 displays the outcome of the model used, namely the AR root result. The fact that all the roots exist within the circle indicates that the model is stationary. All the roots indicated in Figure 2 appear inside the boundaries of the circle, indicating that the VECM employed in this study is stationary.

Figure 2. The inverse root of the AR Characteristic Polynomial



With variance decomposition, we can see how much of the variance in the variable as a result of an unexpected change or shock is explained by itself and other variables. Table 6 presents the findings of variance decomposition for the variables over a duration of 10 periods. The variance in carbon prices can be attributed to different variables as follows: 0.65% is due to fluctuations in Brent oil prices, 0.30% is due to fluctuations in crude oil prices, 0.003% is due to fluctuations in electricity prices, 0.008% is due to fluctuations in gasoline RBOB prices, 0.04% is due to fluctuations in heating oil prices, 0.007% is due to fluctuations in natural gas prices, 0.27% is due to fluctuations in gasoil prices, 0.75% is due to fluctuations in MSCI index value, and 0.54% is due to fluctuations in STOXX index value.

Additionally, we may examine how fluctuations in carbon prices impact the variance of other variables in Table 7. The percentage of variance in Brent oil prices attributed to fluctuations in carbon prices is 0.18%. Similarly, 0.13% of the variance in crude oil prices, 0.02% of the variance in electricity prices, 0.17% of the variance in gasoline rbob prices, 0.15% of the variance in heating oil prices, 0.14% of the variance in natural gas prices, 0.18% of the variance in gasoil prices, 0.02% of the variance in the MSCI index, and 0.02% of the variance in the STOXX index are all due to fluctuations in carbon prices.

Table 6. Variance Decomposition of Carbon Price

Variance Decomposition of CP											
Period	S.E.	CP	BROIL	CROIL	ELEC	RBOIL	HTOIL	NGAS	GASOIL	MSCI	STOXX
1	0.912767	100.000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
2	1.273063	98.2694	0.34683	0.31604	5.704E-	0.01015	0.02183	0.02499	0.14246	0.63413	0.23411
3	1.574893	97.7833	0.50038	0.27634	0.00179	0.00760	0.01482	0.01684	0.18384	0.84578	0.35305
4	1.841657	97.6616	0.52918	0.29328	0.0029	0.00862	0.02574	0.01239	0.23092	0.79612	0.41213
5	2.073478	97.5775	0.57110	0.29795	0.00292	0.00865	0.03081	0.01087	0.23183	0.78800	0.45395
6	2.282765	97.5267	0.59956	0.29778	0.00301	0.00842	0.03125	0.00958	0.23881	0.77707	0.48058
7	2.474686	97.4763	0.62055	0.29926	0.00315	0.00848	0.03347	0.00881	0.24841	0.77047	0.50266
8	2.652454	97.4420	0.63569	0.30109	0.00326	0.00838	0.03494	0.00813	0.25556	0.76304	0.51844
9	2.818952	97.4158	0.64720	0.30280	0.00332	0.00832	0.03591	0.00763	0.26148	0.75727	0.53031
10	2.976105	97.3940	0.65632	0.30424	0.00338	0.00827	0.03673	0.00725	0.26676	0.75268	0.53983

Table 7. Carbon prices impact in Variance Decomposition of Variables

	Carbon Prices Impact in Variance Decomposition of								
	BROIL	CROIL	ELEC	RBOIL	NGAS	HTOIL	GASOIL	MSCI	STOXX
1	0.000000	0.000000	0.000117	0.000000	0.109474	0.000000	0.009707	0.007275	0.009626
...	...	...	...	...	...	...	...	...	...
10	0.183617	0.130100	0.014870	0.175812	0.142631	0.156003	0.187121	0.017790	0.016289

Impulse-response analysis may be utilized to examine the impact of a shock on several variables over time and determine the duration of its influence. The response of carbon prices to a shock given to other variables is seen in Figure 3a below. Impulse-response analysis may be utilized to examine the impact of a shock on several variables over time and determine the duration of its influence. The response of carbon prices to a shock given to other variables is shown in Figure 3a. As a result of a shock to variables, the carbon price quickly reaches its peak during the second and third consecutive intervals, then drops to its lowest point, and finally returns to equilibrium.

Figure 3b shows the response of other variables to a shock to carbon prices. After a shock to carbon prices, all variables first reach their lowest point in the fourth-fifth period, then gradually increase to the equilibrium point.

Figure 3a. Impulse- response

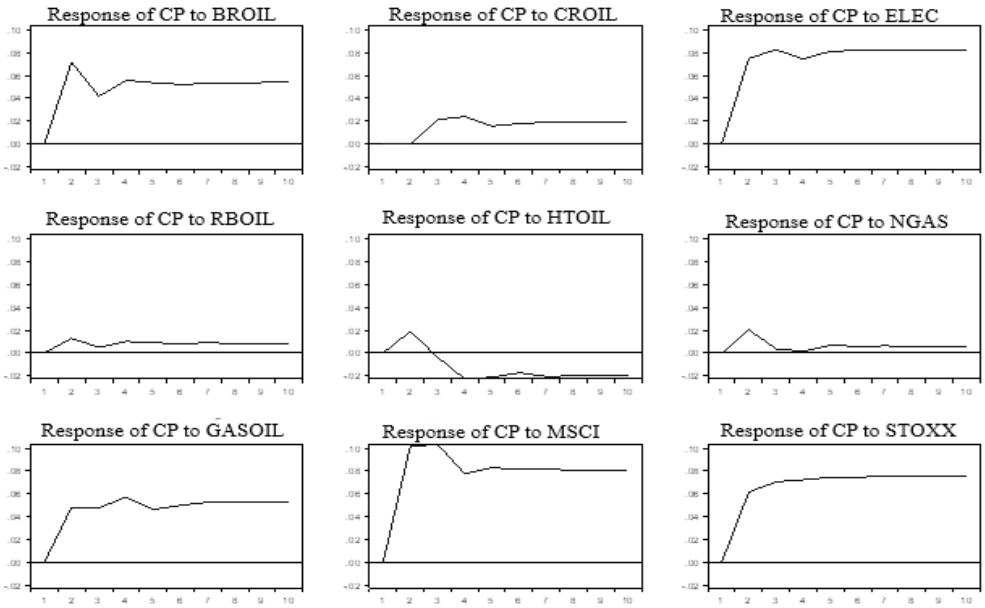
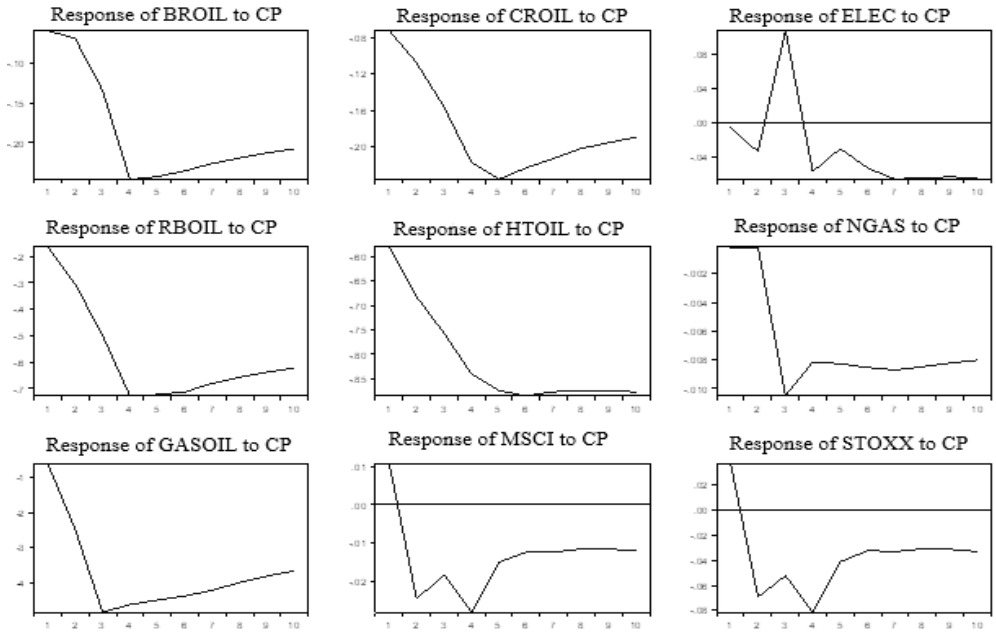


Figure 3b. Impulse- response



Through the use of the cointegration test, the study has successfully identified the presence of a long-run relationship. However, further investigation is required to establish the causal relationship between the variables. The Granger causality test is a useful tool to evaluate a causal relationship between variables. The null hypothesis of the Granger causality test is ''Variable Y does not cause Variable X''. When the Chi-square statistics prob value is less than 0.05 at the 5% significance level, we reject the null hypothesis and prove causality between the variables. In addition, the results of the Granger causality test show that the variables are endogenous. It shows that there is a two-way causal relationship between the variables. (Kovačević, 2022).

The findings of the Granger causality test are presented in Table 8. The first part presents the findings of the causal relationship between carbon price and the other dependent variables. All variables have probability values below the crucial threshold of 0.05, indicating that there is mutual Granger causation between the variable carbon price and other variables.

To establish the two-way relation, each variable was assigned as an independent variable individually, and a Granger causality test was conducted. The probability values of the carbon price in all variables in part II are lower than the crucial threshold of 0.05. That is, carbon prices are the granger cause of all of them.

To strengthen the findings derived from the VECM analysis and to conduct a more comprehensive and comparative investigation, the ARDL analysis was also employed. The ARDL model involves a bounds test for cointegration, which includes an extra F-test on the

lagged level variables in the ARDL equation, making it a comprehensive approach for analyzing cointegration relationships. (Orisadare, Fasoye, 2022).

Table 8. Granger Causality Test

PART I			
Dependent variable: D(CP)			
Excluded	Chi-sq	df	Prob.
D(BROIL)	0.174375	3	0.0000
D(CROIL)	1.502808	3	0.0409
D(ELEC)	3.437517	3	0.0000
D(RBOIL)	0.670774	3	0.0304
D(HTOIL)	9.440084	3	0.0000
D(NGAS)	2.225605	3	0.0000
D(GASOIL)	5.854786	3	0.0000
D(MSCI)	15.18814	3	0.0000
D(STOXX)	18.73030	3	0.0000
All	153.2516	27	0.0000

PART II			
Dependent variable	Excluded	Chi-sq	Prob.
D(BROIL)	D(CP)	17.49224	0.0000
D(CROIL)	D(CP)	6.170370	0.0405
D(ELEC)	D(CP)	8.308596	0.0005
D(RBOIL)	D(CP)	13.91485	0.0301
D(HTOIL)	D(CP)	1.284920	0.0000
D(NGAS)	D(CP)	14.13333	0.0000
D(GASOIL)	D(CP)	104.6587	0.0000
D(MSCI)	D(CP)	2.955036	0.0024
D(STOXX)	D(CP)	3.044606	0.0012

For the application of ARDL analysis, it is necessary for the dependent variable to be integrated at level I. Based on the findings of the unit root test conducted on the data (Table 2), it can be concluded that all variables, including the dependent variable, are integrated at level I. When setting up ARDL analysis, it is necessary to identify a suitable number of lags. According to Table 3, the number of lags is specified as 3.

Starting out, the selection of the model for the ARDL analysis is established. The following Table 9 displays the outcomes of the model selection process. Model selection was performed using the Akaike information criterion (AIC). The findings indicate that the chosen model is ARDL (3, 1, 0, 0, 0, 3, 0, 2, 2, 2). The table displays the number of lags for which a variable is chosen.

Following the selection of the model, the F-bound test is utilized to analyze the existence of cointegration. The null hypothesis of the F-bound test states that there is no cointegration relationship. If the F statistics value is above the threshold of I (1), the null hypothesis (H0) is rejected, thereby confirming the presence of cointegration. The F-bound test results are displayed in Table 10. The F statistic value of 20.90481 is above the critical value of I(I) for all confidence levels (1%, 2.5%, 5%, and 10%), indicating the existence of a cointegration relationship among the variables.

Table 9. ARDL Model Selection

Dependent Variable: CP	
Maximum dependent lags: 3 (Automatic selection)	
Model selection method: Akaike info criterion (AIC)	
Dynamic regressors (3 lags, automatic): BROIL CROIL RBOIL HTOIL NGAS GASOIL ELEC MSCI STOXX	
Fixed regressors: C	
Selected Model: ARDL(3, 1, 0, 0, 3, 0, 2, 2, 2, 2)	
Variable	**Number of Lag**
CP	3
BROIL	1
CROIL	0
RBOIL	0
HTOIL	0
NGAS	3
GASOIL	0
ELEC	2
MSCI	2
STOXX	2
C	
R-squared	0.998595
Adjusted R-squared	0.998587

Table 10. ARDL Long Run Form and Bounds Test

Dependent Variable: D(CP)				
F-Bounds Test			Null Hypothesis: No levels relationship	
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic:n=1000		
F-statistic	**20.90481**	10%	1.8	**2.8**
k	9	5%	2.04	**2.08**
		2.5%	2.24	**3.35**
		1%	2.5	**3.68**
Actual Sample Size	4041	Finite Sample: n=80		
		10%	-1	-1
		5%	-1	-1
		1%	-1	-1

After seeing the presence of a cointegration relationship, we may proceed to analyze the coefficients of the error correction model. As previously stated, the error correction coefficient must be both negative and significant in order to conclude that short-term fluctuations converge to long-term equilibrium. Table 11 displays the outcomes of the ARDL error correction model. The cointegration equation has a coefficient of -0.003473 and a probability value of 0.0000. The results are both negative and statistically significant, as expected. In other words, the model's short-term fluctuations will gradually approach the long-term equilibrium over a duration of 325 periods, with a decrease of 0.003073 in each period. Data was collected regarding the duration for which carbon prices will reach an equilibrium level, which is quite similar to the findings of VECM.

Table 11. ARDL Error Correction Regression

Dependent Variable: D(CP)
Selected Model: ARDL(3, 1, 0, 0, 3, 0, 2, 2, 2, 2)

ECM Regression				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CointEq(-1)*	-0.003073	0.000723	-4.801307	0.0000
R-squared	0.507612			
Adjusted R-squared	0.504334			
Durbin-Watson stat	2.009058			

* p-value incompatible with t-Bounds distribution.

The equation derived from the ARDL model is as follows:

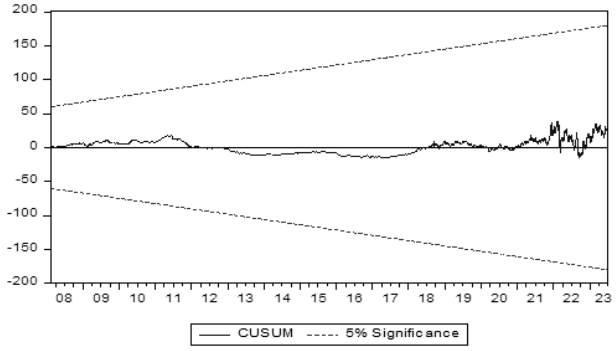
$$CP = 8.3341 + 17.2816*BROIL + 10.4761*CROIL + 3.1860*RBOIL + 18.0819*HTOIL + 2.1182*NGAS - 5.4350*GASOIL + 0.6240*ELEC + 68.7736*MSCI + 66.202*STOXX \quad (10)$$

The ARDL equation displays a strong similarity to the VECM equation. This strengthens the findings of the research. As seen from the equation, there exists a statistically significant relationship between the variables in the long term. For instance, a 1% rise in Brent oil prices results in a significant 17.28% rise in carbon pricing. A 1% rise in natural gas prices leads to a 2.12% rise in carbon prices. A minor impact was observed in the correlation between the carbon price and electricity, similar to the findings of the VECM. An electricity price increase of 1% results in a corresponding increase of 0.62% in carbon prices. The impact of MSCI and STOXX indexes, which serve as indicators of the economic condition, has a significant influence on carbon pricing, similar to the VECM. A 1% rise in the indices results in approximately a 60% increase in carbon pricing.

In the end, a cusum test was conducted to examine the existence of a structural break in the model. The Cumulative Sum (CUSUM) test is a statistical method used to detect structural changes in time series data. The CUSUM test involves the calculation of the cumulative sum of recursive residuals, which are residuals that are uncorrelated with zero means and constant variance (Brown et al., 1975).

If the cusum test line stays inside the lower and higher boundary lines, it indicates the absence of a structural break. When analyzing the cusum test results of our model in Figure 4, it is observed that the cusum line stays within the boundary, indicating that our model exhibits structural stability.

Figure 4. CUSUM Test



To conclude the analysis, diagnostic tests were also utilized, although they are not essential in autoregressive studies. The diagnostic test results for the VECM and ARDL models are presented in Table 12. The LM test findings indicate that there is no serial correlation in any of the models. The Jarque-Bera and White test results indicate the presence of non-normality and heteroscedasticity in both models. Nevertheless, this issue is not likely to significantly affect our cointegration analysis. Nevertheless, this issue is not likely to significantly affect our cointegration analysis. Gonzalo (1994) demonstrated that the desirable properties of asymptotically optimum inferences found in maximum likelihood estimators remain valid in finite samples, even in the absence of heteroscedasticity and normality assumptions. (Gonzalo, 1994; Freitas, Silva, 2015).

Table 12. Diagnostic Tests

Diagnostics of VECM	Conclusion
Serial Correlation Test: LM Test	Prob. = 0.0843, No serial correlation
Normality Test: Jarque-Bera	Prob. = 0.0000, Non-normality
Heteroskedasticity Tests: White	Prob. = 0.0000, Heterocedasticity
Diagnostics of ARDL	Conclucsion
Serial Correlation Test: LM Test	Prob. = 0.2826, No serial correlation
Normality Test: Jarque-Bera	Prob.= 0.0000, Non-normality
Heteroskedasticity Tests: White	Prob.= 0.0000, Heterocedasticity

5. Conclusion

Global warming is a pressing global problem that necessitates coordinated actions at the world, national, and individual scales. Various worldwide initiatives have been in place for years to address this issue, including international agreements, rules and regulations, periodic conferences, carbon trading markets, and carbon taxes. An initial and most comprehensive representation of a carbon trading market established with the intention of mitigating global warming is the EU Emissions Trading System (EU ETS).

The dynamic relationship between the carbon market, the energy market, the power market, and the economic outlook is investigated in this study. Except for phase I, the study covers every phase of the European Trading System with daily data that includes 15 years, it becomes achievable to conduct an extensive analysis and evaluate the carbon trading system in depth. In order to examine this dynamic relationship, two models, namely ARDL and VECM, were employed to ensure more reliable and consistent outcomes.

The EU Emissions Trading System is among the most effective and preventative attempts in the struggle against global warming. Consequently, it is critical to comprehend the market's structure and influence in order to identify its strengths and weaknesses and to facilitate the implementation of necessary updates.

It first examined whether a long-term relationship exists between the variables in both analyses. The presence of a long-term relationship between two variables signifies the existence of a short-term relationship as well. Both analyses demonstrated the existence of a long-term relationship between the variables, as shown in Tables 5 and 10.

The research initially demonstrates that as time proceeds, short-term fluctuations decrease in order to achieve long-term equilibrium (Tables 5 and 11). For instance, after 248 days, fluctuations in the Brent oil price reach long-run equilibrium. After 246 days, fluctuations in the price of electricity reach long-run equilibrium. 309 days pass before the Stoxx 600 index reaches long-term equilibrium with its fluctuations. After 325 days, fluctuations in the price of carbon reach long-run equilibrium. A long-term analysis of the variables is required to arrive at these conclusions. Due to the comprehensive consideration of all three periods of the EU ETSs, an in-depth analysis of the system's long-run and short-run equilibrium has been achievable. An additional strengthening of the results has been achieved through the application of two separate models.

The study provided a better understanding of the long-term positive relationship between the variables (equations 9 and 10). The observed results are strongly consistent with established theory, prior literature, and anticipated outcomes.

Based on the findings of the VECM analysis, a 1% rise in Brent oil results in a 14% rise in carbon pricing. There is the same positive correlation between carbon prices and different oil derivatives, including crude oil, gasoline rbob, gasoil, and heating oil. This is because oil serves as a crucial energy resource for organizations, particularly in their production processes. Companies are turning to less expensive fossil fuels due to the rise in oil prices to maximize profits. The current disincentives and incentives to reduce carbon emissions are insufficient. As firms increasingly utilize fossil fuels, the emissions they produce also increase, leading them to participate in the carbon market. The growing demand in the carbon market leads to an increase in carbon prices. Additionally, carbon prices are influenced by other factors, including changes in cap limits within the cap-and-trade system utilized by the EU ETS, policy interventions, incentives, and other similar considerations.

Although the results relate with the expectations and the established theory, they are not in line with the expected goals. The increase in oil prices is expected to lead companies towards clean energy sources and renewable energy investments rather than fossil fuels. On the contrary, while there are companies that prioritize sustainable energy, unfortunately, there has been no significant decrease in fossil fuel consumption in the European Union.

A rise of 1% in natural gas prices corresponds to an increase of 3.72% in carbon pricing. The reasoning behind this is the increase in the price of natural gas, which serves as a crucial energy source for companies, leading them to shift towards fossil fuels. Both corporations prioritize cost-effective sources, and the shift to renewable energy sources is expensive and requires a long-term commitment. Current infrastructure relies on fossil fuels, and the process of constructing renewable energy infrastructure and systems takes time.

Despite the fact that there is a relationship between the carbon market and the power market, the effect is rather insignificant. For instance, a 1% rise in electricity prices results in a 0.78% increase in the carbon price.

At some point, the study aims to examine the relationship between the outlook for the economy and the carbon market. The MSCI and STOXX600 indexes, which are the most significant and extensive benchmarks in Europe, are examined as indications of the economic outlook.

A 1% rise in the indexes results in a 70% rise in the carbon price. Unfortunately, although this outcome matches expectations, it is not in line with the desired goals. The increase in the indices represents economic growth. Companies that are experiencing financial success boost their emissions by expanding their industrial production. This results in the purchase of carbon certificates, which ultimately leads to a rise in the carbon price. Nevertheless, it is preferable for financially strong companies to allocate resources towards clean, renewable, and sustainable energy initiatives and reduce emissions. The ARDL analysis gives the same results with the same coefficients and equations. This supports the study's main goal, which is to get reliable results with comparable models.

The VECM and ARDL methodologies are used to extensively evaluate the impact of various variables on the carbon market. The objective of the study is to analyze the interrelationship between these markets. The utilization of VECM analysis allows us the opportunity to do so. The Granger test enables us to investigate the presence of a two-way causation relationship among the variables. Variance decomposition and impulse-response tests enable us to comprehensively evaluate the mutual relationship between the variables. Based on the findings of the Granger test, it can be concluded that all factors included in the model are the cause of the fluctuations in carbon pricing (as shown in Table 8). To examine the mutual relationship, a Granger test was conducted on each variable individually. Based on the findings, it can be concluded that carbon prices are the causal factor for each variable in the model.

The findings obtained in this study show great potential in terms of mitigating global warming. The goal of carbon trading systems is to mitigate emissions by imposing an influence on fossil fuel consumption and non-renewable energy sources. The Granger test demonstrates that the carbon market has an influence on other markets. Variance decomposition and impulse-response analysis determine the effect's direction and strength.

Variance decomposition allows us to identify the factors that contribute to the variance in the price of the variable. This study examined the impact of other variables on the variance of carbon pricing, as well as the impact of carbon prices on the variance of other variables. The economic outlook and Brent oil prices show the most significant influence on the variance of carbon pricing, whereas the price of electricity has the lowest impact. Furthermore, the analysis also examines the impact of carbon pricing on the variance of other variables. Carbon pricing has the greatest impact on the variance of energy market variables but has the least impact on the variance of economic outlook and electricity prices. The carbon market has a potential effect on other variables, which are consistent with the aims of carbon trading systems; however, the influence is rather minor.

The direction and timing of the effects observed in variance decomposition can be determined by impulse response analysis. When all variables in the model experience a positive shock, carbon prices respond by increasing and eventually achieve a state of equilibrium during an average of 4-5 periods. The findings are consistent with the previously analyzed VECM and ARDL equations. When carbon prices experience a positive shock, all variables first decrease but then immediately increase to their original level and reach equilibrium.

The recent findings from the two-way assessments are encouraging since carbon trading systems aim to have an influence on other markets, reducing their demand and thereby

mitigating emissions. Our results indicate that the carbon market does indeed provide outcomes that align with the intended aims. Nevertheless, the current impact of these effects is minimal and of short duration.

The results of the cusum test, conducted as part of the study to ensure the accuracy of the model and get robust findings, indicate that there are no structural breaks in the established models. The evaluated models exhibit structural stability. The cointegration graph indicates a divergence in 2022. It is evident that the conflict between Russia and Ukraine has had a significant negative impact on the carbon, energy, and electricity markets, emphasizing the energy challenge at hand. These markets are extremely vulnerable to exogenous shocks.

In summary, the analysis reveals a long-term relationship between carbon markets, energy and power markets, and the economic outlook. Also, there exists a mutual causality relationship between carbon markets and energy and power markets, as well as the economic outlook. The direction of the impact of energy and power markets and economic outlook on carbon markets is positive and the direction of the impact of carbon markets on energy and power markets and the economic outlook is negative but very minor and short-term. Companies choose more cost-effective and environmentally harmful fuels when there is a rise in fossil fuel costs. As the economic outlook improves and enterprises' financial status increases, they tend to raise their industrial production and thus increase their emission levels. The increase in carbon costs leads to a minimal and temporary decrease in companies' demand for fossil fuels.

Global warming is a worldwide issue that is increasingly intensifying. While carbon trading systems have been seen to align with the specified measures, regrettably, their impact is minor and temporary. Based on the study's findings, the following policy recommendations can be proposed; economic incentives such as tax reductions, subsidies, or low-interest loans can be provided to promote investments in renewable energy sources, emission rights given to companies can be reduced, deterrent charges can be applied in cases of exceeding the emission rights, limitations can be imposed on the use of fossil fuels of companies, carbon taxes can be more effectively employed, regulations might be implemented to restrict or diminish the consumption of coal.

For future research, it may be beneficial to include factors such as coal pricing, emission levels, and investments in renewable energy.

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