Environmental Science

https://www.aimspress.com/journal/environmental

AIMS Environmental Science, 12(1): 165–192.
DOI: 10.3934/environsci.2025008
Received: 13 September 2024
Revised: 02 January 2025
Accepted: 20 January 2025
Published: 20 February 2025

Research article

Cointegration analysis of fundamental drivers affecting carbon price dynamics in the EU ETS

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Abstract: This study employed co-integration methodology to explore the fundamental drivers of carbon price in the European Union Emissions Trading System (EU ETS) during the transition from phase III to phase IV, focusing on the interactions between the carbon market, energy sector, and macroeconomic factors. A novel approach of bilaterally modifying dummy variables was used to include the impact of regulatory event announcements on the EU carbon price. Long-term analysis revealed that coal prices exhibited a positive but statistically insignificant impact, while natural gas and oil prices show substantial and significant influences. Short-term dynamics indicated a self-adjusting mechanism, with gas and oil prices playing crucial roles. We found that the European stock market has a dampening effect on short-term carbon prices, whereas the commodity market exerted a counteractive force. In the energy sector, variations in European gas prices and shifts in nonrenewable electricity generation significantly influence short-term carbon price. Regulatory event announcements exhibited an overall negative and statistically significant trend. However, the relatively small magnitude of these coefficients underscored the modest impact of regulatory event announcements on short-term carbon prices within the EU ETS. Additionally, our study estimated the long-term equilibrium relationship between variables using ridge regression, serving as a proxy for the EU's equilibrium carbon price. We examined the disparities between this equilibrium and market prices. Two distinct phases emerged in the analysis. Before April 2018, the market price consistently lagged behind the equilibrium, suggesting an overestimation of the value of carbon emission rights. Subsequently, the market price consistently surpassed the equilibrium. In particular, the sharp increase in carbon prices from April to June 2020, driven by the COVID-19 pandemic, highlighted the sensitivity of the EU carbon market to external shocks.

Keywords: EU ETS; carbon price; energy prices; cointegration

1. Introduction

Since the industrial revolution, increasing the consumption of fossil fuels has significantly increased carbon dioxide emissions, amplifying the greenhouse effect and triggering global warming. The resulting environmental challenges, including rising sea levels, food insecurity, and ecological damage, have compelled nations to prioritize reducing carbon emissions for environmental preservation. Effectively addressing this imperative requires a fundamental transformation of the current industrial system, emphasizing the elevation of low-carbon technologies to a competitive level. This transformation process, akin to the concept of "creative destruction" [1], demands swift action driven by state policies. However, the efficacy of these policies depends on the innovative capacity of private firms, a concern exacerbated by the growing influence of financialization trends in advanced economies. To finance the transition to low-carbon economies, countries are using a burden sharing mechanism between current and future generations by combining carbon pricing with green bonds [2]. Green bonds fund immediate mitigation of climate change, with future generations repaying the bonds, sharing the burden, and benefiting from reduced environmental damage.

In recent decades, the entanglement of advanced economies with volatile financial markets, prioritizing the trading of existing assets over productive investments, has resulted in recurring asset bubbles and subsequent deleveraging periods. This financial focus, while crucial for industrial innovation, poses a threat to the necessary creative destruction of the carbon-intensive industrial system [3]. The emergence of carbon markets is intricately linked to the broader phenomenon of financialization, which has gained momentum since the 1970s. This period witnessed the promotion of speculation-based hedging opportunities in an uncertain global environment [4]. Financialization not only exacerbated global imbalances, but also facilitated the assimilation of resources and enterprises in new regions by businesses seeking cost-effective labor, land, and raw materials. The connection between financialization and the emergence of carbon markets underscores the complex dynamics shaping the global response to environmental challenges, emphasizing the need for a comprehensive and integrated approach to address the intertwined issues of finance, innovation, and environmental sustainability.

The European carbon market, formally the European Union Emissions Trading System (EU ETS), is a complex system closely tied to financial trends that have been growing since the 1970s. It originates from the Kyoto Protocol, which mandated emission reduction targets for developed countries, including a 5.2% reduction from 1990 levels during 2008–2012 [5]. To fulfill these obligations, the EU adopted an emissions permit system, which forms the EU ETS. This cap-and-trade setup limits total emissions allowances, creating scarcity. The member states distribute allowances to participating plants, establishing individual emission caps. Participants trade allowances to meet commitments economically, and they can also use international mechanisms such as the clean development mechanism and joint implementation projects. Crucially, the EU ETS allows emissions allowances to be traded as financial instruments, essentially turning them into commodities with de facto property rights over Earth's carbon cycling capacity. Market liquidity is facilitated through various trading forms, such as spot, futures, forward, swap, and futures options.

The integration of carbon derivatives into the EU ETS signifies a merging of environmental and financial markets, modifying uncertainties related to emissions allowances. The increasing financialization adds complexity as market participants navigate both environmental and financial risks. Examining carbon prices within the EU ETS is essential to understand this financialization trend. Numerous studies have investigated the factors that influence the carbon market [6–8].

The literature demonstrates the existence of interactions among the carbon market, the energy market, and macroeconomic factors, with varying degrees of strength [9–14]. However, existing research on carbon price dynamics in the EU ETS has often overlooked the integration of regulatory events into modeling frameworks. Our study addresses this gap by investigating the factors driving carbon allowance prices, focusing on financialization patterns using monthly data from January 2015 to June 2023. We contribute to the literature by employing a co-integration model along with an innovative dummy variable approach to analyze key events. Specifically, we examine the transition from Phase III to Phase IV of the EU ETS, a period that has received limited empirical attention, and assess the system's sensitivity to the COVID-19 crisis and its impact on carbon price dynamics.

The remainder of this paper is structured as follows. Section 2 reviews the literature on the dynamics and drivers of carbon prices in the EU ETS. Section 3 details our methodological approach for examining the factors influencing carbon allowance prices within the EU ETS. In this section, we introduce the theoretical model that guides our analysis and outlines the econometric methodologies employed. Section 4 presents the empirical findings of our analysis and discusses their relevance to financialization trends in the EU ETS. Lastly, Section 5 summarizes the main conclusions drawn from our research.

2. Literature review

The existing literature on EU ETS can be divided into two main categories. The first examines the impact of fundamental factors, such as fuel prices and weather fluctuations, on EU allowance (EUA) price dynamics during the system's early phases. The second focuses on the stochastic properties of EUA prices, employing term structure models and time series approaches to explain price dynamics.

A significant body of research investigates the key drivers that influence carbon prices and their dynamic interactions with energy markets. Early studies predominantly used time-series modeling techniques to understand carbon prices [15–17]. These studies highlighted the pivotal role of market fundamentals such as weather conditions, fuel prices, regulatory factors, and fuel switching. Economic activity, often measured through stock market indices, also emerged as a critical determinant of carbon prices.

The dependency structures between EUA returns and primary energy price returns have been modeled using advanced methods such as conditional vine copulas [18]. Rodríguez [19] applied a time-varying parameter model to analyze the Granger causality between the European stock market and the carbon market in different phases. Furthermore, Zhao et al. [20] used a mixed decomposition and integrated forecasting model to refine the carbon price forecasts by incorporating energy and economic factors. Meanwhile, Wang and Zhao [14] went into the repercussions and transmission pathways of the stock market and the energy market on the carbon market using a structural equation model. Research consistently highlights the influence of Brent oil returns on carbon prices [12], while acknowledging the variation between EU ETS phases.

The time-varying relationships between carbon prices and other variables have been well documented. Structural break tests [11], Markov regime-switching vector autoregressive (VAR) models [10], and dynamic analyses during different EU ETS phases [21] demonstrated nonlinear dynamics. Quantile regressions [22] and impulse response analyses [23] further explored the influence of energy prices on the dynamic of carbon prices.

Recent advances include the modified decomposition of the variance of Diebold and Yilmaz (DY) [13] to evaluate the connectivity of 'carbon energy finance', predictive modeling of carbon prices using energy variables [24, 25], and the application of Bayesian networks [14]. Wavelet analyses [26] and studies on spillover risks from financial market uncertainty [27] further enrich the literature.

The role of extreme weather events on EUA prices is another focus area. Indicator variables for temperature deviations and interactions with fuel switching costs [11, 28] reveal significant but nonlinear relationships. Electricity prices and clean spark spreads were also included [11], although bidirectional interactions between electricity and EUA prices raise questions about theoretical robustness.

The second strand of literature examines stochastic properties such as jumps, spikes, high-volatility phases, and heteroscedasticity. Term structure models and autoregressive frameworks confirm stylized facts such as excess kurtosis and variable volatility [15, 16]. Generalized autoregressive conditional heteroskedasticity (GARCH) models dominate this domain, offering robust specifications for variance equations [15].

Volatility spillover between markets has been analyzed using the dynamic conditional correlation threshold GARCH (DCC-TGARCH) and the Baba-Engle-Kraft-Kroner GARCH (BEKK-GARCH) models [29, 30], and the spillover index by Diebold and Yilmaz [25, 31]. Time-varying relationships were further investigated using time-varying parameter VAR models with stochastic volatility (TVP-VAR-SV) [32], uncovering diverse transmission dynamics between phases.

In general, the literature consistently identifies gas and oil prices as positive influences on EUA prices, while the role of coal remains ambiguous [28, 33]. The influence of economic activity and market fundamentals underscores the complexity of price dynamics, particularly under varying regulatory and market conditions. Despite extensive analysis, questions about nonlinear dependencies, market spillovers, and the impact of regulatory changes remain fertile ground for future research.

3. Material and methods

This section outlines our methodological approach to investigate the influencing factors of carbon allowance prices within the EU ETS. We begin by introducing the theoretical model that underpins our analysis, detailing the chosen data sources, justifying the variables incorporated. Subsequently, we delve into the specific methodologies employed to assess the impact of regulatory events. Furthermore, we present our approach to studying the intricate relationship between equilibrium price and market price.

3.1. Econometric model

Assuming that carbon price is determined by supply and demand, following the work [34], the relationship can be described as follows:

$$P_{CO_2} = f(\overline{Q}, D_{CO_2}) \tag{3.1}$$

where, P_{CO_2} represents carbon price and D_{CO_2} signifies the demand for permits, reflecting the overall emission intensity of the economy. Additionally, $\overline{Q}$ denotes the number of available permits, which remains constant throughout the year, calculated as the total number issued minus those distributed for free. Table 1 provides a detailed overview of the variables used in our analysis. The demand for permits is allocated between the two primary sectors, electricity and industrial, expressed as:

$$D_{CO_2} = D_{CO_2}^{Elec} + D_{CO_2}^{Ind} \tag{3.2}$$

Electricity is pivotal in our framework, as its generation directly contributes to CO_2 emissions, largely influenced by fossil fuel usage. Policies promoting renewable energy integration further impact carbon pricing dynamics [35, 36]. The total permit demand from the electricity sector is expressed as:

$$D_{CO_2}^{Elec} = \alpha_R \times D_R^{Elec} + \alpha_{NR} \times D_{NR}^{Elec} \tag{3.3}$$

where, α_R and α_{NR} represent the CO_2 emission intensities of renewable and nonrenewable energy sources, respectively. D_R^{Elec} and D_{NR}^{Elec} signify the total demand for renewable and nonrenewable energy sources for power generation. Subsequently, the total CO_2 emissions from industrial production are represented as:

$$D_{CO_2}^{Ind} = \alpha_{gaz} \times D_{gaz}^{Ind} + \alpha_{coal} \times D_{coal}^{Ind} + \alpha_{oil} \times D_{oil}^{Ind} \tag{3.4}$$

Finally, we get that the total demand for CO_2 permits can be expressed as:

$$D_{CO_2} = \alpha_{gaz} \times D_{gaz}^{Ind} + \alpha_{coal} \times D_{coal}^{Ind} + \alpha_{oil} \times D_{oil}^{Ind} + \alpha_R \times D_R^{Elec} + \alpha_{NR} \times D_{NR}^{Elec} \tag{3.5}$$

This model focuses on final energy consumption, attributing positive CO_2 emissions to oil, coal, natural gas, and electricity. It posits that the demand for any energy type is influenced by fundamental factors such as the economy's production level (Y), the relative fuel price (P_i) compared to substitutes, and the price of CO_2 permits. Additionally, E_R and E_{NR} are included to address energy production influences. Thus, the demand for CO_2 permits can expressed as a function of these drivers:

$$D_{CO_2} = f(Y, P_{gaz}, P_{coal}, P_{Elec}, P_{CO_2}, E_R, E_{NR}) \tag{3.6}$$

Equation (3.6) can be linearized using log-linear approximation, where the logarithm of demand for CO_2 permits is determined by a weighted sum of variables. Without loss of generality, the demand for permits price can be represented by a linear function, where the natural logarithm of demand depends on various factors such as the economy's output, renewable and nonrenewable power generation, energy prices, and the price of CO_2 permits:

$$\begin{aligned} \ln D_{CO_2} =& \gamma_1 \ln Y + \gamma_2 \ln E_R + \gamma_3 \ln E_{NR} + \gamma_4 \ln P_{gaz} \\ &+ \gamma_5 \ln P_{coal} + \gamma_6 \ln P_{oil} + \gamma_7 \ln P_{Elec} + \gamma_8 \ln P_{CO_2} \end{aligned} \tag{3.7}$$

The permit price in Eq (3.1) is then expressed as:

$$\ln P_{CO_2} = \ln \overline{Q} + \mu_d \ln D_{CO_2} \tag{3.8}$$

where $\ln \overline{Q}$ represents the natural logarithm of real supply, constant within a year, and μ_d is a coefficient reflecting the demand's significance in the price-setting function. By substituting Eq (3.7) into Eq (3.8) and solving for $\ln P_{CO_2}$, we arrive at:

$$\begin{aligned} \ln P_{CO_2} =& \beta_0 \ln \overline{Q} + \beta_1 \ln Y + \beta_2 \ln E_R + \beta_3 \ln E_{NR} + \beta_4 \ln P_{gaz} \\ &+ \beta_5 \ln P_{coal} + \beta_6 \ln P_{oil} + \beta_7 \ln P_{Elec} + \epsilon_{CO_2} \end{aligned} \tag{3.9}$$

3.2. Data

Due to data constraints, we utilized data from January 2015 to June 2023, covering the transition from Phase III to Phase IV in the EU ETS. Phase IV, in particular, has seen limited empirical analysis in the existing literature, prompting our investigation into later developments in the EU carbon market. Data limitations pose a challenge for a comprehensive analysis of carbon allowance price dynamics. Therefore, we employ a robust econometric methodology suitable for small sample sizes, which is detailed in the following section.

Our dependent variable is the price of carbon allowances. For this analysis, we have chosen to utilize the settlement prices of the year-ahead EUA December futures contract, traded on the Intercontinental Exchange (ICE). This selection is substantiated by various factors. First, carbon futures trading accounts for more than 88% of the total trading volume within the market [37]. Second, futures prices play a critical role in price discovery, as highlighted by Rittler [38], effectively encapsulating market participants' price expectations and providing a comprehensive view of the determinants of carbon prices.

We include several independent variables following previous studies, such as [11, 33, 39]. These variables comprise: The month-ahead futures contract of Brent crude oil, serving as a European oil price benchmark; the month-ahead futures contract of coal settled based on delivery to Rotterdam, The Netherlands, priced against the Argus/McCloskey's API2 index; the month-ahead futures contract of natural gas at the Title Transfer Facility (TTF) in the Netherlands, a significant gas price in Europe; and the monthly average of day-ahead electricity prices across European countries. For electricity production, we incorporate net electricity generation from nuclear, fossil fuels (adjusted for transmission and distribution losses) and renewable sources (including hydroelectric, solar and wind). Additionally, we include the stock index (STOXX) All Europe 100, a widely used benchmark reflecting stock market performance in 18 European countries and considered indicative of European economic activity. Following methodologies from Chevallier and Lutz et al. [40, 41], we integrate non-energy commodity prices measured by the Goldman Sachs Commodity Index excluding energy (GSCI), serving as a reliable performance benchmark for commodity market investments.

In addition, to ensure consistency among price series, they were converted to euros using the daily exchange rate provided by the European Central Bank. Table 1 provides an overview of the variables used in our analysis, along with their respective symbols, detailed descriptions, and units of measurement.

Table 1. Variables description.

Symbol	Description	Unit of measurement
P_{CO_2}	Carbon Allowance Price	€/ton
P_{Oil}	Brent Crude Oil Futures Price	€/BBL
P_{Coal}	Rotterdam Coal Futures Price	€/ton
P_{Gaz}	Dutch TTF Natural Gas Futures Price	€/Therm
P_{Elec}	Electricity Price	€/MWh
E_{NR}	Net Electricity Generation from non-renewable sources	MWh
E_{R}	Net Electricity Generation from renewable sources	MWh
$E_{Nuclear}$	Net Electricity Generation from nuclear	MWh
S	STOXX EUROPE 100 Index	Index Points
C	Goldman Sachs Commodity Index (Excluding Energy)	Index Points
I	Industrial Production Index	Index Points

3.3. Event impact modeling with bilaterally modified dummy variables

Traditional dummy variable modeling assigns 0 or 1 to represent the constant impact of specific events. In this study, we explore an alternative approach to modify the traditional dummy method to analyze the bilateral impact process of verified emissions announcements on carbon prices. Drawing on previous research [42–44], we investigate how the constant impact is established, its duration, and when it dissipates. By bilaterally modifying the traditional dummy variables, we aim to unveil both the potential ex ante impact and the lasting ex post impact of verified emissions announcements. The following procedure outlines the process of bilaterally modifying dummy variables. Let $d^{(0)} = (d_t) = (0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0)$ denote a given sequence.

Step 1. *Duplication of 1s*: After the location of the element equal to 1 in $d^{(0)}$, we add s_1 1s after the location of the original 1 (L designates the lag operator):

$$d^{(1)} = \sum_{i=0}^{s_1} L^i d^{(0)}, \quad s_1 \in \mathbb{N} \tag{3.10}$$

Step 2. *Adjoining a geometric sequence*: After 1 followed by a 0 in $d^{(0)}$, substitute a finite geometric sequence with coefficient s_2 to replace the 0s:

$$d^{(2)} = d^{(1)} + \sum_{i=1}^{k_1} s_2^i L^{s_1+i} d^{(0)} \tag{3.11}$$

where $s_2 \in [0, 1[$ and $k_1 = \min\{m \geq 1 : s_2^{m+1} < 0.1\}$.

Step 3. *Duplication of 1s*: This is similar to step 1, but functions in the opposite direction; we add s_3 ones before the location of the original 1 (F designates the inverse operation of L):

$$d^{(3)} = d^{(2)} + sign(s_3) \sum_{i=sign(s_3)}^{s_3} F^i d^{(0)}, \quad s_3 \in \mathbb{N} \tag{3.12}$$

where $sign(s_3) = 0$ when $s_3 = 0$; $sign(s_3) = 1$ when $s_3 > 0$.

Step 4. *Adjoining a geometric sequence*: Before 1 following a 0 in $d^{(3)}$, substitute a finite geometric sequence backward with the coefficient s_4 to replace the 0s:

$$d^{(4)} = d^{(3)} + \sum_{i=1}^{k_2} s_4^i F^{s_3+i} d^{(0)} \tag{3.13}$$

where $s_4 \in [0, 1[$ and $k_2 = \min\{m \geq 1 : s_4^{m+1} < 0.1\}$.

As seen, a bilaterally adjusted dummy variable $d^{(4)}$ depends on parameters $s_i (i = 1, 2, 3, 4)$, forming a scenario (s_1, s_2, s_3, s_4). The outcome of modifying the sequence $d^{(0)}$ with the scenario $\left(5, \frac{1}{2}, 3, \frac{2}{5}\right)$ is shown in Figure 1. This adjustment process extends traditional dummy modeling. When $s_i = 0$ for $i = 1, 2, 3, 4$, $d^{(4)}$ remains the same as $d^{(0)}$. The assumed impact process builds up gradually and lasts for some time before gradually fading, though the actual process might deviate from this pattern.

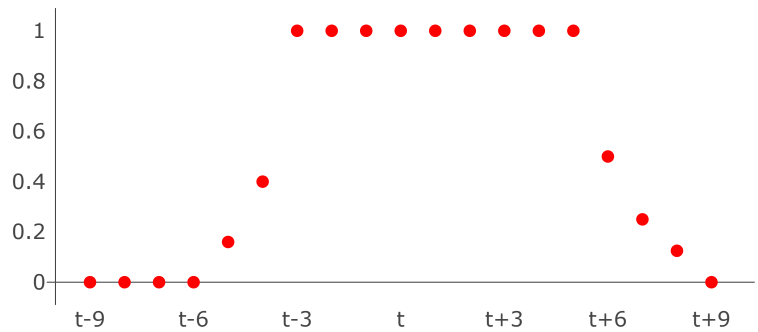


Figure 1. The bilaterally modified dummy variable modeling process.

The European carbon market has evolved through practical implementation, experiencing growth and adapting institutions and regulations to address market challenges, improve operational efficiency, and reduce information asymmetry and market distortions. Using a catalog of 126 regulatory events events from 2005 to 2019 compiled by Kanzig [45] in the EU ETS, including decisions by the European Commission, votes of the European Parliament and decisions of European courts, we update the table of regulatory events to 2023 using data from the research [46]. Adjusting bilaterally modified dummy variable variables for each event, we conduct a step-wise regression to identify the regulatory events significantly impacting carbon allowance prices in the EU ETS. Table 2 displays the selected regulatory events with their respective variable notation.

Table 2. Identified regulatory events.

Notation	Date	Description
b_1	04/2016	Court judgment on free allocation in the EU ETS for the period 2013-2020
b_2	06/2016	Following the court judgment, the commission to modify the cross-sectoral correction factor for 2018-2020
b_3	04/2017	Climate Change Committee approves technical changes to auction rules
b_4	07/2017	Commission publishes status update for New Entrants' Reserve
b_5	04/2019	Iceland, Liechtenstein and Norway to start auctions on the common auction platform soon
b_6	08/2019	Commission amends ETS auctioning regulation for phase 4
b_7	01/2020	Commission publishes status update for New Entrants' Reserve
b_8	11/2020	Commission adopts the Union-wide quantity of allowances to be issued in 2021 and onwards

3.4. Variable importance measures

We also assess the relative importance of the potential factors that determine the carbon price using the Lindeman Merenda-Gold (LMG) metric and the Conditional Adaptive Ranking (CAR) score. The choice of these metrics is driven by significant correlations among independent variables in our model. When explanatory variables are uncorrelated, conventional sensitivity indicators, such as the value t and the correlation coefficient, can be used to analyze the importance of variables [47]. However, analysis becomes challenging with highly correlated input variables [48]. Various metrics have been proposed in the literature to address correlated explanatory variables, including the partial correlation coefficient, LMG, CAR scores, PMVD (proportional marginal variance decomposition), and conditional random forest [49,50]. In this study, we specifically focus on utilizing the LMG metric and CAR score.

The LMG metric computes the average contribution of each variable to the overall R^2 in all possible orderings, providing a unique decomposition of the explained variance when predictors are correlated. This method enables differentiation of the contribution of different correlated predictors in a multiple linear regression model. The CAR score, introduced by Zuber and Strimmer [51], mitigates the correlation among explanatory variables by decomposing the proportion of variance [49]. These techniques are implemented in the `R relaimpo` package [52], which we employ to evaluate the contribution of each variable to carbon prices in the EU.

3.5. Autoregressive distributed lag (ARDL) model

Building upon Eq (3.6) introduced earlier in this section, we expand the functional relationship between carbon prices, energy prices, financial markets, and energy production using an ARDL model. The ARDL model, also known as the bound testing co-integration technique, was originally introduced by Pesaran et al. [53, 54]. This model has the advantages that variables are not required to be in the same order of integration, and that problems of inadequate testing arising from a small sample size can be eliminated to a degree. Simultaneously, we incorporate modified dummy variables (b_i) into the ARDL model to quantify the impact of emission announcements in the EU on carbon prices. Ensuring that none of the series exhibit $I(2)$ or higher integration orders through unit root tests, the model can be formulated as follows.

$$\begin{aligned}
\Delta \ln P_{CO_2,t} &= \beta_0 + \sum_{i=1}^{p} \beta_i \Delta \ln P_{CO_2,t-i} + \sum_{j=0}^{q_1} \delta_{1j} \Delta \ln P_{Coal,t-j} + \sum_{j=0}^{q_2} \delta_{2j} \Delta \ln P_{Gaz,t-j} \\
&\quad + \sum_{j=0}^{q_3} \delta_{3j} \Delta \ln P_{Oil,t-j} + \sum_{j=0}^{q_4} \delta_{4j} \Delta \ln P_{Elec,t-j} + \sum_{j=0}^{q_5} \delta_{5j} \Delta \ln S_{t-j} + \sum_{j=0}^{q_6} \delta_{6j} \Delta \ln C_{t-j} \\
&\quad + \sum_{j=0}^{q_7} \delta_{7j} \Delta \ln I_{t-j} + \sum_{j=0}^{q_8} \delta_{8j} \Delta \ln E_{NR,t-j} + \sum_{j=0}^{q_9} \delta_{9j} \Delta \ln E_{Nuclear,t-j} + \sum_{j=0}^{q_{10}} \delta_{10j} \Delta \ln E_{R,t-j} \qquad (3.14) \\
&\quad + \theta_0 \ln P_{CO_2,t-1} + \theta_1 \ln P_{Coal,t-1} + \theta_2 \ln P_{Gaz,t-1} + \theta_3 \ln P_{Oil,t-1} + \theta_4 \ln P_{Elec,t-1} \\
&\quad + \theta_5 \ln S_{t-1} + \theta_6 \ln C_{t-1} + \theta_7 \ln I_{t-1} + \theta_8 \ln E_{NR,t-1} + \theta_9 \ln E_{Nuclear,t-1} + \theta_{10} \ln E_{R,t-1} \\
&\quad + \sum_{i=1}^{k} \omega_i b_i + e_t.
\end{aligned}$$

In the ARDL bounds test proposed by Pesaran et al. [53], a crucial assumption is that the errors in Eq (3.14) must exhibit serial independence. The subsequent step entails conducting the bounds test, which includes an F-test to assess the hypothesis $H_0 : \theta_0 = \theta_1 = \cdots = \theta_k = 0$, where k represents the number of explanatory variables. Unfortunately, exact critical values for the F test are not readily available for any combination of $I(0)$ and $I(1)$ variables. However, Pesaran et al. [54] offer bounds on critical values for the asymptotic distribution of the F statistic. Assuming the bounds test indicates co-integration, the estimation of long-run equilibrium relationships between variables ensues. Furthermore, Engle and Granger [55] demonstrated that in the presence of co-integration between two variables, an error correction model (ECM) can effectively depict their relationship. In a co-integration model, to ensure precise results, an error correction term must be incorporated into the stationary model, facilitating the derivation of short-run errors from the long-run equilibrium. Consequently, the final model can be expressed as follows.

$$\begin{aligned}
\Delta \ln P_{CO_2,t} = \alpha_0 &+ \sum_{i=1}^{p} \alpha_i \Delta \ln P_{CO_2,t-i} + \sum_{j=0}^{q} \alpha_{1j} \Delta \ln P_{Coal,t-j} + \sum_{j=0}^{q} \alpha_{2j} \Delta \ln P_{Gaz,t-j} \\
&+ \sum_{j=0}^{q} \alpha_{3j} \Delta \ln P_{Oil,t-j} + \sum_{j=0}^{q} \alpha_{4j} \Delta \ln P_{Elec,t-j} + \sum_{j=0}^{q} \alpha_{5j} \Delta \ln S_{t-j} + \sum_{j=0}^{q} \alpha_{6j} \Delta \ln C_{t-j} \\
&+ \sum_{j=0}^{q} \alpha_{7j} \Delta \ln I_{t-j} + \sum_{j=0}^{q} \alpha_{8j} \Delta \ln E_{NR,t-j} + \sum_{j=0}^{q} \alpha_{9j} \Delta \ln E_{Nuclear,t-j} \\
&+ \sum_{j=0}^{q} \alpha_{10j} \Delta \ln E_{R,t-j} + \Gamma ect_{t-1} + \mu_t
\end{aligned} \tag{3.15}$$

where μ_t represents a continuous independent random error term. This equation enables the capture of both short-run and long-run relationships among the variables. For instance, the null hypotheses to test the short-run and long-run relationships between explanatory and explained variables are $\mathrm{H}_0 : \alpha_{1j} = \cdots = \alpha_{10j} = 0$ and $\mathrm{H}_0 : \Gamma = 0$, respectively. The term ect_{t-1} corresponds to the error correction term, while Γ represents the speed of adjustment term, indicating how long the system would take to return to its long-run state following a shock.

3.6. Ridge regression

Co-integration between our variables means that they are linked in the long term, suggesting a lasting relationship. In our case, this connection acts as a stand-in for the EU's equilibrium carbon price. To determine this equilibrium price and examine the disparities between the observed and equilibrium values, we employ a ridge regression methodology. In Eq (3.9), the use of a multiple linear regression model faces potential multicollinearity due to interactions between input variables. Multicollinearity, characterized by high correlation among predictor variables, violates the independence assumption crucial for unbiased ordinary least squares (OLS) estimation in linear regression. When terms are correlated and the columns of the matrix X are nearly linearly dependent, the matrix $\left(X^T X\right)^{-1}$ approaches singularity. As a result, the least squares estimate becomes highly sensitive to random errors in the observed response, leading to increased variance.

To mitigate this problem, the ridge regression, initially proposed by Hoerl and Kennard [56], replaces the traditional OLS for estimation. Ridge regression addresses multicollinearity by calculating regression coefficients using the following formula.

$$\widehat{\beta} = \left(X^T X + kI\right)^{-1} X^T y \tag{3.16}$$

k denotes the ridge parameter, where $k \geq 0$, and I represents the identity matrix.

The selection of k has a significant influence on the quality of the solution, underscoring the importance of exploring a spectrum of allowed values for k. Smaller positive values of k contribute to better problem conditioning and a decreased variance of estimates. Despite their inherent bias, ridge estimates frequently yield smaller mean-square errors in comparison to least-squares estimates. In econometrics, there are several methodologies to determine the optimal value of the ridge parameter. Herein, we adopt the ridge trace plot method, widely used in the literature. Across a range of levels k, from zero to one, the coefficients ($\widehat{\beta_i}$) are estimated. Plotting these coefficients against the corresponding k values facilitates the identification of the optimal point at which the coefficients stabilize.

4. Results and discussions

In this section, we present the empirical results of our analysis aimed at identifying the influencing factors within the EU ETS. After verifying the level of stationarity of the selected variables, we assess the presence of long-term co-integration between them. We provide the results of both long-term and short-term estimations of the ARDL model and discuss their implications for the financialization trend in the EU ETS. The last part of this section analyzes the disparity between the carbon equilibrium price determined by ridge regression and the market price.

4.1. Preliminary analysis

The ARDL methodology is shown to be applicable when the variables under examination exhibit stationarity at $I(0)$, $I(1)$, or a combination of both. Therefore, to determine the level of integration of the variables analyzed in this study, we employ the Dickey-Fuller augmented test (ADF) proposed by Dickey and Fuller [57] and the Perron-Phillips (PP) test introduced by Perron and Phillips [58]. The results of the unit root tests, as shown in Table 3, indicate that none of the variables show second-order integration. Consequently, we proceed with the bound test approach. We also conducted a correlation analysis between the selected variables. The results are presented in Table 4.

Before estimating our ARDL model, we assess the significance of factors influencing EU carbon prices. We employ the LMG metric and the CAR score, as detailed in the methodology section, to gauge their importance. Initially, we estimate a multiple linear regression model based on the specification in Eq (3.9). Given that our variables have an integrated order of one and to avoid spurious regression, we differentiate the variables before estimating the model. Figure 2 illustrates the contributions of each variable in explaining the price variations of EUA using both metrics. Although the values of the LMG and CAR metrics may differ, their magnitudes are comparable. Significantly, both methods identify P_{oil} as the most influential variable. The regression model explains 97.21% of the variations in P_{CO_2}, with P_{oil} accounting for 83% to 90%. The graph also illustrates that the key influencing factors include P_{Elec}, S, C, and P_{Gaz}, with values around 3.9%, 4.3%, 1.6%, and 1%, respectively. These results confirm earlier studies, suggesting the pivotal role of the energy, electricity, stock, and commodity markets in affecting carbon prices within the EU [59–61]. The influence of other factors was negligible, contributing less than 1%, which implies that they had an insignificant effect on EUA dynamics throughout the study period. Consequently, the main determinants of EUA from 2015 to 2023 were prices in the oil, gas, and electricity markets, coupled with movements in the stock and commodity markets.

Table 3. Unit root test results.

	Variables	ADF unit root test		PP unit root test	
		Statistics	Probability	Statistics	Probability
Level	$\ln P_{CO_2,t}$	-2.360	0.398	-2.464	0.344
	$\ln P_{Coal,t}$	-1.426	0.847	-1.594	0.787
	$\ln P_{Gaz,t}$	-2.025	0.580	-7.743	0.723
	$\ln P_{Oil,t}$	-2.319	0.419	-1.966	0.611
	$\ln P_{Elec,t}$	-2.028	0.578	-2.074	0.552
	$\ln S_t$	-2.819	0.194	-2.843	0.186
	$\ln C_t$	-2.328	0.414	-2.843	0.186
	$\ln I_t$	-3.250	0.080	-1.595	0.786
	$\ln E_R$	-1.781	0.705	-3.373**	0.062
	$\ln E_{NR}$	-1.611	0.780	-4.373***	0.004
	$\ln E_{Nuclear}$	-1.523	0.710	-3.677	0.051
First Difference	$\ln P_{CO_2}$	-8.112***	0.000	-8.485***	0.000
	$\ln P_{Coal}$	-8.155***	0.00	-9.190***	0.00
	$\ln P_{Gaz}$	-6.879***	0.00	-6.314***	0.000
	$\ln P_{Oil}$	-8.086***	0.000	-11.622***	0.000
	$\ln P_{Elec}$	-9.567**	0.013	-8.888***	0.000
	$\ln S_t$	-9.034***	0.000	-8.482***	0.000
	$\ln C_t$	-6.707***	0.000	-2.843	0.186
	$\ln I_t$	-7.687***	0.000	-1.595	0.786
	$\ln E_R$	-8.622***	0.000	-9.708***	0.000
	$\ln E_{NR}$	-3.924***	0.000	-17.131***	0.000
	$\ln E_{Nuclear}$	-7.612***	0.000	-6.413***	0.000

*Source: Authors' calculation. Note: ** and *** indicate statistical significance at 5% and 1% levels respectively.

Table 4. Correlation matrix.

	P_{CO_2}	P_{Coal}	P_{Oil}	P_{Elec}	S	IP	C	E_R	E_{NR}	E_{Nuc}
P_{CO_2}	1									
P_{Coal}	0.63***	1								
P_{Oil}	0.99***	0.64***	1							
P_{Elec}	0.77***	0.94***	0.78***	1						
S	0.86***	0.67***	0.85***	0.76***	1					
IP	0.51***	0.63***	0.5***	0.67***	0.68***	1				
C	0.42***	0.77***	0.44***	0.73***	0.52***	0.57***	1			
E_R	0.72***	0.31***	0.72***	0.4 ***	0.62***	0.27***	0.15	1		
E_{NR}	-0.39***	-0.018	-0.39***	0.0058	-0.27***	0.19***	-0.022	-0.4***	1	
$E_{Nuclear}$	-0.58***	-0.49***	-0.59***	-0.48***	-0.45***	-0.17***	-0.31***	-0.23***	0.66***	1

*Source: Authors' calculation. Note: *, **, *** denote a test statistic is statistically significant at the 10%, 5%, or 1% level of significance, respectively.

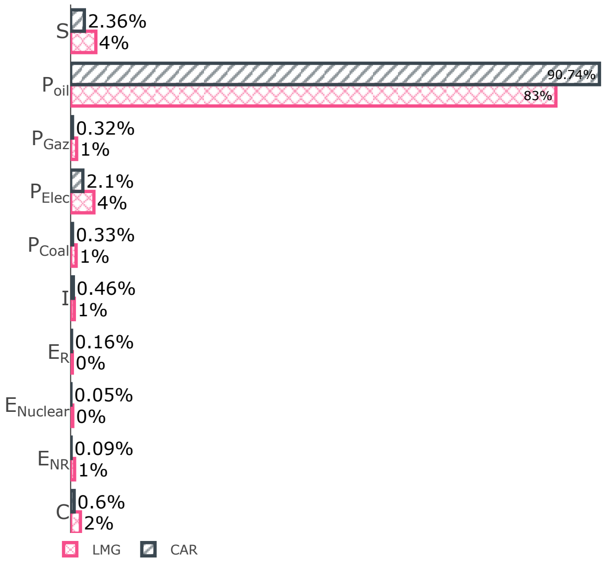


Figure 2. Relative importance of factors explaining carbon price variability using LMG metric and CAR score.

The results of the ARDL bound test, presented in Table 5, strongly support co-integration. The value of the F statistic exceeds the critical value in the upper bound of 1%, indicating a long-term relationship between the estimated variables. Before delving into the short- and long-run estimation results, we validate the ARDL model through various statistical tests. These tests include the Breusch-Godfrey Lagrange Multiplier (LM) test for serial correlation, the Breusch-Pagan-Godfrey (BPG) and ARCH tests for heteroskedasticity, and the Jarque-Bera test (J-B) for the normality assumption in error terms. The results of the diagnostic check are presented in Table 6. All statistical requirements are satisfied, including the absence of heteroscedasticity, serial correlation, and the adherence to a normal distribution of residuals. Additionally, the Ramsey regression equation specification error test (RESET) indicates the absence of specification errors. An additional examination of the parameter stability is carried out using the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) tests [53, 62]. As illustrated in Figure 3, the stability of the estimated parameters throughout the sample period is affirmed, with the blue CUSUM and CUSUMQ lines remaining within the boundaries of the 5% critical lines, demonstrating parameter stability.

Table 5. Results of the bound test.

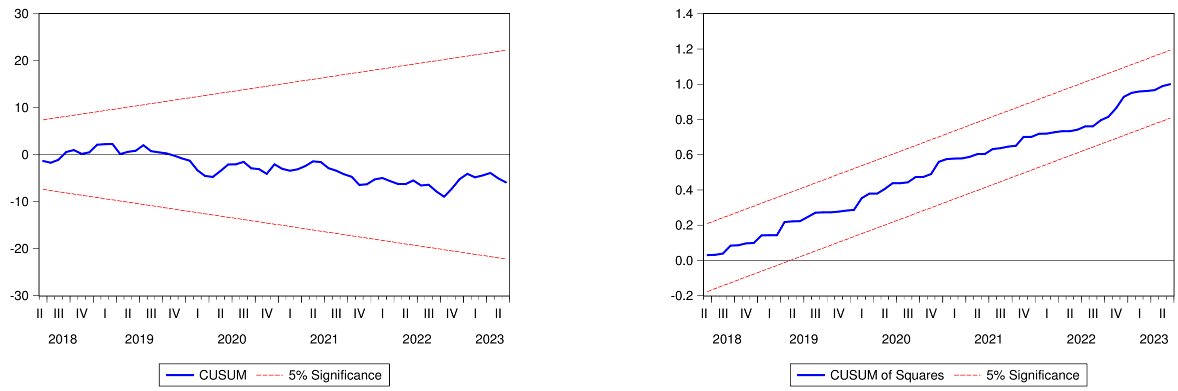
Test statistics	Value	
F statistic	4.125	
	Critical values	
Significance level	Lower bound I(0)	Upper bound I(1)
10%	1.76	2.77
5%	1.98	3.04
1%	2.41	3.61

*Source: Authors' calculation. Note: Critical values [54].

Table 6. Diagnostic test results for the ARDL model.

Diagnostic tests	Coefficient	p-value
LM	0.900	0.412
B-P-G	0.602	0.950
ARCH	0.347	0.707
J-B	0.137	0.933
Ramsey RESET	0.710	0.495

*Source: Authors' calculation.



(a) **(b)**

Figure 3. Cumulative sum of recursive and squares of recursive residuals.

4.2. *The long-term impact of influencing factors*

The results of the long-term relationship estimation are presented in Table 7. The coal price coefficient indicates a positive relationship with the carbon price, although statistically insignificant. This suggests that coal's impact on carbon prices in the EU ETS might be less substantial than expected, despite its significant role in greenhouse gas emissions. In contrast, both the natural gas and oil price coefficients exhibit positive signs and statistical significance. Our estimates reveal that an increase 10% in the price of oil corresponds to an average increase of 5.8% in the price of carbon within the EU ETS, aligning with the intensity of carbon of oil as an energy source. Elevated oil prices increase energy production costs, which promotes increased demand for carbon allowances in the long run [29, 39].

Table 7. Long-term effect of influencing factors.

Variable	Coefficient	Std. Error	t-Statistic	p-value
$\ln P_{CO_2,t-1}$	-0.5921***	0.1066	-5.5566	0.0000
$\ln P_{Coal,t-1}$	0.0090	0.0120	0.7498	0.4563
$\ln P_{Gaz,t-1}$	0.0742***	0.0193	3.8495	0.0003
$\ln P_{Oil,t-1}$	0.5834***	0.1043	5.5952	0.0000
$\ln P_{Elec,t-1}$	-0.1154***	0.0342	-3.3758	0.0013
$\ln S_{t-1}$	0.1165**	0.0471	2.4739	0.0162
$\ln C_{t-1}$	-0.1255***	0.0310	-4.0554	0.0001
$\ln I_{t-1}$	0.1895**	0.0793	2.3893	0.0200
$\ln E_{NR,t-1}$	-0.0505	0.0436	-1.1584	0.2512
$\ln E_{Nuclear,t-1}$	0.0112	0.0384	0.2920	0.7713
$\ln E_{R,t-1}$	0.0955***	0.0352	2.7174	0.0086
c	-1.0666**	0.5172	-2.0624	0.0434

*Source: Authors' calculation. Note: ** and *** indicate statistical significance at 5% and 1% levels respectively

In addition, a 1% increase in natural gas prices is associated with a 0.7% increase in allowance prices due mainly to a substitution effect. Rising natural gas prices prompt a shift to less carbon-intensive energy sources, reducing carbon emissions and leading to a decrease in demand for allowances. Consequently, the decline in demand results in increased prices of carbon allowances due to their relative scarcity. Our findings align with previous research presenting oil and gas prices as the main drivers of carbon price in the EU ETS [11, 33]. The statistically significant coefficient related to the price of electricity indicates an average 1.1% decrease in the price of carbon in the EU ETS for every 10% increase in the price of electricity. This decrease may be attributed to the growing use of renewable energy sources in electricity generation, which places carbon-intensive sources on the outskirts, reduces emissions, and decreases demand for carbon allowances, ultimately leading to lower allowance prices.

In examining the influence of financial markets on carbon prices, we identify statistically significant effects. The European stock market has a positive impact, with a 10% increase in the European stock market index corresponding to an approximate 1.2% increase in carbon prices. This underscores the intricate relationship between financial markets and carbon trading, diverging from the findings of the Chinese ETS pilots [63]. In contrast, the commodity market indicator exhibits a statistically significant negative coefficient, signifying a 1.2% decrease in the price of carbon with a 10% increase in this indicator. This inverse connection may be attributed to resource availability and market dynamics. Furthermore, the coefficient associated with industrial production is positive and statistically significant, indicating that an increase in 10% industrial production is related to approximately an increase in the price of carbon 2%. highlighting the substantial impact of industrial activity on carbon pricing within the EU ETS.

The absence of statistically significant coefficients related to net electricity generation from non-renewable and nuclear sources in the model is noteworthy within the EU ETS context. This suggests that these energy sources do not exert a statistically significant influence on long-term carbon prices, indicating an effective discouragement of carbon-intensive energy production within the EU ETS. Stringent emission reduction targets and an increase in the adoption of renewable energy technologies likely contribute to the diminished role of nonrenewable and nuclear sources in driving carbon prices. The prevalence of cleaner energy technologies may have displaced the demand for electricity from nonrenewable and nuclear sources, resulting in reduced carbon emissions and, consequently, a lower demand for carbon allowances. This reduction in demand offers a plausible explanation for the lack of statistical significance in the coefficients associated with nonrenewable and nuclear sources. In contrast, the positive and statistically significant coefficient associated with net electricity generation from renewable sources indicates that a 10% increase in the share of electricity generated from renewable sources corresponds to a modest long-term increase in carbon prices, approximately 1%. This aligns with the broader objectives of the EU ETS, emphasizing the reduction of carbon pollution and the promotion of cleaner energy practices.

4.3. The short-term impact of influencing factors

The estimation results of the short-term dynamic relationship, as documented in Table 8, indicate a negative and statistically significant error correction term within the short-run ARDL model, suggesting a self-regulating mechanism capable of mitigating short-term disturbances to maintain long-term equilibrium. Changes in past carbon prices significantly affect present prices, as indicated by a positive and statistically significant coefficient. This indicates that recent price changes influence the current market dynamics, leading to similar patterns in the following periods. In the short term, coal prices remain statistically insignificant with regard to fluctuations in carbon prices, while gas and oil prices exhibit significant and positive coefficients, highlighting their influential role. Elevated gas and oil prices, both in current and previous periods, are correlated with increased carbon prices, reflecting the immediate and enduring effects of the energy market dynamics on carbon pricing. The rise in fossil fuel prices contributes to the increase in carbon costs within the EU ETS, aligning with the broader objective of promoting cleaner energy practices and achieving emissions reduction.

Table 8. Short-term effects of influencing factors.

Variable	Coefficient	Std. Error	t-Statistic	p-value
$\Delta \ln P_{CO_2,t-1}$	0.2168***	0.0775	2.7972	0.0069
$\Delta \ln P_{Coal,t}$	-0.0196	0.0125	-1.5672	0.1222
$\Delta \ln P_{Gaz,t}$	0.0526***	0.0152	3.4644	0.0010
$\Delta \ln P_{Gaz,t-1}$	0.0219*	0.0116	-1.8966	0.0626
$\Delta \ln P_{Oil,t}$	1.0238***	0.0149	68.5724	0.0000
$\Delta \ln P_{Oil,t-1}$	0.2047***	0.0792	-2.5840	0.0122
$\Delta \ln P_{Elec,t}$	-0.0473***	0.0171	-2.7638	0.0075
$\Delta \ln P_{Elec,t-1}$	0.0359**	0.0146	2.4556	0.0169
$\Delta \ln P_{Elec,t-2}$	-0.0272***	0.0090	-3.0167	0.0037
$\Delta \ln S_t$	-0.0706*	0.0365	-1.9315	0.0581
$\Delta \ln S_{t-1}$	-0.1319***	0.0417	-3.1625	0.0024
$\Delta \ln C_t$	-0.0222	0.0274	-0.8091	0.4216
$\Delta \ln C_{t-1}$	0.0848***	0.0276	3.0778	0.0031
$\Delta \ln C_t - 2$	-0.0370*	0.0208	-1.7837	0.0795
$\Delta \ln E_{NR,t}$	-0.0199	0.0160	-1.2457	0.2176
$\Delta \ln E_{NR,t-1}$	0.0686***	0.0173	3.9693	0.0002
$\Delta \ln E_{NR,t-2}$	0.0984***	0.0169	5.8066	0.0000
$\Delta \ln E_{R,t}$	0.0070	0.0163	0.4328	0.6667
b_1	-0.0117	0.0074	-1.5852	0.1181
b_2	-0.0135***	0.0037	-3.6476	0.0005
b_3	0.0003	0.0048	0.0560	0.9555
b_4	-0.0064	0.0073	-0.8739	0.3856
b_5	0.0052	0.0050	1.0405	0.3022
b_6	0.0036	0.0056	0.6309	0.5305
b_7	-0.0360***	0.0069	-5.2480	0.0000
b_8	0.0305***	0.0072	4.2275	0.0001
ect_{t-1}	-0.5921***	0.0775	-7.6439	0.0000

*Source: Authors' calculation. Note: ** and *** indicate statistical significance at 5% and 1% levels respectively

In the energy sector, fluctuations in gas prices, particularly in liquid gas prices, directly influence the cost structures of industries that rely on liquid gas. In fact, the EU ETS's definition of scope 1 emissions emphasizes the relevance of liquid gas industries. Higher gas prices can raise production costs for these industries, encouraging through incentives the adoption of emission reduction measures and decreasing the demand for carbon allowances. Conversely, lower gas prices can make greenhouse gas emissions more cost-effective, potentially leading to an excess of allowances and subsequent price reduction. Although electricity prices exhibit statistical significance, their impact on short-term carbon price fluctuations is limited, likely due to the transient nature of the analysis and the dominance of other determinants influencing short-term carbon prices. From a financial perspective, the European stock market shows a significant negative impact on current and lagged variables. This suggests that an upturn in stock market performance leads to lower short-term carbon prices, indicating that a flourishing stock market diminishes the attractiveness of carbon allowances as an investment, contributing to a decrease in their prices. In contrast, the commodity index exerts its primary influence through lagged values, emphasizing the greater relevance of past commodity market fluctuations than its current state in shaping short-term carbon prices within the EU ETS.

Positive coefficients linked to changes in net electricity generation from nonrenewable sources indicate a significant influence of historical fluctuations in nonrenewable electricity generation on short-term carbon allowance prices. Industries that rely on nonrenewable energy sources require carbon allowances to comply with emissions, resulting in a variable demand for allowances in response to past shifts in nonrenewable electricity generation. An increase in past nonrenewable generation signals higher carbon emissions, leading to greater demand for allowances and a subsequent uptick in short-term carbon prices. However, nonsignificant changes in net electricity generation from renewable sources suggest that recent developments in renewable energy generation do not significantly impact short-term carbon prices. In addition, policy support and subsidies for renewables can mitigate their direct cost impact on production processes, minimizing their influence in the short term.

Incorporating dummy variables that represent institutional decisions in the model reveals an overall negative and statistically significant trend, with some exceptions showing positive coefficients. The relatively small magnitude of these coefficients emphasizes the modest impact of institutional decisions on short-term carbon prices within the EU ETS. Generally, such decisions exert downward pressure on carbon prices in the short run, aligning with the system's goal of encouraging emission reductions and cleaner energy practices. Instances with positive coefficients suggest that specific institutional choices can lead to transient increases in carbon prices, often associated with changes in regulatory stringency or policies that increase the demand for carbon allowances. However, these impacts are typically modest and coexist with the prevailing downward pressure.

In addition, dynamic portfolio shifts can significantly impact carbon prices by affecting energy prices and the green transition. Semmler et al. [64] examined how the focus of investors on short-term gains leads to fluctuating wealth allocations between fossil fuel and renewable energy assets. Their results showed that high discount rates and shorter decision horizons prompt investors to prioritize immediate returns, often at the expense of long-term investments in green technologies. As asset allocations adjust on the basis of new market information, energy prices shift, impacting the demand for both carbon-intensive and low-carbon assets. This short-term focus can slow the transition to renewable energy, affecting the overall trajectory of carbon prices and delaying climate goals.

4.4. Equilibrium carbon price

The bounds test has shown the existence of a long-term association, indicative of the equilibrium carbon price within the European Union. We estimate this equilibrium price and undertake a comparative analysis of the discrepancies between it and the observed market price. The correlation matrix in Table 4 demonstrates notable and significant correlations among the independent variables, thereby indicating potential multicollinearity issues. To mitigate these concerns, ridge regression was used to determine the long-term equilibrium relationship between carbon price and its determinants. The results of the ridge regression are presented in Table 9, where the low and near-1 values of the variance inflation factor (VIF) signify effective mitigation of multicollinearity. The equilibrium and market prices are visualized in Figure 4, with the price deviation illustrated in Figure 5. Two distinct phases are observed during the study period. Initially, before April 2018, the market price consistently trailed below the equilibrium price, signifying an overestimation of the value of carbon emission rights. The deviation during this phase remained within a 33% relative error range. Subsequently, a change in the EU ETS occurred, marked by a market price that exceeded the estimated equilibrium price, thus overestimating the carbon allowance price and indicating a change in market dynamics. In April 2020, the relative error peaked at 88%, indicating a substantial price deviation. Throughout the remaining period, the relative error fluctuated within the range 22%. When the carbon price exceeded the equilibrium price, it signified an overestimation of the value of the carbon emission rights. Conversely, when the carbon price fell below the equilibrium price, it indicated an underestimation of the value of carbon emission rights. From the figures, it becomes apparent that the underestimation and overestimation of the value of the carbon emission quotas alternated throughout the study period.

Between 2015 and 2018, the EU ETS witnessed a consistent trend of market prices consistently falling behind the estimated equilibrium. This lag resulted from various factors. In Phase 3 (2013–2020), an initial surplus of approximately 2 billion tons of carbon allowances emerged, resulting from the aftermath of the 2008 economic downturn, increased clean development mechanism (CDM) credits and renewable energy policies [65]. In January 2016, the EU ETS suffered a major setback with the announcement of the UK referendum, causing CO_2 prices to plummet to a three-year low below 5€/tons [66]. While other markets recovered, the carbon market continued its losses. The subsequent year, 2017, saw successive rebounds, ending with an average price of 6.2€/ton. In 2018, there was a significant increase in emission allowance price, rising over threefold from 8€, to 25€/ton by year-end. The increase was driven by the implementation of the market stability reserve (MSR) policy. Agents accumulated allowances, expecting a rise in future sales prices, based on the prediction that Europe would increase the minimum sale price [67]. Despite price fluctuations in 2019, averaging around 26€/ton, the policy landscape failed to realign market dynamics and prices with equilibrium. The economic crisis and the aftermath of the Copenhagen negotiations relegated carbon pricing to a lower political priority, perpetuating the gap between market and equilibrium prices [68]. External economic and political factors significantly influenced allowance demand, maintaining the disparity between market and equilibrium prices. The perception of oversupply by market participants and doubts about the effectiveness of the policy probably undermined confidence, shaping trading behavior, and prolonging the delay in market prices behind the estimated equilibrium.

Table 9. Ridge regression estimators of variables (k = 0.16).

Variables	Coefficient	t-Statistic	p-value	VIF
$\ln P_{Coal}$	-0.0440	-1.14453	0.1516	1.0246
$\ln P_{Gaz}$	0.0326*	1.7451	0.0842	0.7667
$\ln P_{Oil}$	0.5098***	28.3873	0.000	1.0773
$\ln P_{Elec}$	0.2435***	13.2885	0.000	0.7490
$\ln S$	1.1164***	8.0153	0.000	1.2344
$\ln I$	0.4030	-2.9824	0.2615	1.1240
$\ln C$	-0.2338***	1.1296	0.0036	1.1001
$\ln E_R$	1.0788***	8.0800	0.000	0.9824
$\ln E_{NR}$	-0.3232***	-2.7190	0.0078	0.9193
$\ln E_{Nuc}$	-0.5077***	-4.0769	0.000	0.9641
c	-10.3884***	-6.9112	0.000	—
R^2	0.8610			
Adj.R^2	0.8474			
F-stat	329.0716			
p-value	0.000			

*Source: Authors' calculation. Note: *, **, *** denote a test statistic that is statistically significant at the 1%, 5%, or 10% level of significance; VIF indicates Variance Inflation Factor.

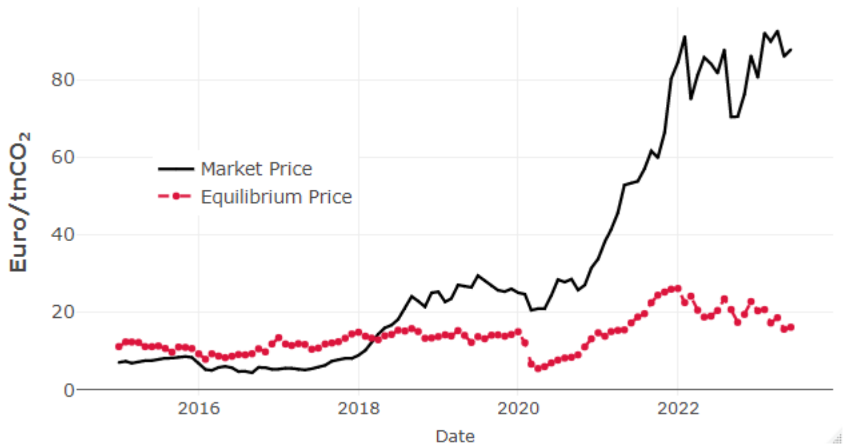


Figure 4. Market and estimated equilibrium prices in the EU ETS.

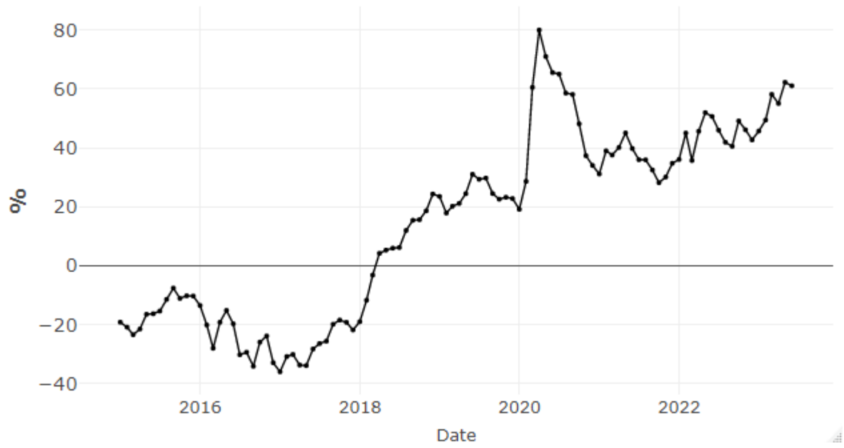


Figure 5. Relative error between estimated carbon equilibrium and market prices in the EU ETS.

Between April 2018 and March 2023, a distinct shift occurred in the EU ETS, marked by the market price consistently exceeding the equilibrium price. The initiation and finalization of the Phase 4 reforms, which span from 2015 to 2030, played a pivotal role during this period [69]. These reforms aimed to align the EU ETS with the 2030 EU target of reducing CO_2 emissions by at least 40% below 1990 levels. The Phase 4 reforms demonstrated a strong commitment to strict emission reduction targets. Accelerating the annual linear reduction factor, maintaining the MSR, and earmarking auction revenue for innovation and modernization funds signaled a commitment to robust climate goals. The reforms led to an increase in the auctioning of allowances, creating a mechanism to manage the supply of allowances in the market more effectively. The combination of political impetus, increased auctioning, and the broader regulatory framework instilled confidence in market participants. The reforms aimed to address past issues, and the market responded positively to the prospect of a more robust and well-regulated carbon pricing mechanism [69, 70].

The significant discrepancy between the two prices can be attributed to increased volatility during the initial half of 2020, driven by the extreme market fluctuations resulting from the Covid-19 pandemic [71]. This period saw a sharp decline in mid-March, directly in relation to the market response to the health crisis. Having started the year at €25 per ton of CO_2, the price of CO_2 allowances plummeted to its lowest point in March 2020, hitting 20€/ton. The negative reaction observed in the energy and financial markets during this time reflected the anticipated forecasts of wealth loss and employment due to pandemic-induced containment measures. This led to a notable downturn in various sectors, such as a 5.6% reduction in electricity demand in Spain for 2020, contributing to a substantial 27.8% decrease in CO_2 equivalent emissions from electricity production [72]. The ensuing economic uncertainty and reduced industrial activity triggered a surge in price volatility, resulting in a considerable increase in the volume of allowances traded on exchanges during March and April. In March alone, a record-breaking 677.7 million December 2020 delivery allowances changed hands at the Intercontinental Exchange, with total volumes slightly decreasing to 477.9 million in April [73]. As the second and third quarters of 2020 unfolded, the carbon price rebounded. This coincided with several major European economies initiating the process of easing Covid-19 lockdown restrictions, fostering optimism due to the imminent start of vaccination campaigns to curb the pandemic. This positive outlook was reflected in the increase in prices, reaching 31.9€/ ton in December, as the market responded to the prospect of economic recovery and normalization. This observation shows that the EU carbon market, like any financial market, can be sensitive to external shocks. The unprecedented nature of the COVID-19 pandemic and its impact on economic activities probably contributed to increased sensitivity and fluctuations in carbon prices.

5. Conclusions

This study aims to analyze recent financialization trends in carbon markets, with a specific focus on the EU ETS. We investigate the dynamics among the carbon market, the energy market, and macroeconomic factors. Using data spanning from January 2015 to June 2023, our research delves into the influencing factors of carbon allowance prices, particularly during Phase III and the first half of Phase IV, which has received limited empirical analysis. To quantify the impacts of energy prices, stock and commodity markets, energy and industrial production, and institutional decisions within the EU ETS, we employ the ARDL model. In addition, we used event impact modeling with bilaterally modified dummy variables to incorporate institutional decisions into our analysis.

The long-term analysis of carbon prices in the EU ETS reveals that while coal prices show a positive impact, their lack of statistical significance suggests limited influence despite significant greenhouse gas emissions. In contrast, natural gas and oil prices exhibit substantial and statistically significant impacts, which emphasizes their pivotal role. Elevated oil prices contribute to higher energy production costs, fostering a higher demand for carbon allowances. Financially, the European stock market positively impacts carbon trading. The negative coefficient of the commodity market indicator suggests counteractive forces on carbon prices. Industrial production significantly influences carbon pricing, while the reduced influence of nonrenewable and nuclear sources aligns with emission reduction targets. On the flip side, the positive coefficient for renewable sources signals a modest long-term price increase, aligning with cleaner energy goals.

In short-term dynamics, the significant and negative error correction term indicates a self-adjusting mechanism for stability. Historical fluctuations, especially in gas and oil prices, play a crucial role, as evidenced by a positive coefficient for lagged changes in carbon prices. Coal prices remain statistically insignificant, while gas and oil prices have significant positive coefficients that influence the short-term dynamics. Financially, a thriving European stock market lowers short-term carbon prices, contrasting with the lagged influence of the commodity index.

In the energy sector, gas price fluctuations, especially in liquid gas, directly impact relevant industries. However, electricity prices minimally affect short-term carbon fluctuations, likely due to the transient nature of the analysis and the dominance of other determinants. Historical shifts in non-renewable electricity generation significantly influence short-term carbon allowance prices, reflecting variable demand tied to past changes. However, recent developments in renewable energy have a nonsignificant impact, suggesting that policy support and subsidies mitigate their direct influence on short-term prices. The dummy variables reflecting institutional decisions reveal an overall negative trend, aligned with emission reduction goals. Instances with positive coefficients indicate that specific institutional choices can transiently increase carbon prices, often linked to changes in regulations or policies that increase the demand for carbon allowances. However, these impacts are typically modest and coexist with the prevailing downward pressure.

Our analysis concludes by examining the market price and estimated equilibrium in the EU ETS carbon market. Using ridge regression to address multicollinearity, we confirmed a long-term dynamic relationship. Two phases were evident: before April 2018, the market price was consistently lagged, overestimating the value of carbon emission rights. Subsequently, a shift occurred, with the market price surpassing the equilibrium, peaking in April 2020. From 2015 to 2018, a trend emerged as the market price lagged consistently. Factors included a surplus of carbon allowances, increased CDM credits, and renewable energy policies. Despite interventions like the MSR and backloading, the surplus persisted, influencing market dynamics. External economic and political factors further affected carbon pricing, contributing to the persistent gap. Between April 2018 and March 2023, the market price consistently surpassed the equilibrium, marked by Phase 4 reforms aligning with the EU's 2030 emission reduction target. The reforms aimed to address past issues, instill confidence, and positively impact the market. Lastly, the sharp rise in carbon prices from April to June 2020, driven by the COVID-19 pandemic, saw reduced industrial production and heightened anticipation of allowance demand in the post-pandemic recovery, fueling the price surge.

Although our study provides valuable information on the dynamics of carbon prices in the EU ETS, it has limitations. The model could be enhanced by incorporating factors such as speculative trading, policy uncertainty, and renewable energy penetration, which would offer a more comprehensive view of price fluctuations. Additionally, exploring nonlinear relationships, structural breaks, or alternative methods like machine learning could improve robustness, particularly during disruptions like the COVID-19 pandemic. Despite these constraints, the methodology, rooted in supply-demand dynamics and log-linearization, can be adapted to other financial markets by considering their unique drivers. In energy markets, such as those for crude oil or liquefied natural gas, price relationship modeling can involve incorporating production levels, alternative products, or regulatory impacts. A tailored event-based dummy variable approach can be employed to evaluate the effects before and after specific announcements in these sectors, such as regulatory updates or earnings disclosures. In a similar vein, the fertilizer market provides another relevant case in which price dynamics can be assessed by integrating production levels, alternative products, and regulatory influences. Institutional decisions, such as imposing export restrictions on vital fertilizer ingredients or offering subsidies to local producers, can strongly impact market pricing. Such policy changes can shift the supply-demand equilibrium, affecting both domestic and international markets. A modified dummy variable approach excels in analyzing these scenarios. For example, this method can be customized to examine the impacts before and after a government declaration about export limitations.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

All authors declare no conflict of interest in this paper.

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