Can Energy-Related Uncertainty Serve as a Barometer for Carbon Pricing?[1]

CHI WEI SU – XIN YUE SONG** – MENG QIN*** – Santiago BUDRÍA*****

Abstract

This investigation examines the reciprocal connection between energy-related uncertainty (EUI) and carbon trading prices (CTP). Empirical results indicate that EUI can positively affect CTP. This positive impact confirms that high EUI prompts businesses to increase demand for carbon emissions permits to cope with energy market risks, ultimately driving up CTP. The intertemporal capital asset pricing framework explains the findings. Conversely, the relationship between EUI and CTP is beneficial and detrimental, demonstrating that ongoing carbon market development contributes to energy market stabilisation and lowers EUI. However, disputes over energy supply and demand can undermine this effect. Within sustainable development, these findings contribute to governments employing EUI to indicate the effectiveness of carbon pricing policies, thereby better addressing energy market risks. Simultaneously, businesses can regard EUI as a signal to anticipate future carbon pricing changes and take corresponding risk management measures.

Keywords: *carbon trading price, energy-related uncertainty, rolling-window, time-varying*

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Introduction

This article explores the intricate relationship between energy-related uncertainty (EUI) and carbon trading prices (CTP), offering valuable insights and perspectives for managing the dynamics of carbon price fluctuations. Following the outbreak of the Industrial Revolution, the worldwide economy has experienced tremendous growth, culminating in the widespread utilisation of numerous energy sources, including coal, oil, and natural gas (Ma et al., 2021). These fossil fuels are significant contributors to carbon emissions (Wang et al., 2024). For instance, upstream and downstream activities in the oil and oil products supply chain generate considerable CO2 emissions, thus exacerbating global warming. Within this context, carbon-emitting trading marketplaces effectively promote sustainable economic growth and reduce CO2 emissions (Wen et al., 2020). Over the past few years, energy price volatility, supply instability, and supply chain disruptions have caused turmoil in the energy sector, significantly affecting the carbon market's stability and sustainable growth (Su et al., 2024c). Elevated EUI delays investments in energy projects by investors and consumer spending on energy products, consequently altering carbon quota demand and inducing carbon market fluctuations (Xu, 2021; Li and Su, 2024). Additionally, CTP curbs emissions by raising the production costs of fossil fuels, facilitating an energy transition and thus mitigating the risk factors connected with traditional energy sector instability (Su et al., 2023). Therefore, understanding the interaction between these variables is crucial for analysing CTP trends, which support government and corporate decision-making and contribute to the carbon market's healthy development.

In the trajectory towards global carbon neutrality, Europe consistently serves as a vanguard. The European Union established the European Union Emissions Trading System (EU ETS) in 2005. As the largest and earliest-established carbon emissions trading marketplace globally, the EU ETS reached an allowance of 1.855 billion tons in 2019, affecting the progress of the worldwide carbon emission sector (Ren et al., 2021; Ma et al., 2021). Influenced by the EU's climate objectives for 2030, the carbon trading price rises throughout 2021. However, carbon prices experience sharp fluctuations throughout the preceding decade, delivering significant barriers to the EU ETS (Su et al., 2024b). Since the combustion of energy, particularly traditional sources like coal and natural gas, represents a significant contributor to carbon emissions, events like fluctuations in energy

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supply, policy changes, and technological innovations affect CTP (Tang et al., 2023). Energy crises and various uncertainty events especially increase the risks associated with carbon trading (Adediran and Swaray, 2023). For instance, the financial crisis of 2008 overspilled into economic recession, which led to a sharp contraction in energy-intensive industries and a consequent reduction in energy demand, resulting in lower carbon emissions in European enterprises. Furthermore, in 2022, the Russia-Ukraine conflict caused an energy supply crisis in Europe. The need to pursue alternative supplies of energy forced Europe to rely on more carbon-emitting energy sources, increasing the demand for carbon allowances and thus jacking up CTP. In light of the frequent climate disasters and the significant decline in energy supply and demand imbalances, this paper investigates the connection between EUI and CTP to assist market participants in determining actions and eventually achieving long-term carbon emission objectives.

This paper makes several significant contributions. Initially, existing literature primarily focuses on analyzing the impact of specific uncertainty factors, such as single energy prices (Wen et al., 2020), economic policy adjustments (Yuan and Yang, 2020), or geopolitical risks (Feng et al., 2023), on CTP. However, it often overlooks the potential role of the EUI in explaining fluctuations in CTP. Although macroeconomic risks can be captured by traditional uncertainty measures, they fall inadequate in capturing the particulars of energy market uncertainties. In a similar vein, measuring energy shocks with single energy prices or weighted averages of multiple energy prices does not fully capture the total risk dynamics of the energy market. Additionally, research on the causal link between CTP and EUI remains insufficient, which is critical to both government and market participants. Therefore, this study employs the EUI proposed by Dang et al. (2023), which provides a more thorough and comprehensive depiction of diverse energy market risks and a trustworthy analytical framework for delving deeper into the relationship between EUI and CTP. Furthermore, previous studies have ignored the structural dynamics of time series, which may lead to causal misjudgement in full-sample analyses. To address this, we adopt a rolling-window Granger causality test to increase the robustness of results and capture time-varying causal relationships (Liu et al., 2023; Su et al., 2024a). The results show that EUI positively leads to CTP, which confirms its validity for predicting CTP fluctuations and supports the intertemporal capital asset pricing model (ICAPM). Conversely, the reduction in CTP has both adverse and beneficial impacts on EUI. From a pessimistic standpoint, the continual improvement of the carbon sector fosters stability in the energy market, whereas energy supply and demand disputes undermine this effect. Based on these findings, market participants can use EUI to forecast CTP trends and optimize portfolios to mitigate energy market volatility, while policymakers can stabilize carbon prices through international cooperation and conflict reduction.

This article is arranged as follows: Section 1 examines the literature relevant to the subject matter. Section 2 delves into the intertemporal capital asset pricing formwork. Section 3 explains the methodologies for full and sub-sample causality tests. Section 5 outlines the dataset utilised in the study. The empirical findings are in Section 5. The last section summarizes the study's findings.

1. Literature Review

Along with the development of EUI by Dang et al. (2023), which captures various key factors such as energy prices, supply and demand, imports and exports, policies, extraction, and climate, this uncertainty is widely used in multiple studies (Su et al., 2025b). Zhang and Guo (2024) highlight the predictive power of EUI for the trend of oil prices. Furthermore, Yasmeen and Shah (2024) show that EUI has a dual effect on energy consumption: on one hand, it suppresses the consumption of fossil fuels, while on the other hand, it promotes the growth of renewable energy consumption. Additionally, Demirkale and Duran (2025) show that there is a long-run positive association between EUI and sustainable development goals. These studies fully validate the role of EUI in energy prices, protection of ecosystems, and achieving sustainability. However, with the excessive combustion of fossil fuels intensifies greenhouse gas emissions, the demand for a low-carbon transition has been increasing rapidly. Carbon pricing mechanisms have been put forward as one of the climate policy tools to mitigate energy-related emissions (Li et al., 2023). Current studies have focused on single energy costs, policy uncertainties, and geopolitical risks, whereas discussions about how EUI affects CTP remain relatively limited. By employing the conditional volatility of spot crude oil returns in China as an indicator of energy market uncertainty, Xu (2021) concludes that energy market uncertainty has substantial adverse cascading effects on China's carbon pilot. Wei et al. (2022) argue that increased uncertainty in global petroleum prices may suppress carbon emissions, causing a fall in CTP. Gao et al. (2023) demonstrate a significant adverse association between uncertainty and carbon prices, meaning that heightened uncertainty decreases CTP. Wang et al. (2023) state that the turmoil in the worldwide petrol marketplace and the downturn in the carbon market have forced many countries to retreat in environmental preservation and other courses, leading to a plummet in CTP. Furthermore, Wang et al. (2024) find that, in most periods, an escalation in coal prices triggers a decrease in CTP, showing a negative correlation between the two.

Conversely, a few investigations have also put forth opposing viewpoints. Trabelsi et al. (2023) argue that the main energy sectors (namely coal, electricity, Brent, and natural gas) have increased the demand for carbon emission permits through substitution incentives, thereby raising CTP. Liu et al. (2023) also suggest that a beneficial variation in fuel prices boosts carbon prices. Cao et al. (2023) argue that energy crises drive petroleum and natural gas price shocks, prompting a shift to cheaper coal, which increases carbon dioxide emissions, raising demand for carbon permits and pushing up CTP. Zhang et al. (2024) indicate that the spillover effects of fossil fuel futures return exert a notable and beneficial influence on the volatility of carbon futures. Nevertheless, according to research by Chen and Yuan (2024), petroleum prices are regarded as a representation of energy volatility and argue that its impact on the fluctuation of China's carbon exchange is comparatively minor.

The EU ETS is seen as the preeminent global carbon market, demonstrating substantial interconnection between the carbon trading and energy sectors (Yang et al., 2023). Yuan and Yang (2020) assess the degree of uncertainty in the energy sector by utilizing the Chicago Board Options Exchange Crude Oil Volatility Index (OVX) and discover substantial risk spillovers from crude oil market volatility to the EU ETS. Dou et al. (2022) investigate the correlation between variations in economic uncertainty and returns in the European carbon exchange. They note that variations in economic instability exert a considerable adverse spillover effect on the CTP. Yang et al. (2023) report that tail uncertainty shocks in international energy markets adversely affect CTP. Moreover, Wei et al. (2025) assert that crude oil prices adversely affect the financialization of the EU carbon market due to the output suppression impact. However, Ren et al. (2022) observe a notable positive correlation between the carbon and fossil energy markets, indicating a potential risk synergy effect between the two. Su et al. (2024b) similarly assert that during extreme weather events, the demand for electricity will surge, resulting in a short-term increase in energy consumption, which will consequently elevate carbon emissions and CTP.

Existing studies primarily focus on the impact of energy prices, policies, geopolitical risks, and climate uncertainties on CTP, with limited attention to the role of EUI. This paper aims to investigate the interaction between EUI and CTP and its predictive significance, thereby providing a novel instrument for carbon price forecasting. Additionally, to address the limitations of conventional Granger causality tests, which frequently overlook structural breaks and non-stationarity in time series, we employ a bootstrap subsample methodology to accurately delineate the dynamic causal relationship between EUI and CTP.

2. Intertemporal Capital Asset Pricing Model

Adopting the intertemporal capital asset pricing model (ICAPM) constructed by Cifarelli and Paladino (2010) makes clarifying the association between EUI and CTP feasible. We assume that buyers in the carbon trading market comprise rational investors and feedback investors, with the former optimizing returns based on market conditions and EUI, while the latter trade in response to carbon price fluctuations. This implies that rational investors consider future expectations in asset pricing and systematically assess investment risks (Cifarelli and Paladino, 2010). Furthermore, systemic risks, such as uncertainty, cannot be mitigated through investment strategies (Liu et al., 2024). Therefore, we use EUI_t to represent the EUI in period *t*, thus further inferring the rational investors' demand for carbon emission allowances:

$$R_t = \frac{E_{t-1}\left(CTP_t\right) - CTP^f}{\mu\left(EUI_t\right)} \tag{1}$$

where the percentage of carbon emission permits that the rational section requires is denoted by R_t. The $\mu\left(EUI_t\right)$ graph exhibits a monotonically growing trend inside the framework and is favourable. $E_{t-1}\left(CTP_t\right)$ represents the conditional expectation of CTP changes. The risk-free interest rate is symbolised by CTP^f. If all participants in the carbon market behave rationally, then $R_t = 1$. In this case, Equation (1) in the classical capital asset pricing model (CAPM) proposed by Sharpe (1964) can be transformed into Equation (2). Consequently, an increase in EUI will drive the growth of CTP.

$$E_{t-1}\left(CTP_t\right) = CTP^f + \mu\left(EUI_t\right) \tag{2}$$

Additionally, in light of the previous CTP, the remaining participants in the carbon emissions marketplace alter their current investing arrangements. After implementing into account the feedback batch, the formula for calculating the percentage of emission allowance proposals (F_t) is as below:

$$F_t = \tau CTP_{t-1} \tag{3}$$

where $\tau > 0$ implies that the feedback organisation acquires carbon emission allowances in reaction to an alteration in CTP during the preceding segment. When the rational and feedback segments get involved in the carbon emissions marketplace, $R_t + F_t = 1$, we remain with the following:

$$E_{t-1}\left(CTP_t\right) = CTP^f + \mu\left(EUI_t\right) - \tau\mu\left(EUI_t\right)CTP_{t-1} \tag{4}$$

The term $-\tau\mu\left(EUI_t\right)CTP_{t-1}$ is inserted into Equation (2) utilising Equation (4), triggering the emergence of instability in CTP. EUI persists in having a significant impact on CTP by virtue of the reality that the overarching coefficient incorporating $\mu\left(EUI_t\right)$ is $1 - \tau CTP_{t-1}\left(\tau CTP_{t-1} = F_t\right)$. This means that with the development of EUI, many uncertainties-supply chain disruption, policy adjustments, or huge fluctuation of energy prices-would force market participants to increase demand for carbon allowances in order to hedge potential cost risks and ensure future compliance in carbon emissions in production, thus driving up the CTP. We determine the presumption, in compliance with the ICAPM structure, that energy sector volatility or uncertainty could culminate in a rise in EUI, subsequently influencing CTP. This demonstrates the shifting connection between these variables.

3. Methodology

3.1. Bootstrap Full-Sample Causality Test

In the conventional vector autoregression (VAR) framework, the test statistics for Granger causality do not adhere to the principles and characteristics of standard asymptotic distributions. Therefore, we introduce a new method Shukur and Mantalos (1997) recommended, namely threshold values for the residual-based bootstrap (*RB*) technique. This approach enhances the accuracy of Granger causality tests and reduces bias. Furthermore, even in scenarios with restricted sample sizes, this approach applies to cases involving standard asymptotic distributions and traditional asymptotic distributions. The modified likelihood ratio (*LR*) statistic specified by Shukur and Mantalos (2000) is defined by power and significance level characteristics. Using the *RB*-based modified-*LR* metric, this article evaluates the Granger causal association between EUI and CTP. The expression of the bivariate VAR (p) model is provided below:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + ... + \alpha_p Y_{t-p} + \upsilon_t \qquad t = 1, 2, ..., T \tag{5}$$

The Schwarz Information Criterion (SIC), which is constructed, is applied to determine p. The breakdown of the VAR (p) procedure containing two variables into EUI and CTP yields the explicit expression $Y_t = \left(EUI_t, CTP_t\right)'$. Furthermore, natural gas (NP) and oil prices (OP) serve as intermediaries between the EUI and CTP, particularly noting the EUI's sensitivity to oil price fluctuations (Dang et al., 2023). Natural gas is not only critical for assessing the EUI but also constitutes a primary heating source in Europe (Song et al., 2022). The fluctuations in these fossil fuel prices impact carbon emissions, subsequently affecting CTP. Consequently, OP and NP are closely linked with the EUI and CTP. To improve the accuracy of the results, we select OP and NP as control variables, thereby reformulating the VAR (p) process as Equation (6):

$$\begin{bmatrix} EUI_t \\ CTP_t \end{bmatrix} = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix} + \begin{bmatrix} \alpha_{11}(L) & \alpha_{12}(L) & \alpha_{13}(L) & \alpha_{14}(L) \\ \alpha_{21}(L) & \alpha_{22}(L) & \alpha_{23}(L) & \alpha_{24}(L) \end{bmatrix} \begin{bmatrix} EUI_t \\ CTP_t \\ NP_t \\ OP_t \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v_{1t} \end{bmatrix} \tag{6}$$

where a white-noise operation with a covariance matrix and the median of zero is symbolised by the expression $\upsilon_t = (\upsilon_{1t}, \upsilon_{2t})'$. $\alpha_{ij}(L) = \sum_{k=1}^{p} \alpha_{ij,k} L^k$, $i, j = 1, 2$ with L representing a lag operator, and we maintain $L^k Y_t = Y_{t-k}$. Referring to Equation (6), the null hypothesis that EUI exerts no effect on CTP can be scrutinised ($\alpha_{12,k} = 0$ for $k = 1, 2, \ldots, p$). Likewise, under specific conditions, the alternative hypothesis that CTP has no impact on EUI can also be tested.

3.2. Parameter Stability Test

Parameter stability is crucial in the full-sample causality analysis utilising the VAR framework. However, assuming stability may introduce bias into the full-sample evaluation. To assess the stability of parameters, *Sup-F*, *Ave-F*, and *Exp-F* tests by Andrews (19993) and Andrews and Ploberger (1994) are used; among them, the *Sup-F* detects structural shifts, while *Ave-F* and *Exp-F* test temporal trajectories in the trend variables. Furthermore, as indicated by the *Lc* statistics examination proposed by Nyblom (1989) and Hansen (1992), the stability assessment is employed to test if variables adhere to a random-walk procedure. In summary, the stability tests can be conducted to determine parameter non-stationarity and grasp the time-varying relationship between EUI and CTP. The bootstrap sub-sample rolling window approach is adopted in this paper to further investigate their causal dynamics.

3.3. Bootstrap Sub-Sample Rolling-Window Causality Test

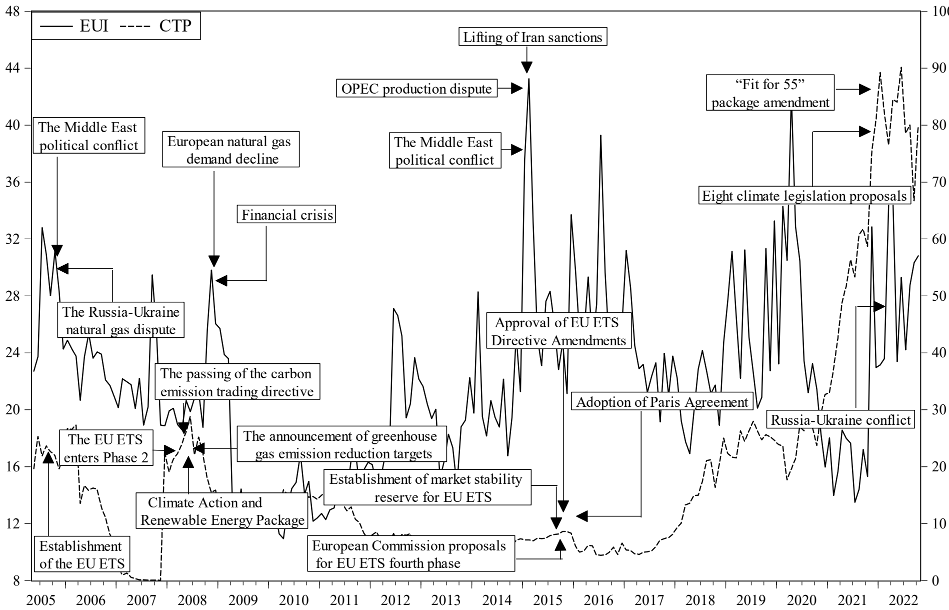
Balcilar et al. (2010) propose a rolling window subsampling approach that trades precision and stability by choosing window width. Narrow windows may produce unstable results, while wide windows may detect changes less effectively (Liu et al., 2024; Qin et al., 2024c). In addition, Pesaran and Timmermann (2005) underline that under parameter instability, the window width must be 20 for analytical validity. The thorough approaches are outlined below: Determine the duration of the time sequence to be T and configure the rolling window spanning to 1. By assigning the termination point of every segmented minor example to 1, 1 + 1, ..., *T*, it is feasible to obtain subsamples numbered *T* – 1 + 1. The possibility for a Granger causality consequence exists for every subsample under consideration when implementing the *RB*-based modified-*LR* investigation. Afterwards, conclusions obtained from the bootstrap sub-sample rolling window evaluation are deduced through the sequential presentation of *LR* metrics and *p*-values through subsamples as time passes. The means of $N_b^{-1} \sum_{k=1}^{p} \hat{\alpha}_{12,k}^{*}$ and $N_b^{-1} \sum_{k=1}^{p} \hat{\alpha}_{21,k}^{*}$ are calculated by combining a substantial number of projections, and every figure indicates the effect of EUI on CTP. The quantity of bootstrap repeats is indicated by N_b. The coefficients $\hat{\alpha}^*_{12,k}$ and $\hat{\alpha}^*_{21,k}$ are specified in Equation (6). Regarding this research, a 90% confidence interval is applied to encompass the lower and higher restrictions, meaning that they correspond 5th and 95th percentiles of $\hat{\alpha}^*_{12,k}$ and $\hat{\alpha}^*_{21,k}$, correspondingly (Balcilar et al., 2010).

4. Data

This article investigates the relationship between EUI and CTP by using monthly data from 2005:M5 to 2022:M10. In 2005, various factors such as supply-demand dynamics, natural disasters, and production accidents drove up international oil prices. In the same year, a dispute over natural gas prices and supplies between Russia and Ukraine caused an energy crisis in Europe (Qin et al., 2024b), which greatly influenced the energy market and policy of Europe. The EU ETS was thus implemented in 2005 by the EU to help reduce dependence on imported energy, enhance energy security, and ensure a low-carbon transition. The carbon allowance futures market has been considered the main channel of carbon pricing with efficient trading, low costs, and no restrictions on short selling, hence the effective reflection of supply-demand dynamics and market expectations (Ibikunle et al., 2016; Qin et al., 2025). Accordingly, this study adopts the EU ETS carbon allowance futures price as a proxy for CTP and employs the Energy-Related Uncertainty Index (EUI) proposed by Dang et al. (2023) to capture energy market fluctuations. Moreover, EUI significantly influences crude oil prices (OP) and natural gas prices (NP), which in turn affect CTP. An increased EUI amplifies volatility in OP and NP, quickens the energy structure adjustment and cuts carbon emission while increasing the CTP (Zhang and Guo, 2024). Consequently, we adopt the price of Brent crude oil futures as a proxy for OP and the price of Dutch Title Transfer Facility Natural Gas Futures as a proxy for NP, both of which are obtained from the Bloomberg database. Figure 1 shows the trend graphs for EUI and CTP.

Figure 1 shows that EUI has not always aligned with CTP. In 2005, rising oil prices driven by the Russia-Ukraine gas dispute and Middle East geopolitical instability increased EUI, while the expansion of the EU ETS boosted CTP. In 2007, the EU's Carbon Emission Trading Directive set clear greenhouse gas reduction targets, reducing carbon market uncertainty and driving CTP upward. In 2008, the global financial crisis, oil market instability, and declining European natural gas demand heightened EUI volatility. In response, the EU's second-phase (2008 – 2012) ETS introduced auctions, stricter carbon caps, and tighter regulations, strengthening CTP. In 2015, the EU proposed ETS reforms for phase four (2021 – 2030), including the Market Stability Reserve, while the Paris Agreement enhanced carbon market stability, further supporting CTP. Concurrently, the breakdown of Russia-Ukraine negotiations, Petroleum Exporting Countries (OPEC) production competition, and the lifting of Iran sanctions lowered oil prices, increasing EUI. In 2022, the Russia-Ukraine conflict triggered a global energy crisis, further raising EUI. In 2022, the onset of the Russia-Ukraine conflict sparked a global energy crisis, raising EUI. To address the energy crisis and reduce greenhouse gas emissions, the European Parliament approved the "Fit for 55" package amendment in 2022:M4. Subsequently, in June of the same year, the European Commission proposed eight legislative proposals on climate change, including the "European Union Carbon Border Adjustment Mechanism" and the establishment of a "Social Climate Fund" to fulfil the European Climate Change Law requirements. By increasing carbon costs and promoting the adoption of low-carbon technologies, these measures drive an increase in CTP.

F i g u r e 1
The Trends of EUI and CTP



Note: This figure presents the trends of EUI (solid line) and CTP (dashed line), along with annotations of key events.

Source: Authors' calculations.

As indicated in Table 1, the mean values of EUI, CTP, NP, and OP are 21.949, 18.395, 25.684, and 61.174, respectively. The four variables exhibit right skewness attributable to positive skewness. The kurtosis values of EUI, CTP, and NP surpass 3, indicating a leptokurtic distribution. Conversely, OP has a platykurtic distribution. The Jarque-Bera test results indicate that EUI, CTP, and NP deviate from a normal distribution at the 1% level, while OP does not conform to a normal distribution at the 5% level. In light of this, employing a traditional VAR model for Granger causality testing is unsuitable. This study adopts the *RB* method to circumvent this potential issue with non-normal distribution. Subsequently, we obtain stable time series data by applying first differencing to these four variables (Jain and Ghosh, 2013; Nyblom, 1989).

Table 1

Descriptive Statistics for EUI, CTP, NP and OP

	EUI	CTP	NP	OP
Observations	210	210	210	210
Mean	21.949	18.395	25.684	61.174
Median	21.747	13.320	20.287	57.108
Maximum	43.257	90.160	231.000	114.461
Minimum	10.942	0.010	3.770	20.727
Std. Dev.	6.153	19.087	27.947	17.642
Skewness	0.568	2.200	4.521	0.465
Kurtosis	3.417	7.566	26.515	2.724
Jarque-Bera	12.810***	351.857***	5553.716***	8.240**

Note: ***, ** and * identify significance at the 1%, 5% and 10% levels, accordingly.

Source: Authors' calculations.

5. Empirical Results

Variable stationarity is assessed by applying the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Table 2 presents the outcomes. The table indicates that all variables are I(1) processes. Data stationarity suggests that the VAR model utilizes the first differences of EUI, CTP, NP, and OP. To examine variable correlations, Granger causality is further tested.

Table 2

The Outcomes of Unit Root Tests

		ADF	PP	KPSS
Levels	EUI	–4.152 (1)***	–5.352 [5] ***	1.168 [8]*
	CTP	0.635 (1)	0.861 [2]	0.683 [11]**
	NP	–2.703 (2)	–2.547 [7]	0.428 [10] *
	OP	–2.517 (1)	–2.140 [1]	1.185 [8]
First Differences	EUI	–11.715 (1)***	–26.896 [19]***	0.049 [15]
	CTP	–16.907 (1)***	–16.841 [4]***	0.079 [2]
	NP	–6.219 (1)***	–22.204 [13]***	0.302 [16]
	OP	–10.872 (1)***	–10.608 [6]***	0.077 [2]

Note: The values in parentheses point out the optimal lag order selected by SIC. ***, ** and * identify significance at the 1%, 5% and 10% levels, accordingly.

Source: Authors' calculations.

Utilising Equation (6), the full-sample causality testing framework is employed to analyse the entire sample and investigate the Granger causality between EUI and CTP. Concerning the SIC, we are inclined to a postponed order of 3. The testing outcomes derived from the entire dataset are presented in Table 3. The *p*-value indicates a certain relationship between EUI and CTP, thereby demonstrating Granger causality from EUI to CTP, as suggested by existing literature (Wang and Chueh, 2013; Jain and Ghosh, 2013) and the ICAPM model. However, the full-sample Granger test reveals only a singular causal relationship and overlooks the temporal dynamics of causality, potentially failing to fully capture the complex interactions between the variables.

T a b l e 3

Full-Sample Granger Causality Tests

Tests	**H_0: EUI does not Granger cause CTP**		**H_0: CTP does not Granger cause EUI**	
	Statistics	*p-value*	*Statistics*	*p-value*
Bootstrap *LR* test	7.536	0.037	7.578	0.062

Notes: Applying 10,000 bootstrap iterations to calculate *p*-values.
Source: Authors' calculations.

It must be acknowledged that, due to the assumption of constant parameters in the aforementioned VAR model, the full-sample causality test can only reveal a fixed causal relationship. Furthermore, the parameters may experience short-term instability as a result of structural changes, which could then lead to inaccurate conclusions. Consequently, the complex interrelations between EUI and CTP may not be adequately captured by full-sample causality tests, which require consideration of the temporal dynamics of the series and potential structural breaks (Balcilar et al., 2010). To boost the precision of causality evaluation, we can investigate this feature in VAR frameworks including EUI and CTP through applying *Sup-F*, *Ave-F*, and *Exp-F* tests (Andrews and Ploberger, 1994). Besides, to determine if the coefficients in the VAR frameworks conform to a random walk process, the *Lc* statistics inspection, which is initially proposed by Nyblom (1989) and Hansen (1992), is executed. Table 4 depicts the conclusions of the parameters' stability assessment.

T a b l e 4

The Results of Parameter Stability Test

Tests	**EUI**		**CTP**		**VAR system**	
	Statistics	*p-value*	*Statistics*	*p-value*	*Statistics*	*p-value*
Sup-F	29.347***	0.003	72.105***	0.000	47.224***	0.000
Ave-F	17.416***	0.002	17.675***	0.000	26.504***	0.002
Exp-F	12.207***	0.001	31.062***	0.000	19.867***	0.000
Lc					6.608***	0.005

Notes: We employ 10,000 rounds of bootstrap repetitions to determine the *p*-value. ***, ** and * identify significance at the 1%, 5% and 10% levels, accordingly.
Source: Authors' calculations.

Table 4 confirms that the *Sup-F* exhibits a significant and sudden shift within the EUI and CTP, exhibiting a threshold of significance of 1%. The statistical relevance is indicated with a 1% confidence range by the *Ave-F* test, which reveals the potential for incremental alterations in the parameters of the EUI, CTP, and VAR algorithms. The time-dependent variation of parameters in EUI, CTP and VAR frameworks is validated by the *Exp-F* test at an acceptable threshold of 1%. Limitations of the VAR approach to random walk actions are indicated when the null hypothesis is ruled out at a significance threshold of 1% by the *Lc* statistics analysis. The occurrence of parameter volatility within the VAR frame is apparent in this refusal. The analyses of *Sup-F*, *Ave-F*, *Exp-F*, and *Lc* imply significant inconsistency in the data parameters in sequence (EUI and CTP) alongside the overall VAR construction.

Therefore, the causality analysis conducted on the entire sample suggests a singular causal relationship between EUI and CTP, a conclusion that may be subject to scrutiny. Afterwards, an extensive review of the smaller group is conducted, adopting the *RB*-based modified-*LR* technique to clarify the changing connection between EUI and CTP.

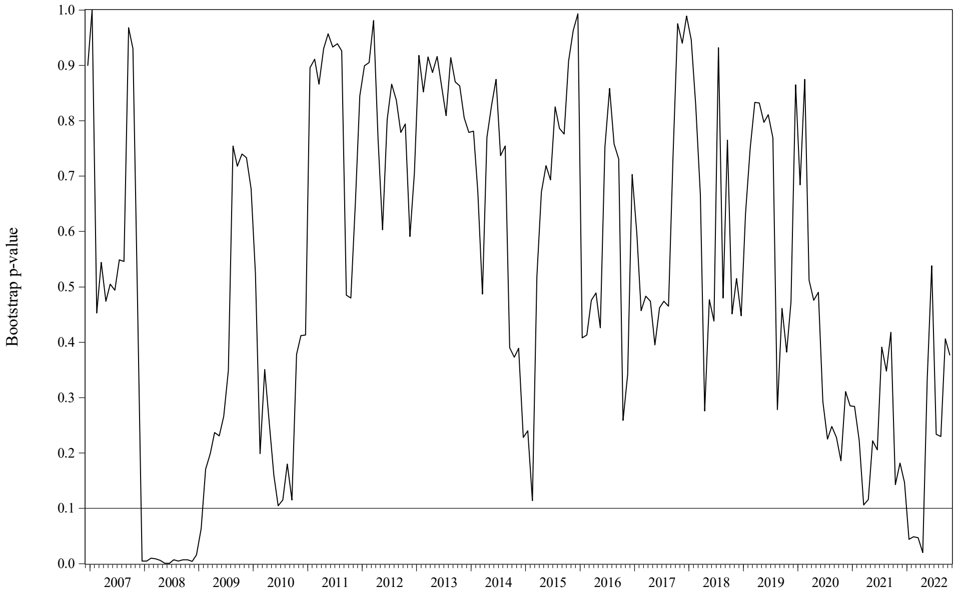
For determining bootstrap *p*-values and *LR*-statistics, the VAR architectures delineated in Equation (6) are applied in this article. In relation to EUI to CTP, the null hypothesis specifies to be devoid of Granger causality; inversely, the contrary remains accurate. Most of the obstacles affiliated with this causal test is determining the optimum effective rolling-window dimension. The diminution in repetition frequency facilitated by a wider window boosts precision in the causal testing. In contrast, preserving reliability in the outcomes turns troublesome when the window grows more restricted. In this investigation, a window breadth of 24-months is determined to safeguard the precision of causality evaluation. Additionally, applying this subsample evaluation allows the trajectory of the impact of CTP on EUI to be explored.

Figures 2 and 3 respectively depict the *p*-values and the directional impact of EUI on CTP. In light of the observations, it can be concluded that EUI has a positively significant impact on CTP throughout 2008:M1 – 2008:M10 and 2022:M1 – 2022:M4, with a 10% significance level.

The positive impact of EUI on CTP serves as one of the strong testimonies to the validity of the ICAPM hypothesis. The 2008 financial crisis exacerbated the instability of the energy market on multiple levels, increasing EUI. On one hand, the global economic recession weakened the demand from energy-intensive industries, such as manufacturing and transportation, leading to significant price volatility in traditional energy sources like oil and natural gas (Andriosopoulos et al., 2017; Su et al., 2025a).

F i g u r e 2

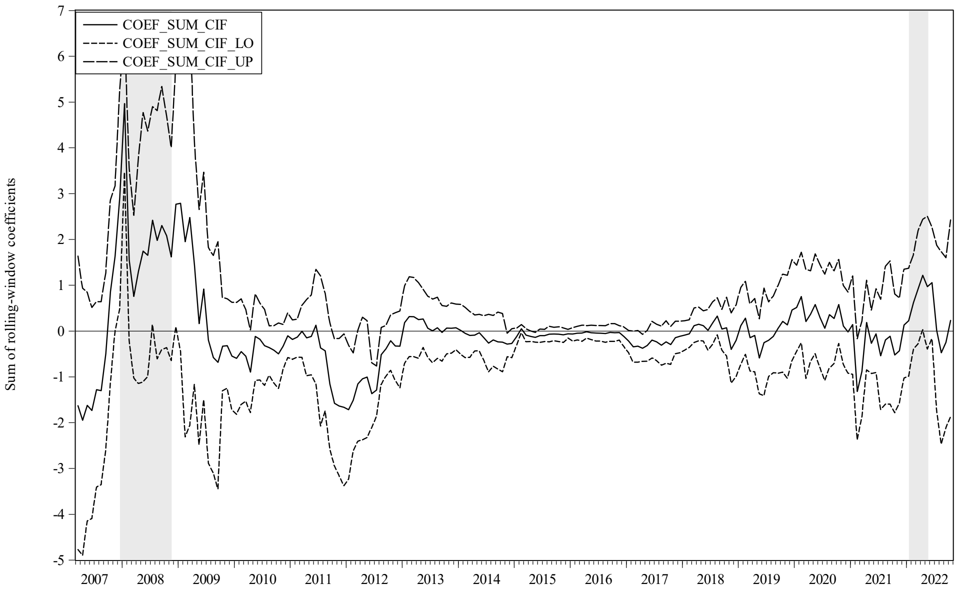
The Bootstrap *p*-values for a Rolling Test Statistic that Examine the Null Hypothesis that Granger Causality from EUI Does Not Affect CTP



Source: Authors' calculations.

F i g u r e 3

Bootstrap Estimates of the Entirety of the Rolling-Window Coefficients for the Impact of EUI on CTP



Source: Authors' calculations.

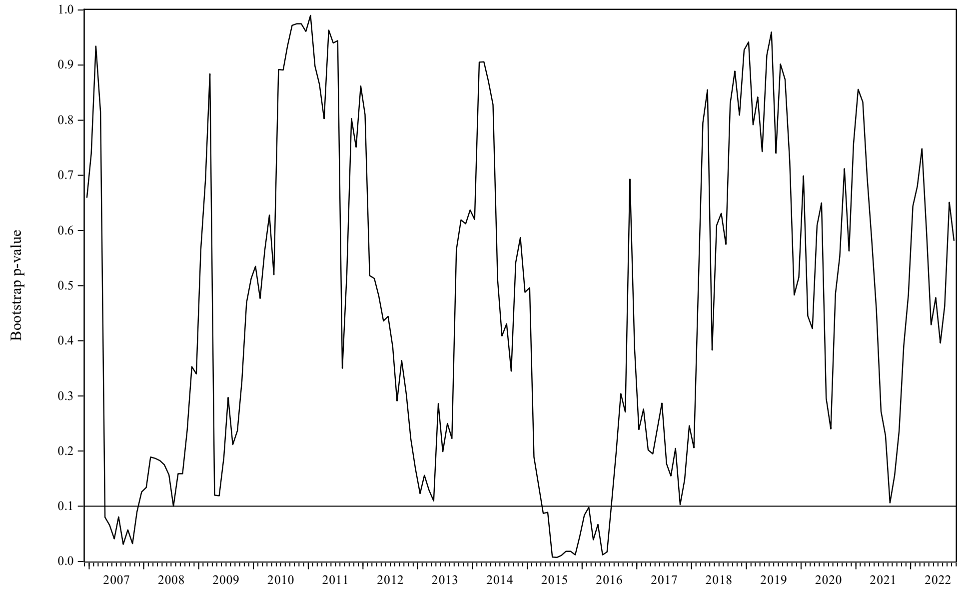
At the same time, the sharp decline in energy demand led production firms to cut investments and reduce capacity, further intensifying supply instability. Contrarily, the turbulence in the international financial markets became a barrier to energy trade financing and cross-border energy investment, boosting the systemic risks of the energy market gradually (Wu et al., 2023). Reacting to the economic slump and fluctuations in the energy sector, governments adjust energy policies, increasing investment and support for clean energy, thereby promoting the reduction of carbon emissions (Ma et al., 2021). In the same year, the European Commission adopted a legislative plan named "Climate Action and Renewable Energy Package" to meet the environmental and energy targets for 2020. Additionally, the EU ETS implements new measures in its second phase (2008 – 2012), including introducing an auction mechanism, reducing emission caps, and enhancing penalties. Under the collective effect of these measures, the supply of carbon quotas decreases (Su et al., 2024b). Simultaneously, high-carbon companies, aiming to mitigate risks associated with energy market fluctuations and rising carbon emission costs, have increased their demand for carbon credits (Yin et al., 2019), which has driven up CTP. Therefore, during the period from 2008:M1 to 2008:M10, EUI positively impacts CTP.

At the beginning of 2022, Russia cut the supply of natural gas to Europe, while the import restrictions of the EU on Russian oil and coal disrupted key channels of global energy trade and substantially increased EUI. Meanwhile, the COVID-19 further amplified such uncertainty, given the disruption to supply chains and weakened economic activity that it had caused. In this highly uncertain environment, the imbalance in energy supply and demand was aggravated, leading to severe price volatility. Especially, further dependence on fossil fuel worsened the use of high-carbon energy, thus increasing carbon dioxide emissions. In 2022:M4, in an effort to advance the EU's climate neutrality objectives and decrease greenhouse gas emissions, the European Parliament approved a sequence of amendments that alter the European Commission's "Fit for 55" package. In June of the same year, the EU Commission proposed eight climate-related legislative initiatives, including the "EU Carbon Border Adjustment Mechanism" and the creation of a "Social Climate Fund" to implement the European Climate Change Law. These policies encourage enterprises to decrease their dependence on fossil fuels and foster improvements in energy efficiency, thereby decreasing carbon emissions, which ultimately results in an increase in CTP. Therefore, it can be concluded that EUI positively impacts CTP during the period from 2022:M1 to 2022:M4.

Figure 4 provides the p-values for the impact of EUI on CTP, while Figure 5 offers evidence regarding the direction of impact. The observations indicate that during the period from 2007:M5 – 2007:M11, CTP exerts a negative impact on EUI, reaching a significance level of 10%; during the period from 2015:M4 – 2016:M5, a positive impact exists.

F i g u r e 4

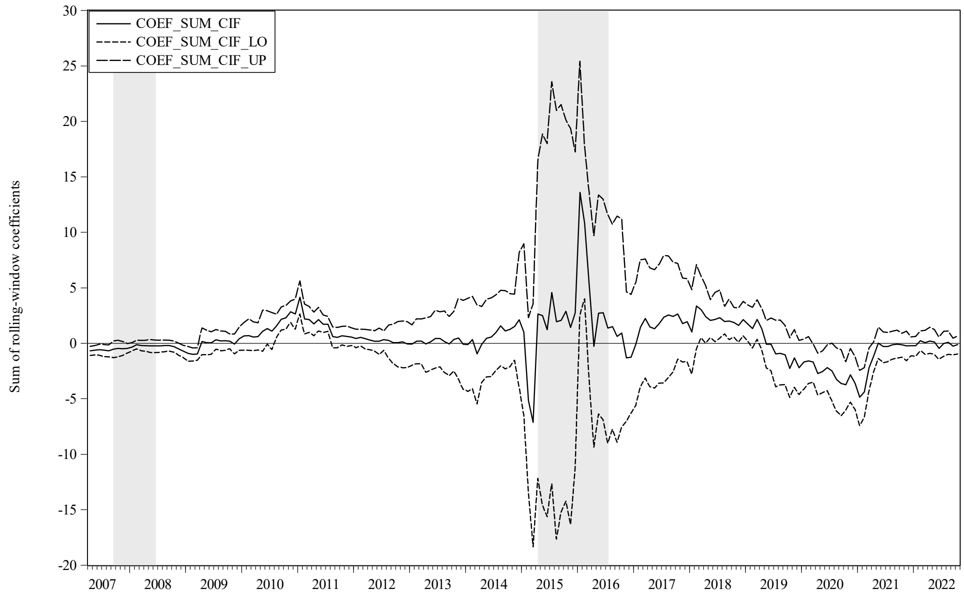
The Bootstrap *p*-values for a Rolling Test Statistic that Examine the Null Hypothesis that Granger Causality from CTP Does Not Affect EUI



Source: Authors' calculations.

F i g u r e 5

Bootstrap Estimates of the Entirety of the Rolling-Window Coefficients for the Impact of CTP on EUI



Source: Authors' calculations.

In 2007:M5, the EU passed the Carbon Emission Trading Directive, establishing the framework and rules for the EU ETS. The adoption of this directive marks the formal operational phase of the carbon market and lays the foundation for implementing the carbon emission trading system within enterprises across EU member states. In November of the same year, the EU released more explicit greenhouse gas emission reduction targets to accelerate the reduction of the EU's greenhouse gas emissions. Implementing these policies increases control over carbon emissions, driving up CTP. These measures provide clearer policy guidance, helping energy companies more accurately predict future carbon emission limits and market dynamics and reducing uncertainty in the energy industry. With the increase in CTP, the cost of using high-carbon-emitting energy sources will increase significantly, thereby enforcing firms to promptly adjust their energy use strategy by switching to other forms of energy that are efficient and cheaper. In improving the energy structure, firms will definitely reduce their sensitivity to price fluctuations within the traditional energy market and increase the stability of energy supply in the overall market (Dutta, 2019; Shi et al., 2023). Therefore, the energy sector becomes quite relieved of uncertainties, and hence its EUI decreases.

However, the notion that CTP and EUI are moving in contrary directions is not supported by the beneficial effects noted during the interval from 2015:M4 – 2016:M5. In 2015, the European Commission proposed modifications to the fourth phase (2021 – 2030) of the EU ETS, intended to reduce carbon emissions, facilitate the transition to clean energy, and enhance green economic growth. In October of that year, the European Parliament and the Council enacted resolutions regarding the Market Stability Reserve. At the end of 2015, the Paris Agreement was established, unequivocally offering the legislative guidance that the global carbon market required to enhance trust in low-carbon technologies and facilitate the growth of CTP. During this time, EUI shows an upward trend. This can be interpreted as the rise in CTP encouraging a shift to clean energy and reducing dependence on the fossil fuel market, thereby decreasing the overall uncertainty in the energy market. However, short-term fluctuations in energy supply and demand can still rapidly trigger drastic changes in energy market prices, leading to the persistence of uncertainty (Guo et al., 2022; Qin et al., 2024a). In 2015, the stalemate in natural gas price negotiations between Ukraine and Russia heightened market apprehensions regarding energy supplies. Moreover, Saudi Arabia's high-production strategy intensified competitiveness among OPEC members, exacerbating the global crude oil oversupply. In the same year, Iran struck a nuclear agreement with six countries (the U.S., the U.K., France, Russia, China, and Germany), to restrict its nuclear activity in return for the removal of international sanctions. This contributed to the excess of oil, significantly reducing OP. These energy supply and demand conflict events further elevate EUI. Therefore, CTP positively impacted EUI during the period from 2015:M4 to 2016:M5.

In summary, rolling-window Granger causality tests address parameter instability and validate the dynamic interaction between EUI and CTP. Empirical study indicates that EUI improves CTP. This indicates that frequent energy uncertainty events push the energy market to transition to cleaner, more sustainable energy sources, hence decreasing carbon emissions. These results corroborate the assumptions of the ICAPM. Moreover, EUI both benefits from and is adversely affected by CTP. This indicates that enhancing CTP facilitates high-carbon companies' transition to low- or zero-carbon alternatives, hence reducing energy supply and price volatility. However, since the energy supply and demand relationship directly determines its price, the drastic fluctuations in energy prices under a high CTP context cause EUI to change in the same direction.

Conclusions and Policy Implications

This investigation examines the dynamic causality between EUI and CTP through monthly data analysis from 2005:M5 – 2022:M10. To delve deeper into their dynamic relationship, we apply a subsample rolling window approach for Granger causality testing to uncover their interactions. Additionally, OP and NP are included as key control variables to ensure the accuracy of the results. The findings suggest a positive impact of EUI on CTP, possibly due to the turbulence in the energy market environment fostering the energy transition process. This aligns with the theoretical framework hypothesising a positive effect of EUI on CTP. Furthermore, the effect of CTP on EUI demonstrates both favourable and unfavourable characteristics. Negatively, the carbon emissions trading market has promoted energy stability and sustainable development. However, the efficacy of reducing EUI is diminished due to frequent energy disputes. This comprehensive analysis underscores the complex interplay between energy utilisation intensity and carbon trading mechanisms, highlighting the need for strategic considerations in energy policy and market regulation to foster sustainable development.

An in-depth comprehension of the connection between EUI and CTP is essential for guiding policymakers and market participants in developing targeted policies. Initially, the elevated value of EUI positively impacts CTP, which is clearly seen in the daily operations of the carbon market. Regulatory agencies must build a carbon market risk management system to offset energy market volatility on carbon prices. This involves putting in place monitoring and warning systems for real-time risk analysis, as well as intervention measures like adjusting carbon quotas or carbon tax optimization to smooth out prices during volatility. Second, in expanding the market to encompass additional high-emission enterprises, the government must augment its involvement in advocating for the utilization of financial derivatives like carbon futures. The variety of these derivatives, which facilitate the establishment of a secondary carbon market, improves the market's liquidity (Su et al., 2024b). Third, the government can lower the transition costs to low-carbon growth of carbon-intensive industries through green funds, tax relief, and the like. Green funds finance low-carbon technology and low-carbon renewables, whereas tax relief facilitates the transition to clean energy. The measures lower the dependence on fossil fuels and stabilize the carbon market. Ultimately, in carbon trading, participants and the government need to enhance information sharing to enhance investors' knowledge about EUI and carbon price projections to enable them to make appropriate choices.

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Appendix

Table A1

Descriptive Statistics for All Variables after First Differencing

	EUI	CTP	NP	OP
Observations	209	209	209	209
Mean	0.039	0.289	0.331	0.262
Median	–0.166	0.130	–0.005	0.774
Maximum	17.539	22.400	54.350	12.988
Minimum	–11.179	–13.750	–82.000	–25.196
Std. Dev.	4.466	3.535	10.723	5.166
Skewness	0.728	1.240	–1.718	–0.960
Kurtosis	5.290	14.349	31.146	5.871
Jarque-Bera	64.109***	1175.267***	7001.487***	103.850***

Note: ***, ** and * identify significance at the 1%, 5% and 10% levels, accordingly.

Source: Authors' calculations.