18 Years of Market-Based Climate Action: Efficacy of the European Union Emissions Trading System

A research dissertation submitted in partial fulfilment of the requirements for the MSc in Sustainable Finance

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Declaration

I hereby declare that this study has been conducted solely by me under the guidance of my supervisor and has not been submitted, in whole or in part, in any previous application for any degree or examination. All the implemented code and data are available here: https://github.com/BaibhabiGoswami/EU_ETS. The total word count of this study excluding references and appendices is 12558.

Abstract

One of the main pillars of the European Union's (EU) strategy to fight climate change by lowering greenhouse gas emissions is the EU Emissions Trading System (ETS). The substantial existing literature includes studies on the pricing signals sent by the EU ETS, price volatility, EU ETS's price drivers and its efficacy in emission reduction at lengths covering various time frames. However, to the best of our knowledge, there lacks the effort to characterise EU ETS comprehensively covering a timespan of 19 years, from its inception. To bridge this gap, this thesis examines how the EU ETS has evolved since its inception in March 2005 to December 2023, and assesses how well it has performed in terms of achieving emission reduction goals. The study employs Granger causality tests for EU ETS prices which reveal a significant causal relationship at a one-year lag, suggesting that increases in the EU ETS prices are likely to reduce verified emissions within the following year. The lack of significant causation for longer lags suggests that the influence of price fluctuations is limited to the current year. The study employs the conditional entropy to capture the non-linear dependencies between these variables revealing a maturing market over time, getting closer to the emission reduction targets with increasing influence of ETS prices on emissions. Considering the larger macroeconomic context, the study employs OLS and SVAR regression models to examine how various macroeconomic indicators interact with the EU ETS prices and impact the emissions. Contrary to the goals of the EU ETS programme, a positive coefficient for the EU ETS pricing for verified emissions suggests an increase in emissions with rising spot prices. Nevertheless, phase-by-phase analysis shows a tendency, especially in Phase III, towards a more desired negative coefficient. Finally, the study examines the carbon pricing signals sent by the EU ETS over the years and finds strong evidence of stochasticity and random shocks. The findings suggest that while prices were more volatile in previous stages, the EU ETS prices have been more stable and trending upward in recent years, aligning with its underlying policy objective of emission reduction.

Acknowledgement

This thesis broadens my understanding of climate finance and carbon pricing while serving as a springboard for my future career prospects. Looking back, all I can say is that I'm thankful for the help and chances I've received.

First and foremost, Dr. Kevin (Yong Kyu) Gam, my supervisor, has been incredibly encouraging, accommodating, and supportive of my requests and circumstances during this one-year MSc program. He has always been an email away from guidance and assistance whenever I needed his help.

I also thank Prof. Don Bredin, who provided invaluable suggestions that helped shape my research outlook. His prior work on carbon trading and EU ETS prices paved the way for one of the central research questions of this thesis.

Finally, I would like to mention the name Bhakti Mahanti, my mother, for whom no words of gratitude or fables of acknowledgement would be enough.

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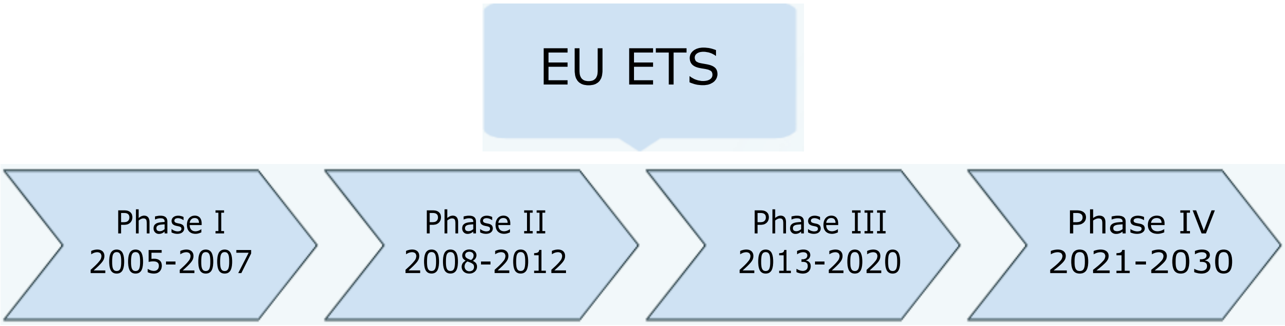

Figure 1: EU ETS phases from 2005-2030. Source: Self-compiled.

1 Introduction

The European Union Emissions Trading System (EU ETS) [1], has been the cornerstone of the EU's policy efforts to combat climate change over the past 18 years. It represents a pioneering attempt to use market mechanisms to regulate carbon emissions. Established in 2005, the EU ETS is the world's first major carbon market and remains the largest one to date, aimed at reducing industrial greenhouse gas emissions (European Commission, 2023).

ETS is a critical component of climate policy, designed to internalise the social cost of carbon emissions (Backman, 2021) where emissions are capped and allowances are traded— thus putting a price on carbon and providing economic incentives for emissions reduction through investments in clean energy and energy efficiency (Asdourian and Wessel, 2011). The system works on the *Cap-and-trade* principle (Schakenbach et al., 2006): a *Cap* is set on the total amount of certain greenhouse gases that can be emitted by installations covered by the ETS [2]. The companies receive or purchase emission allowances, which can be traded. If more allowances are needed, they have the option to purchase them or sell any extra allowances. There is an annual allocation of emission allowances to firms, followed by a mandatory year-end reconciliation of allowances with actual emissions and the firms are penalised for non-compliance. The policy assumes that allowance scarcity should drive upward price trends in EU ETS and that the increasing cost will encourage firms to reduce their emissions. Since its inception in 2005, the EU ETS has been launched in phases, intending to refine the system by learning from past mistakes and improving its effectiveness (Figure 1).

Despite its pioneering role, the EU ETS has faced numerous challenges like price volatility characterised by the now infamous "periodic unstable price", over-allocation of carbon allowances, issues with the carbon leakage list, and the ETS's inability to set a strong carbon price signal (European Commission, 2016). Previous studies like Alberola et al. (2008), Benz and Trück (2009), Bredin and Muckley (2009*b*), Daskalakis et al. (2009) among others have examined the pricing signals provided by the EU ETS and its price volatility. Studies like Alberola et al. (2009*a*), Chevallier (2009), Jiao et al. (2018), Li et al. (2021) among others have investigated the EU ETS price drivers and its efficacy in reducing emissions in EU ETS prices

[1] https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets_en

[2] https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/what-eu-ets_en

at lengths comprising a variety time periods and phases of the EU ETS.

To the best of our knowledge, however, there has not been any attempt to comprehensively characterise the EU ETS for the course of its 18-year existence, beginning in March 2005. To close this gap, this thesis analyses the evolution of the EU ETS from its launch in March 2005 to December 2023 and evaluates the extent to which EU climate policy objectives are reflected in the ETS carbon market prices and the system's effectiveness in emission reduction over the years. The central research question this study addresses is:

RQ. How has the EU ETS evolved over its 18-year existence in terms of its efficacy at reducing emissions, and what are the key factors influencing its performance?

To address this, the study investigates the causal relationship between the EU ETS prices and verified emissions. To capture the non-linear dependencies between the ETS prices and the emissions, the study employs conditional entropy. The impact on emissions caused by the interaction between various macroeconomic indicators with the EU ETS prices and shocks to these variables over the years is investigated. Finally, the study attempts to analyse the carbon pricing signals generated by the EU ETS prices and how it has evolved over time. For this, the study analyses the movements and trends in the EU ETS prices both as a whole and in phases.

The study finds strong evidence of a strong non-linear influence of EU ETS prices on verified emissions and a strong causal relationship with a lag of one year between the ETS prices and verified emissions. A rise in emissions is observed in correlation with rising spot prices for EU ETS, rendering a counterproductive trend. Phase-wise analysis, however, points toward an emergent efficiency in the later years. The study finds evidence of random stochastic trends in the EU ETS prices, however, a phase-wise analysis depicts progress towards the upward deterministic trend as envisioned by the policymakers in the recent phases and indicates the EU ETS's transition towards attaining its emission reduction goals by sending strong carbon pricing signals in the later years.

The rest of the study is structured as follows. This introduction is followed by the study's reviews of the existing literature (☛ Section 2), background discussion on the EU ETS (☛ Section 3), data description (☛ Section 4), methodology and findings of the study (☛ Section 5), and concluding remarks and insights (☛ Section 6).

2 Literature review

The theoretical underpinnings of the EU ETS Cap-and trade mechanisms suggest that by internalising the negative externality of carbon emissions, it can provide cost-effective incentives for emission reductions (Stavins, 2008). EU ETS spot prices offer a practical case study to analyse these theoretical expectations (Ellerman and Buchner, 2007). The effectivity of the ETS as a policy highly depends on its potential to reflect the carbon emissions costs using price signals (Ellerman and Buchner, 2007). The main goal of the EU ETS system is establishing an environment with carbon allowance shortages which will drive carbon prices toward mean reversion with an upward trajectory (Paolella and Taschini, 2008). This will result in a decreasing number of random shocks around a price series (EU ETS in this case), and a persistently rising deterministic trend over time. Simply put, the market forces of supply and demand affecting the price of carbon are emission credits or allowances.

Price drivers. The price discovery process, which reflects how well market prices incorporate information about the cost of carbon, is crucial for the system's credibility and the predictability needed by firms to make long-term investments (Hintermann, 2011). Several studies have investigated the price drivers and efficacy of the EU ETS across various phases employing an array of econometric models like the Autoregressive conditional heteroskedasticity (ARCH), the Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) and the Vector Autoregressive (VAR) models. Chevallier (2009) studies Phase I EU ETS price determinants and finds significant volatility associated with policy announcements and energy prices. Keppler and Mansanet-Bataller (2010) employ Granger causality tests on Phase I and Phase II EU ETS prices emphasising the significance of energy prices and macroeconomic conditions. Studies like Chung et al. (2018), Jiao et al. (2018) among others expand the literature illustrating the substantial non-linear dependencies of EU ETS carbon prices on macroeconomic indices, such as GDP growth and industrial production. Studies like Galán-Valdivieso et al. (2018), Li et al. (2021) investigate how policy changes affect market efficiency and price stability within the EU ETS environment highlighting that although regulatory changes have contributed to price stabilisation, problems such as allowance over-allocation in Phase I and Phase II (Section 3) and regulatory uncertainty have persisted in undermining the efficacy of the EU ETS. However, while volatility has not entirely disappeared, the Market Stability Reserve (MSR), which was implemented in Phase III, was crucial in lowering surplus permits and stabilising the ETS prices (Li et al., 2021). Mirzaee Ghazani and Jafari (2021), Bordignon and Gamannossi degl'Innocenti (2023) analyse Phase III ascertaining the effect of external shocks like the COVID-19 pandemic and geopolitical unrest on EU ETS prices. Günther et al. (2024) argue that although the EU ETS prices have stabilised in recent years, challenges in terms of making sure that these prices offer a reliable and strong carbon pricing signal for effectively reducing emissions continue to persist.

Energy prices & market sentiments. Studies like Chevallier (2009), Gronwald et al. (2011), Hammoudeh et al. (2014), Sousa et al. (2014), Gargallo et al. (2021) among others explore the interaction between the energy prices and the carbon pricing mechanisms like the EU ETS. These studies underline the impact of volatility in energy prices (e.g., electricity, coal, and gas) on the stability and efficacy of the EU ETS prices. Koch et al. (2014) suggest that the economic sentiment indicator is a particularly helpful economic state variable for interpreting ETS price movements and that the marginal abatement cost theory cannot fully explain its dynamics. Ye and Xue (2021) employs the Latent Dirichlet allocation approach to analyse a carbon tone index built from news coverage of the EU ETS between 2017 and 2020 highlighting the consequences of media disposition on market perceptions and EU ETS carbon prices. Similarly Kooshna (2023) highlights the impact of news announcements on carbon pricing worldwide covering a period from 2015 to 2020 using sentiment analysis.

Price signals. The effectiveness of the EU ETS in its early years has been extensively analysed in the context of its ability to reflect carbon prices that align with its underlying policy objectives employing various unit root tests on EU ETS spot and future prices by the likes of Alberola et al. (2008), Paolella and Taschini (2008), Bredin and Muckley (2009*b*), Alberola et al. (2009*b*), Bredin and Muckley (2009*a*), Daskalakis et al. (2009), Benz and Trück (2009), Dechezleprêtre et al. (2023) among others. These studies have provided mixed results. While most studies indicate that the EU ETS prices show a stochastic trend and market dynamics that potentially dampen the carbon price signals (Laing et al., 2013), few reject the presence of unit root and find that the EU ETS has led to a measurable reduction in emissions within the European Union member countries (Anderson and Di Maria, 2011). The contradictory results can be ascribed to various factors like the different types of unit root tests employed, the types of price series used (e.g., Spot or Futures etc.), consideration of the structural breaks within the data sets and the various lengths of time covered by the concerned studies.

Building on this vast literature, this study analyses various aspects of the EU ETS as a whole over the past 18 years since its inception, and incorporates a phase-wise analysis, having a look into the EU ETS's long-term effectiveness and evolution. It investigates the causal relationship between ETS prices and verified emissions and the extent of information transfer between them. It also explores the interaction of various external macroeconomic factors with carbon prices and their impact on emissions. The study further examines spot price movements of the EU ETS, analysing the impact of policy changes across different phases. For this, the study covers the period from EU ETS's inception on March 09, 2005, to December 31, 2023.

3 Background

Kyoto Protocol & Paris Agreement. Greenhouse gas emissions are a contributing factor to the effects of climate change and need to be addressed. The Kyoto Protocol was created in 1997 during a summit of world leaders in Kyoto, Japan and followed a "top-down" approach [3]. It established three market-based mechanisms, namely, Emissions Trading (ET), Clean Development Mechanism (CDM), and Joint Implementation (JI) (UNFCCC, 1997). Despite the market-based mechanisms seeing varying degrees of success following the activation of the Kyoto Protocol in 2005 (Black, 2018), there was little expectation that it would continue after 2012. World leaders convened once more in 2015 to draft the Paris Agreement. This is a "bottom-up" approach [4] that lets nations assume accountability for their emissions by letting

[3] **"Top-down" approach** under the Kyoto Protocol entailed imposing regulations and binding emission reduction targets by a central authority. Its rigid framework caused challenges in willing global participation and compliance (Grubb, 2004).

[4] **"Bottom-up" approach** under the Paris Agreement allows countries to set and pursue their emission reduction targets independently based on respective national circumstances encouraging broader participation and flexibility (Dimitrov, 2016).

each select its own nationally determined contribution (or emission reduction target) and pursue it independently (Dimitrov, 2016). Likewise, there is no expiry date and no legal restriction in the agreement. Compared to the Kyoto Protocol, this is more sustainable, flexible, and inclusive ensuring voluntary participation from more nations (Stavins, 2016).

EU ETS. Based on the framework extended by the Kyoto Protocol, the EU ETS was created. A report on "GHG emissions trade within the European Union" was released by the European Commission in March 2000, along with some preliminary concepts for the EU ETS's layout (Pohlmann, 2009). As a result, the EU ETS directive was adopted in 2003 and subsequently introduced in 2005. It employs the Cap-and-trade theory, in which governments set a cap on the overall amount of emissions in one or more economic sectors (ICAP, 2015). For each tonne of emissions, businesses in these industries are required to possess a permit. A portion of the free carbon allowances are distributed annually, with the remainder being sold, primarily at auctions. Firms are required to repay one unit of allowance for each tonne of CO_2 emitted at the end of each year. A firm must either cut its emissions or purchase more allowances from the market (by trade or by auctions) if its allowances are insufficient (European Commission, 2015*a*). In terms of trading, active trading is permitted for all entities and the EU ETS allowances can be traded both in spot and futures markets. Refer to Appendix B for further details on the EU ETS market structure. Refer to Appendix C for the proposed EU ETS 2 for the transport and building sectors.

Cap-and-trade model. The European Commission (2015*a*) lists four key arguments behind implementing a Cap-and-trade model under the EU ETS. First, quality prevails over quantity. Implementing a system cap increases the likelihood that the emissions target will be met. Second, since all businesses pay the same carbon price, it is economical. Businesses can only sell carbon allowances if they lower their yearly emissions. Third, the ETS makes money through auctions, which can be utilised to finance environmental projects or the development of local communities. Lastly, the EU ETS can be connected to other ETSs to gain more advantages. Companies do not need to purchase foreign units to fulfil obligations in other nations because the EU ETS is already connected to those of many other nations.

EU ETS phases. The EU ETS, the first and biggest carbon market globally, covers about 45% of the EU's greenhouse gas emissions [5] and is operational in all EU member states as well as Iceland, Liechtenstein, and Norway. Launched in a phase-wise manner (Figure 1), the EU ETS has undergone several noteworthy policy changes to improve its efficacy and efficiency in promoting emission reductions. Based on lessons learned and changing climate goals, each phase of the system has added new mechanisms, increased coverage, and improved the system.

- **Phase I.** When the EU ETS was introduced in 2005, it represented a critical turning point in global climate policy. The system encompassed power plants and energy-intensive

[5] https://www.carbontrust.com/our-work-and-impact/guides-reports-and-tools/eu-emissions-trading-scheme-eu-ets

sectors throughout the EU in its **initial phase (2005-2007)**. This was a three-year "learning by doing" pilot programme [6]. The provision of **free emission allowances** to industries [7], which let them emit a specific amount of greenhouse gases without facing immediate financial penalties, was one of the key features of Phase I. However, plagued by an over-allocation of carbon allowances in the market, the carbon prices fell drastically during this phase. As a result, the EU ETS was criticised for failing to achieve significant emissions reductions. Despite these early issues, Phase I established the framework for later advancements (European Commission, 2015*b*).

- **Phase II.** In this phase, the EU ETS established specific emissions reduction targets to meet for each participating nation aligning with the first commitment period under the Kyoto Protocol. The EU ETS underwent significant policy amendments and structural changes during **Phase II (2008-2012)**. Firstly, the industry was granted **fewer allowances** and the emissions restrictions were tightened [8]. Companies were obliged to make strategic decisions as a result of this intentionally driven allowance scarcity; either by cutting emissions internally or by buying more allowances from the market. The objective was to encourage a shift towards cleaner practices and provide incentives to firms for reducing emissions. Second, the EU ETS market developed as trading volumes rose in Phase II. The participating firms acquired expertise in navigating through the complicated regulations of carbon trading over time. As the ETS prices levelled off, indications for investment decisions and carbon price signals became more consistent. Finally, the EU ETS was extended to include the **aviation sector** partially. Intra-European flights were required to either meet the emissions limitations or find a way to compensate for any excess carbon emissions through other means like allowances [9]. This phase saw a reduction in the permit cap based on actual emissions as verified annual emissions data from the pilot phase was now available. On the other hand, emissions decreased more than anticipated as a result of the 2008 financial crisis. This unanticipated significant fall in emissions led to an excess of allowances and credits available in the system (Bel and Joseph, 2015), which in turn highly affected the EU ETS prices during the initial years of Phase II.

- **Phase III.** During **Phase III (2013-2020)**, strategic policy adjustments were made in the EU ETS with the goal of maximising its efficacy. Emission allowances were actively regulated with the introduction of the **Market Stability Reserve (MSR)** [10]. The MSR absorbed excess allowances when the total number of allowances in circulation surpassed the predefined thresholds and the resultant scarcity of allowances led to further releases by the MSR. The MSR contributed to the stabilisation of carbon pricing by modifying

[6] https://www.carbontrust.com/our-work-and-impact/guides-reports-and-tools/eu-emissions-trading-scheme-eu-ets

[7] The EU ETS followed **"Benchmarking"** for free allocation. Allowances were allocated following industry-specific benchmarks for total output and emission intensity (Wang et al., 2022).

[8] https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/free-allocation/allocation-industrial-installations_en

[9] https://climate.ec.europa.eu/eu-action/transport/reducing-emissions-aviation_en

[10] https://emissions-euets.com/carbon-market-glossary/957-market-stability-reserve

supply in response to market conditions. This gave market players certainty and promoted long-term planning (Pahle and Quemin, 2020). Cleaner technology was encouraged by the establishment of a **Linear Reduction Factor (LRF)**, which guaranteed a progressive fall in emissions caps (Appendix B). The overall amount of allowances that were made available fell annually at a steady pace [11]. Industries were incentivised to invest in cleaner technologies and implement emission-reducing practices as a result of this steady drop. Companies were able to connect their strategy with long-term climate goals because of the linear trajectory, which made emissions planning easier. The **Carbon Leakage List** [12] offered extra allowances and encouraged emission reductions to sectors that were in danger of relocating because of compliance expenses (Simon, 2020). During this phase, the EU ETS expanded to include all flights inside the **European Economic Area (EEA)**.

- **Phase IV.** In **Phase IV (2021–2030)**, the EU committed to aggressive climate goals. Among them is a 62% drop in emissions below 2005 levels by 2030, which will call for more drastic cutbacks and a greater reliance on the EU ETS. Furthermore, emissions in the **maritime sector** are now covered, and ships must adhere to emissions regulations. Fuels for buildings and road transport are planned to be included in the EU ETS as of 2027 or 2028 [13]. To guarantee fair competition for home industries, the EU also intends to apply a carbon price through the **Carbon Border Adjustment Mechanism (CBAM)** on specific imports [14].

4 Data description

EU ETS prices. EU ETS spot prices since its inception on March 09, 2005, to December 31, 2023 (Figure 2), have been sourced from the data library hosted by the European Energy Exchange (EEX) group [15]. Henceforth, the study will refer to the whole dataset of EU ETS spot prices spanning 18 years from 2005 to 2023 as the **Cumulative series**. Similarly **Phase I** will encompass 2005 to 2007, **Phase II** from 2008 to 2012, **Phase III** from 2013 to 2020, and **Phase IV** from 2021 to 2023 (Figure 3).

[11] The **LRF** reduces the overall cap on emission allowances annually by a fixed percentage, ensuring a gradual and predictable decrease in the total number of available allowances within the EU ETS. Initially set at 1.74% per year, the LRF was later increased to 2.2%, 4.3% and ultimately 4.4% in Phase IV.

[12] The EU ETS industries and sub-sectors that are disproportionately in danger of moving production outside the EU owing to the cost of compliance due to the carbon regulations are identified on the **Carbon Leakage List**. These businesses receive a larger portion of free emission allowances to reduce this risk. The list is routinely updated and revised to reflect shifting global trade and carbon policy.

[13] https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/emissions-cap-and-allowances_en

[14] The purpose of the **CBAM** is to stop carbon leakage and guarantee that imported goods incur the same carbon costs as those made in the EU. It seeks to level the playing field for EU industries by placing a price on carbon emissions from nations with lenient climate regulations. Source: https://ec.europa.eu/commission/presscorner/detail/en/qanda_21_3661.

[15] https://www.eex.com/en/markets/environmental-markets/eu-ets-spot-futures-options

[16] https://www.eex.com/en/markets/environmental-markets/eu-ets-spot-futures-options

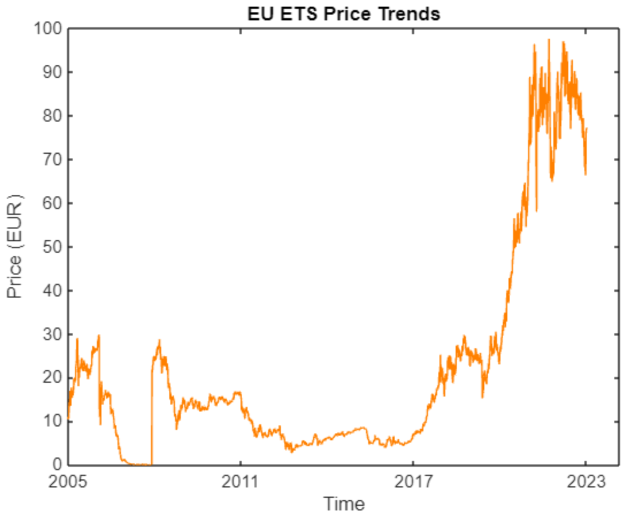

Figure 2: EU ETS spot prices from March 09, 2005, to December 31, 2023. Source: Self-compiled using data from EEX [16].

Verified emissions. Verified emissions within the EU ETS scheme are retrieved from the online data library hosted by the European Environment Agency (EEA) [17]. Verified emissions refer to the actual greenhouse gas emissions reported by companies participating in the EU ETS, which are independently audited by accredited verifiers. It is used as a proxy for emissions as it emulates the EU ETS's sectoral coverage. The verified emissions data has evolved to reflect the wider scope of the EU ETS scheme as its sectoral coverage has grown over the phases. It ensures that the emissions data accurately reflect the same range of firms and activities covered by the EU ETS offering a consistent basis for evaluating the efficacy of the scheme in emission reduction.

Other data sources. Wholesale energy prices have been obtained from the European Network of Transmission System Operators for Electricity (ENTSO-E) transparency platform [18]. The yearly GDP growth rates from 2005 to 2023 for the EU have been sourced from Eurostat [19] and inflation rates for the same timeframe has been obtained from Inflation tool [20].

Descriptive statistics. Table 1 depicts summary statistics for the first, second, third, and fourth moments of the EU ETS spot price series (cumulative and phase-wise), along with the hypotheses tests for the null of normality and homoskedasticity. The Jarque Bera test (Jarque and Bera, 1980) is employed for normality, and for homoskedasticity, the ARCH test (Engle, 1982) is considered. All price series demonstrate statistically significant deviations from normality and heteroskedasticity at 5% level. Figure 3 depicts the phase-wise EU ETS spot prices. Refer to Appendix D for more descriptive statistics.

[17] https://www.eea.europa.eu/data-and-maps/dashboards/emissions-trading-viewer-1
[18] https://transparency.entsoe.eu/dashboard/show
[19] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=National_accounts_and_GDP
[20] https://www.inflationtool.com/rates/euro/historical
[21] https://www.eex.com/en/markets/environmental-markets/eu-ets-spot-futures-options

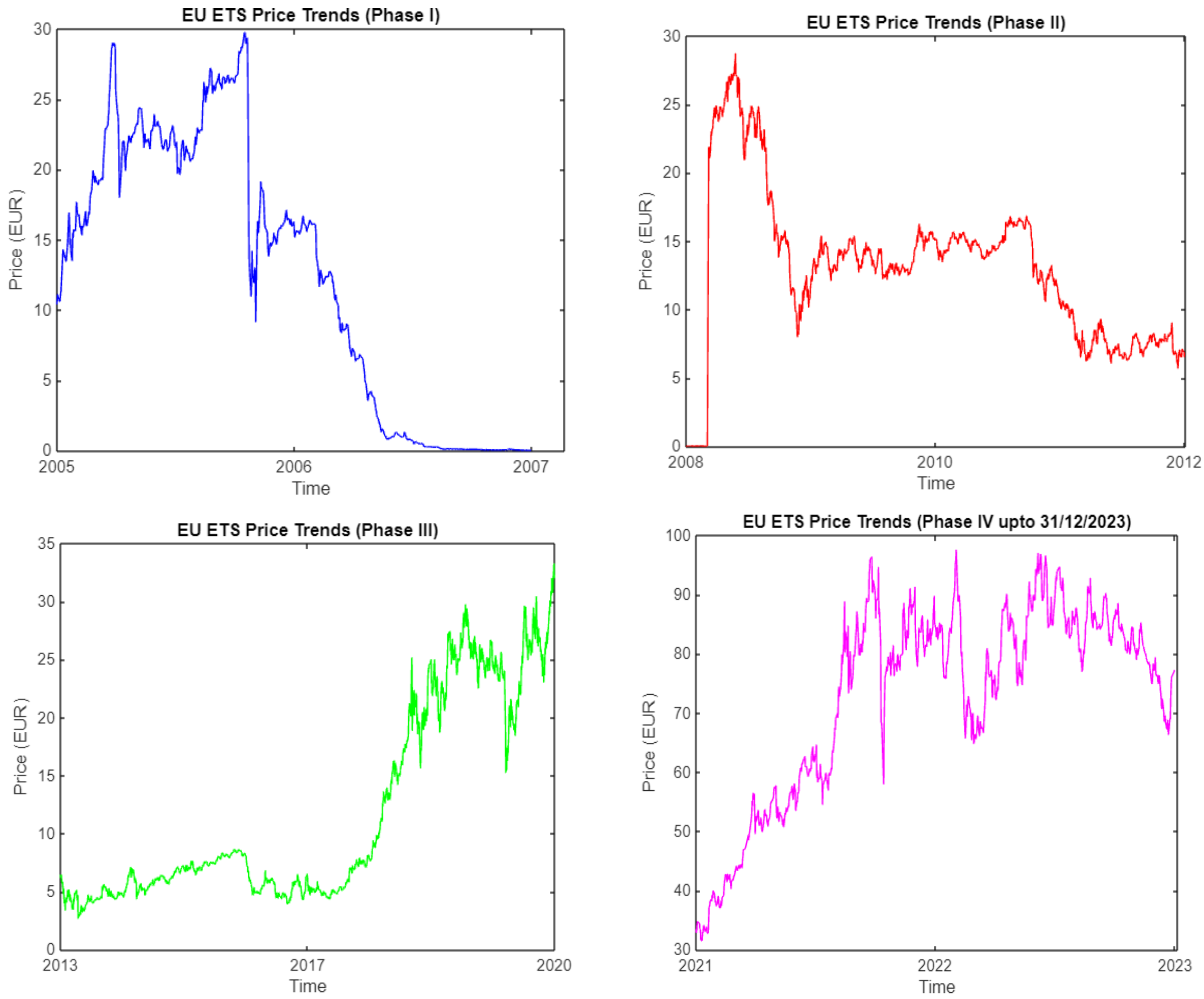

Figure 3: Phase-wise EU ETS spot price trends from March 09, 2005, to December 31, 2023. Source: Self-compiled using data from EEX [21].

Statistics	Cumulative	Phase I	Phase II	Phase III	Phase IV
Mean	22.04	12.29	13.04	11.85	72.61
Variance	589.67	97.77	32.70	72.28	268.62
Skewness	1.73	-0.01	0.24	0.83	-0.83
Exc. Kurtosis	1.80	-1.50	0.53	-0.96	-0.39
JB	3006.00**	65.19**	26.55**	313.97**	92.97**
ARCH	4739.77**	689.60**	1247.20**	2018.37**	750.42**

Table 1: Summary statistics of EU ETS price series. Statistical significance at 5% is denoted with **. All values are rounded off to two decimal places.

5 Methodology & findings

All analyses are implemented through MATLAB (2023b) [22] and Python 3.12.4 [23]. Table 2 depicts all the notations used in this study along with their corresponding denotations. The concerned datasets have been tested for the presence of unit root and non-stationarity wherever the tests/models employed by the study call for stationarity of data sets to avoid spurious test

[22]MathWorks, Inc., MATLAB version 2023b https://www.mathworks.com/products/matlab.html
[23]https://www.python.org/downloads/release/python-3124/

Notations	Denotations
t	Time trend variable.
k	Maximum number of lagged terms included in the model.
i	Lag index indicating the specific time periods before time t.
y_{t-1}	Change in y from one period $(t)$to the next.
Δy_t	First difference of any time series y.
α	Constant or intercept term.
β_t	Coefficient of the related term.
γ	Coefficient associated with the lagged dependent variable.
δ_i	Coefficient associated with the variable.
ϵ_t	Random disturbances or errors.
TD_t	Time dummy variable that captures the effect of different time intervals.
ID_t	Binary indicator Dummy variable that takes the value 1 if a specific condition or is present at time t, and 0 otherwise.
CD_t	Dummy variable that represents a different condition or event at time t.
λ	Coefficient associated with the lagged variable.
$\rho(X, Y)$	Pearson correlation coefficient between X and Y.
$x \in X, y \in Y$	Sets of observations x and y from random variables X and Y respectively.
$(x - \bar{X})^2$	Sum of the squares of the deviations of X from its mean $(\bar{X})$.
$p(X = x, Y = y)$	Joint probability mass function of X and Y, where X takes the value x and Y takes the value y simultaneously.
$p(X = x)$	Marginal probability mass function of X, representing the probability that X takes the value x.
$H(X)$	Entropy of the random variable X.
$-p(x)$	Probability mass function of the random variable X.
$H(X\|Y)$	Conditional entropy of a random variable X, given another random variable Y.
y_k	Value of the time series y at time k.
m	Lagged values of y are included in the Autoregressive model.
y_{k-i}	Lagged values of the time series y.
σ_1^2	Mean squared error (variance of the residuals).
Y_t	Current value of the dependent variable.
Y_{t-j}	Past values of the dependent variable.
X_{t-i}	Past values of the independent variable.
VE	Verified emissions.
$\alpha_n VE_{t-n}$	Coefficient (weight assigned to past values of VE), multiplied by Lagged values of the variable VE.

Table 2: List of notations used in the study along with their respective denotations.

results by employing the ERS test. In the events where non-stationarity is identified, the time series are converted to stationary series before the relevant analysis is carried out. For this, the study employs the differencing technique and uses the first-order differences to ensure stationarity for each time series [24].

[24] Toda and Yamamoto (1995) extend an approach for testing economic hypotheses stated as restrictions on the parameters of the VAR models without pretesting for a unit root by adding extra lags to the original equations, the number of which equals the order of integration, to account for the non-stationarity of the data. However, this study chose to stick to the traditional approach of testing for stationarity followed by converting

To address the primary research question of characterizing the efficacy of the EU ETS at emission reduction, the study begins with an investigation of the presence of a causal relationship and impact of lagged effects between the EU ETS prices and the verified emissions (☛ Section 5.1). The study then expands to employ conditional entropy to capture the non-linear dependencies between the ETS prices and the verified emissions (☛ Section 5.2). Keeping in consideration the interaction between various macroeconomic indicators and EU ETS prices, the study attempts to analyse its impact on the verified emissions over the years (☛ Section 5.3). Lastly, the study looks at the carbon pricing signals generated by the EU ETS prices that influence emissions and how those signals have evolved. For this, the paper examines the fluctuations and patterns in the overall and phased pricing of the EU ETS (☛ Section 5.4).

5.1 Causal relations

This section initially looks at the linear correlation between the EU ETS spot prices and verified emissions to determine if the EU ETS prices have affected verified emissions. Upon confirmation of the existence of a strong significant correlation between the EU ETS prices and the verified emissions, the study attempts to ascertain whether this relation varies over time and how long it takes for changes in the ETS spot prices to affect emissions by exploring any underlying causal links between these two variables.

5.1.1 Methodology

Pearson's Correlation Coefficient (Benesty et al., 2009), is an indicator of linear correlation between two random variables X and Y.

$$\rho(X,Y) = \frac{\sum_{x\in X, y\in Y}(x-\bar{X})(y-\bar{Y})}{\sqrt{\sum_{x\in X}(x-\bar{X})^2 \sum_{y\in Y}(y-\bar{Y})^2}} \tag{1}$$

Here, $\rho(X,Y)$ depicts the correlation coefficient of random variables X and Y and x and y are individual data points from the variables. $\bar{X}$ and $\bar{Y}$ are the sample means of the variables, respectively.

However, the testing hypothesis of the correlation test, that there is a greater likelihood that the two variables are reliant on one another with a stronger correlation coefficient does not include the whole inter-dependency between any two variables. The correlation tests merely offer static data ignoring any causal relationships between the variables in consideration. To overcome this, the study employs the Granger Causality test (Granger, 1969) and investigates the causal relationship [25] between the EU ETS prices and the verified emissions. This test examines the precedence between two stationary variables' time series to determine a causal relationship (Keppler and Mansanet-Bataller, 2010) by examining how much the past iterations

the concerned series into stationary series.

[25]This test is chosen among several causality tests because of its superior methodologies, as supported by studies such as Guilkey and Salemi (1982), Geweke et al. (1983) among others.

of one variable (EU ETS spot prices in this case)explain the later iterations of the other variable (verified emissions in this case).

The lead and lag structure between two variables must be specified to perform the Granger causality test (Cartwright et al., 1989). The study designs the test model building upon the framework extended by Kholdy and Sohrabian (1990). For two stationary time series $X = x_0, x_1, ..., x_n$ and $Y = y_0, y_1, ..., y_n$, autoregression of Y with a given lag is defined by:

$$y_k = \alpha_0 + \sum_{i=1}^{m} \alpha_i y_{k-i} + \epsilon_t \tag{2}$$

One can then conclude that Y (verified emissions in this case) is causally reliant on X (EU ETS prices in this case) if adding similar lagged components of x_j terms to this autoregression (Equation 2) improves its expressiveness (i.e., lower mean error) in Equation 3.

$$\sigma_1^2(Y_t : Y_{t-j}, X_{t-i}) < \sigma_2^2(Y_t : Y_{t-j}) \tag{3}$$

F-statistics are computed to test the null hypothesis ($\mathcal{H}_0$) of no causality. To ensure the validity of the causality test, due to the presence of unit roots, indicating non-stationarity in the data sets (Table 8), data sets are transformed through the differencing technique before running the test model (Section 4).

5.1.2 Findings

Table 3 displays the interdependence test results for EU ETS and verified emissions. For the cumulative dataset, Pearson's correlation coefficient (ρ) is -0.086 depicting a weak negative linear relationship. A closer look at the phase-by-phase analysis reveals a more promising picture. Phase I depicts an ideal scenario with a strong negative correlation where with the rise in the EU ETS prices, there has been a corresponding fall in the emissions. Things take a downhill turn during Phase II. However, with further policy reforms and maturing of the EU ETS market, Phase III (moderate negative correlation) and Phase IV (strong negative correlation) depict the gradual shift towards an ideal market scenario.

Series	ρ	**p-value**
Cumulative	-0.086	0.727
Phase I	-0.980	0.126
Phase II	0.947**	0.015
Phase III	-0.150*	0.057
Phase IV	-0.616***	0.010

Table 3: Pearson's correlation coefficient (ρ) and p-value for EU ETS prices and verified emissions. Significant positive values (highlighted in green) indicate a direct relationship and significant negative values (highlighted in red) indicate an inverse relationship. All values are rounded off to three decimal places. Statistical significance at 10% is denoted with *, at 5% is denoted with **, and at 1% is denoted with ***.

Table 4 displays the causal test results for different lags. At lag 1, results indicate that, at the 10% significance level, there is strong evidence against the null hypothesis ($\mathcal{H}_0$). This suggests that there is a causal relation between EU ETS at this latency. For lags 2 to 4, all test statistics, however, display significant p-values, suggesting that the null hypothesis ($\mathcal{H}_0$) of no causal relationship is not successfully rejected. In particular, there is no significant causation at lag 2 as indicated by the SSR F-test statistic of 0.532 (p-value = 0.602) and the SSR χ^2 statistic of 1.547. At lags 3 and 4, similar patterns persist, with p-values staying above conventional thresholds of statistical significance. With no convincing evidence for longer lag structures, the results imply that any causal influence of the EU ETS spot pricing on verified emissions is restricted to short-term (immediate next year) only.

Lags	**SSR F-test**	**SSR χ^2**	**LR χ^2**	**P F-test**
1	3.220*	3.910	3.519	0.094
2	0.532	1.547	1.477	0.602
3	0.593	3.336	3.012	0.637
4	0.297	3.331	2.988	0.868

Table 4: Granger Causality test statistics for assessing the causal impact of ETS prices on verified emissions. "Lags" depicts the number of time lags in years, "SSR F-test" depicts the F-statistics for sum of squared residuals, "SSR χ^2" illustrates the strength of causal impact, "LR χ^2" includes likelihood ratio of the model, and "P F-test" shows the corresponding p-value for each "SSR F-test" statistics. All values are rounded off to three decimal places. Statistical significance at 10% is denoted with *.

These findings suggest that an increase in EU ETS spot prices today is likely to lead to a reduction in verified emissions over the immediately following year. This highlights the efficacy of the EU ETS pricing mechanism in influencing short-term emission reductions. This also serves as an example of how market-based instruments like the EU ETS carbon allowances can be used to prompt immediate action among the market participants in terms of emission reduction. The lack of significant causal impact at longer lags (two, three, and four years) implies that the impact of the EU ETS spot price changes on emission reductions may not extend beyond the immediate next year, drawing attention to the effectiveness of carbon price signals sent by the EU ETS (refer to Section 5.3 for analysis of carbon price signals generated by the EU ETS). This also calls for further aligning EU ETS with long-term climate objectives by the introduction of other complementary measures or policies.

5.2 Conditional entropy

Pearson's Correlation Coefficient (Benesty et al., 2009) and the Granger Causality test (Granger, 1969) are crucial to exploring any linear relationships between two random variables, however, they are limited to capturing only linear relationships. In the case of EU ETS market and the verified emissions, various market factors like sudden shocks in macroeconomic factors (Section 5.3), growing media coverage and public scrutiny (Appendix H), policy interventions etc. are at play. For instance, the 2008 financial crisis significantly impacted the EU ETS market as discussed in Section 3. Hintermann (2010) highlights how these external factors can induce non-linear reactions, where the resultant impact on the EU ETS carbon pricing and emissions may be major, delayed, or amplified. Hence, the study makes an effort to capture the non-linear reinforcement cycles between the EU ETS spot prices and verified emissions to analyse how the ETS prices have affected the verified emissions over the years.

5.2.1 Methodology

The study goes on to employ Conditional entropy (Shannon, 1948) to explore the non-linear interdependence between the EU ETS spot prices and the verified emissions over the years. Entropy-based metrics are not restricted to linear associations, unlike linear correlation measures, which only quantify linear relationships. The study builds on the framework extended by Veyrat-Charvillon and Standaert (2009) and designs an econometric model suitable for the concerned datasets.

Shannon entropy. Shannon entropy, as proposed by Shannon (1948) represents a random variable's degree of uncertainty. On a space χ, the Shannon Entropy $H(X)$ for a random variable X is given by:

$$H(X) = \sum\nolimits_{x \in X} -p(x) \log_2 x \tag{4}$$

$$H(X) = -\sum\nolimits_{x \in X} p(X = x) \log_2 \cdot [p(X = x)] \tag{5}$$

The probability of observing a specific value x for the random variable X is given by $p(x)$. So, $-p(x) \log_2 x$ represents the contribution of each value of x to the overall entropy.

Joint entropy. Joint entropy expands Shannon entropy (Shannon, 1948) to multiple variables and quantifies the amount of information needed to represent the joint distribution of numerous variables (Cover, 1999). For a pair of random variables X and Y, joint entropy conveys the degree of uncertainty associated with the combination of these variables and can be expressed as:

$$H(X, Y) = -\sum\nolimits_{x \in X} -\sum\nolimits_{y \in Y} p(x, y) \log_2 \cdot [p(x, y)] \tag{6}$$

Here. $p(x, y)$ depicts the joint probability of both variables taking specific values simultaneously. Only in the case that Y is a deterministic function of X, does the joint entropy (Equation 6) equal that of $H(X)$ or $H(Y)$ as per Equation 5.

Conditional entropy. The conditional entropy, which is always more than zero, for any random variable X with another variable Y depicts the unpredictability on X once Y is known (Veyrat-Charvillon and Standaert, 2009). The conditional entropy between random variables X and Y is given by:

$$H(X|Y) = \sum\nolimits_{x \in X, y \in Y} p(X = x, Y = y) \log_2 \cdot [p(X = x|Y = y)]. \tag{7}$$

No particular functional form—linear or otherwise—between the variables is assumed by conditional entropy. Regardless of whether they are quadratic, linear, or more complicated types of non-linear interactions, it may identify dependencies (Cover, 1999). For each phase of the EU ETS as well as the cumulative time period, this study computes both, $H(\text{VE}|\text{ETS})$, and $H(\text{ETS}|\text{VE})$, to investigate the influence and information transfer in either direction.

5.2.2 Findings

Table 5 displays the conditional entropy test results for EU ETS and verified emissions. For the cumulative dataset, text results suggest a significant influence of the EU ETS spot prices on the emissions. This indicates that changes in levels of emissions at large can be explained by the changes in EU ETS spot prices. However, the results indicate that emissions have a weak influence on the ETS prices and cannot explain the uncertainties associated with the EU ETS prices. A further delve into the phase-wise analysis illustrates how this relationship between the EU ETS spot prices and the emissions have evolved over the years. While some phases adhere to expectations, others defy conventional expectations. The results of the phase-wise analysis can be attributed to the significant policy changes during the respective phases.

Series	H(**VE**|**ETS**)	H(**ETS**|**VE**)
Cumulative	0.208	0.661
Phase I	0.500	0.500
Phase II	0.183	0.250
Phase III	0.005	0.510
Phase IV	0.167	0.500

Table 5: Conditional entropy between EU ETS spot prices and verified emissions. "H(ETS|VE)" depicts the conditional entropy of VE on EU ETS prices, and "H(VE|ETS)" depicts the conditional entropy of EU ETS prices on VE. Lower values indicate a greater influence and vice versa. Significantly strong influences are highlighted. All values are rounded off to three decimal places.

In Phase I, during the first two years after the launch of the EU ETS, the test results are relatively high, with a test statistic of 0.500 for both directions, indicating a weak influence in both directions. In this scenario, neither the verified emissions could explain the uncertainties associated with EU ETS prices, nor could the EU ETS prices influence the emissions significantly. Phase I statistics are driven by two factors. First, this can be explained by the fact that the EU ETS was just launched and was in its infancy during this phase. Market participants were adapting to the new environment and were highly responsive to the newly implemented ETS which led to significant fluctuations and shocks in the prices. Second, the lack of banking provisions during this phase (Appendix B) meant that the over-allocated excess allowances (Section 3) could not be banked for the future. This drove market participants to actively utilise and trade the allowances during this phase further amplifying the fluctuations in the ETS prices. Naturally, emissions could not be adjusted to accommodate this price volatility in the short term.

Phase II provides an interesting picture. The conditional entropy for both directions falls significantly highlighting a strong bi-directional influence between the EU ETS prices and the verified emissions. This sudden fall in the reciprocal conditional entropy among the two variables was a product of the introduction of banking facilities during this phase (Appendix B). As carbon allowances could now be banked for future usage, the immediate pressure on the ETS market was reduced.

Phase III results highlight the negligible influence of verified emissions on the EU ETS prices. However, the test statistics for EU ETS prices influence on verified emissions signifies the considerable effect of the ETS prices on the emissions, once again. By this phase, ETS prices could highly predict emissions. The introduction of the MSR (Section 3) handling the surplus allowances and tighter emission caps during this phase might have driven the EU ETS prices to influence the emissions heavily.

Phase IV presents an almost similar picture to that of Phase III. The ETS prices continue to significantly influence the emissions, as is desired by the policymakers. Unlike Phase III, Phase IV also reflects a maturing market system closer to the desired goal with significant information exchange from the ETS prices to the emissions and some amount of information exchange from emissions to the ETS market. As the market developed, prices started to reflect stable and predictable carbon costs more accurately. This generated signals for investments in emission reduction that were easier to understand and made emissions more price-responsive (refer to Section 5.3 for more on carbon pricing signals). Similarly, the fall in emission's influence on EU ETS prices was driven by tighter caps and market stabilisation efforts. These reforms lowered the impact of emissions on EU ETS spot prices since long-term expectations and policy signals increasingly drove the ETS prices instead of short-term emissions data, highlighting the maturing nature of the EU ETS market.

The study's findings imply how the EU ETS has evolved over the last two decades. Across most phases, the levels of emissions are strongly influenced by the EU ETS spot prices. This highlights the EU ETS's success in influencing emissions over the years as the market has developed and grown more receptive to policy reforms. This also serves as a lesson for other emerging ETSs regarding the path towards achieving the desired policy objectives.

5.3 Macroeconomic indicators

So far, the study has examined linear and non-linear dependencies between EU ETS prices and emissions. However, these relationships should not be studied fully in isolation. Various macroeconomic factors, such as GDP growth rate, inflation rate, and wholesale energy prices, interact with the EU ETS prices to substantially impact emissions over time. Variations in GDP growth, for example, impact energy consumption and industrial output, which can then influence changes in emission levels. For example, the 2008 financial crisis during Phase II of EU ETS (Section 3) significantly impacted emissions and the EU ETS allowances prices (Bel and Joseph, 2015)). Parallel to this, changes in the cost structure of energy-intensive businesses can have an impact on emissions by influencing wholesale energy prices. For instance, following the conflict between Russia and Ukraine, which has caused major disruptions in the world energy markets, policy changes intended to improve energy sufficiency have caused volatility in energy prices, emissions, and EU ETS prices as European nations attempted to lessen their reliance on Russian energy (Kirkegaard, 2023)). As a result, a more inclusive picture of the EU ETS's effectiveness in reducing emissions can be obtained by examining these factors alongside the EU ETS prices.

5.3.1 Methodology

This study adopts a Structural Vector Auto-Regressive (SVAR) model to understand the interactions between EU ETS pricing and macroeconomic factors like the GDP growth rate, wholesale energy prices and inflation rate and their impact on emissions due to the SVAR

Particulars	Emissions	ETS prices	GDP growth	Inflation	Wholesale energy
Emissions	1.000	-0.602	0.398	0.353	-0.516
ETS prices	-0.602	1.000	-0.070	0.079	0.886
GDP growth	0.398	-0.070	1.000	0.442	-0.141
Inflation	0.353	0.079	0.442	1.000	0.098
Wholesale energy	-0.516	0.886	-0.141	0.098	1.000

Table 6: Correlation matrix of residuals depicting pairwise correlations between the residuals of the variables considered for the SVAR model. While values close to 0 indicate weaker or no correlations, values closer to 1 or -1 indicate stronger relationships. Positive values show direct relationships and negative values (highlighted in red) indicate inverse relationships. All values are rounded off to three decimal places.

model's ability to consider the endogenous relationships [26] between multiple time series variables. Unlike an Ordinary Least Squares (OLS) regression, which primarily examines static relationships between variables (refer to Appendix E for OLS regression between these variables), a SVAR model is capable of detecting the reinforcement cycles among the variables. For, endogenous variables emissions, EU ETS spot prices, GDP growth rate, and inflation rate [27] and for exogenous variable wholesale energy prices [28], the SVAR model can be expressed by the following equation:

$$AY_t = BY_{t-1} + CX_t + u_t \tag{8}$$

Here, Y_t represents the vector of endogenous variables, X_t stands for the vector of exogenous (controlled) variables, A and B identifies the relationship between the endogenous variables and their lags, C represents the impact of exogenous variables, while u_t stands for the vector of shocks. Despite the drawback of Equation 8 only considering the variables' time series, which results in a poor explanatory capacity for the theoretical link between them, as Chung et al. (2018) highlights, the benefit is that it may be used to predict targets values with great ease and utility. All concerned time series are tested for the presence of unit roots and converted to stationary series by differencing technique (Section 4) before running the model to avoid spurious observations. The controlled variables, also known as exogenous variables are used to identify structural shocks that affect the endogenous variables.

5.3.2 Findings

Table 6 depicts the correlation matrix of residuals obtained from the SVAR model. A strong negative correlation between the emissions and EU ETS indicates that emission reduces with higher ETS prices. This is consistent with the underlying policy objective of the EU ETS to raise the price of carbon to reduce emissions. As expected, emissions have a moderately positive correlation with both GDP growth and inflation. This is because a rising GDP usually

[26] **Endogenous relationship** refers to a situation where the variables in a model are interdependent, which means that modifications to one variable might have an impact on other variables in the system and vice versa.

[27] These variables are selected as endogenous variables since they are interdependent, impacting each other.

[28] Wholesale energy price is selected as an exogenous variable because several external factors affect the energy prices, and consequently, emissions which are not covered by the EU ETS.

Lag 1						
Particulars		**Emission**	**ETS**	**GDP**	**Inflation**	**Energy**
ETS	**Coefficient**	0.000	-0.069	0.214	0.759	-0.351**
	P-value	0.763	0.864	0.640	0.158	0.030
GDP	**Coefficient**	0.000	-0.279	-1.731**	0.317	0.383
	P-value	0.047	0.660	0.015	0.706	0.128
Inflation	**Coefficient**	0.000	-0.213	-0.709*	0.990**	0.098
	P-value	0.924	0.545	0.073	0.034	0.481
Energy	**Coefficient**	0.000	-0.698	-3.269*	5.440***	0.946
	P-value	0.811	0.662	0.069	0.010	0.136
Lag 2						
Particulars		**Emission**	**ETS**	**GDP**	**Inflation**	**Energy**
ETS	**Coefficient**	0.000	-0.260	-0.125	0.850	0.343***
	P-value	0.919	0.513	0.589	0.560	0.001
GDP	**Coefficient**	0.000	0.155	0.563	-3.613	-0.328**
	P-value	0.173	0.803	0.119	0.112	0.048
Inflation	**Coefficient**	0.000	-0.316	-0.037	-1.930	-0.201**
	P-value	0.719	0.359	0.855	0.127	0.030
Energy	**Coefficient**	0.000	-1.374	-0.580	-7.592	-0.185
	P-value	0.749	0.380	0.525	0.186	0.659

Table 7: Coefficient values and their corresponding p-values for various lags (Lag 1 and Lag 2) obtained from the SVAR analysis. Significant positive values (highlighted in green) indicate a direct relationship and significant negative values (highlighted in red) indicate an inverse relationship. All values are rounded off to three decimal places. Statistical significance at 10% is denoted with *, at 5% is denoted with ** and at 1% is denoted with ***. Refer to Table F.1 in Appendix F for the corresponding t-statistics and standard errors.

stimulates the economy and increases energy consumption, which in turn causes emissions to rise. The negative correlation between emissions and wholesale energy prices indicates that higher energy prices may contribute to a reduction in emissions. A significantly strong positive correlation between EU ETS prices and wholesale energy prices reflects the "Cost-push effect" [29] of higher energy prices on carbon pricing. In contrast, the impact of inflation yields inconsistent results, with larger p-values reflecting weaker or less consistent relationships.

Table 7 includes key statistics of the SVAR analysis across various lags. Refer to Appendix E for detailed findings. The findings reveal that the relationship between the variables evolves over time. For example, the immediate statistically significant negative effect of wholesale energy prices on ETS prices (Lag 1) followed by a significant positive impact in later years (Lag 2) suggests that initial shocks may reduce demand for carbon allowances, but over time, as firms adjust, the price rebounds. This confirms the importance of wholesale energy prices in influencing carbon pricing as discussed by Convery and Redmond (2007). A similar pattern is observed in most cases. It suggests that among all the macroeconomic factors considered by the study, the exogenous effect of wholesale energy prices is most significant on emissions.

The findings confirm the interdependence between macroeconomic factors like wholesale energy prices and GDP growth rate and EU ETS prices and emissions and how these interactions evolve over various lags. The negative correlation between ETS prices and emissions confirms

[29] As per Holzman (1960), the term **"Cost-push effect"** describes a circumstance where increasing production costs cause an overall increase in the price level of any given good (in this case, carbon allowances).

the EU ETS's efficacy in reducing carbon emissions by incentivising lower emissions. The shifting nature of these relationships across various lags implies that although initial shocks could have a short-term impact on carbon pricing and emissions, the market and firms eventually adapt over time.

5.4 Carbon pricing signals

The carbon pricing signals put a monetary value on the release of greenhouse gases by internalising the environmental costs of carbon emissions (Boyce, 2018). By putting a cap on overall emissions and enabling market players to exchange emission allowances (Section 3), the EU ETS generates carbon pricing signals. There are several ways in which these carbon pricing signals can affect emissions. In principle, high EU ETS carbon allowance costs should encourage firms to switch to cleaner technology or cut back on production from carbon-intensive operations, which will reduce overall emissions. On the other hand, low EU ETS carbon allowance costs may reduce these incentives, which could result in increased emissions.

This section looks at the stochastic characteristics of the EU ETS spot prices to investigate how well these carbon pricing signals have affected emissions over time. For instance, the existence of a unit root in the EU ETS price series would suggest that the pricing signals might be less dependable and more vulnerable to random external shocks. However, if the ETS prices exhibit stationarity, it implies that such price shocks are temporary and that market forces ultimately bring prices back to mean, yielding a signal that is more steady and predictable. To analyse the carbon pricing signals generated by the EU ETS over the years, this study builds upon the methodological framework extended by Bredin and Muckley (2009*b*) and analyses the EU ETS spot prices over its various phases of implementation.

5.4.1 Methodology

To ascertain if a time series is non-stationary, one can use a unit root test. The mean, variance, and covariance of non-stationary time series fluctuate over time, rendering them less stable and unpredictable. The carbon pricing signals become distorted if the ETS prices have a unit root, indicating that price shocks may have long-lasting consequences.

The Elliot, Rothenberg and Stock (ERS) test, proposed by Elliot et al. (1996), which is a revised version of the Augmented Dickey-Fuller (ADF) tests (Dickey and Fuller, 1979, 1981) (Equation 9), offers an effective performance for the assessment of stochasticity. It assumes that the model errors are normally distributed. It checks the null hypothesis ($\mathcal{H}_0$) of $\gamma = 0$ against the alternative hypothesis ($\mathcal{H}_a$) of $\gamma < 0$.

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{k} \delta_i y_{t-i} + \epsilon_t \tag{9}$$

Here, Δ depicts the first difference, t shows the time trend variable, k depicts the lags incorporated, and ϵ_t depicts the auto-correlations from the residuals. k is determined by minimising the Bayesian Information Criterion (BIC) as forwarded by Schwarz (1978).

Perron (1989) identifies that the ADF tests (Dickey and Fuller, 1979, 1981) and in extension, the ERS test (Elliot et al., 1996) are biased for non-rejection of the null hypothesis ($\mathcal{H}_0$) of a unit root if structural breaks are present. The alternative proposed by Perron (1989), depicted in Equation 10, provides for a possibility of a structural break under both hypotheses.

$$\Delta y_t = \alpha + \alpha_1 ID_t + \lambda CD_t + \beta_0 TD_t + \beta_1 t + \gamma y_{t-1} + \sum_{i=1}^{k} \delta_i y_{t-i} + \epsilon_t \tag{10}$$

Here, the intercept dummy, ID_t, depicts shifts in the series level, TD_t is the trend regression coefficient dummy, and $CD = 1$ is the crash dummy at the time point immediately following the break ($t = TD + 1$) and zero at all other times.

However, predetermination of the break date dismisses the distribution theory for classical unit root tests (Christiano, 1992). The Zivot-Andrews (ZA) test, as proposed by Zivot and Andrews (1992) overcomes this as it internally identifies the break date where the evidence for the null hypothesis ($\mathcal{H}_0$) of a unit root is weakest. It incorporates a dummy under the alternate hypothesis ($\mathcal{H}_a$) (Equation 10).

Finally, the assumption of a unit root as the null hypothesis ($\mathcal{H}_0$) imposes a significant burden on the data to reject the null hypothesis ($\mathcal{H}_0$) if the data is trend-stationary. To overcome this, the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test as suggested by (Kwiatkowski et al., 1992) introduces a Lagrange multiplier test that evaluates the null hypothesis ($\mathcal{H}_0$) of stationarity around a deterministic trend. This study also incorporates the Augmented Dickey-Fuller (ADF) tests (Dickey and Fuller, 1979, 1981), the Phillips-Perron (PP) test (Phillips and Perron, 1988), and the Lee-Strazicich (LS) test (Lee and Strazicich, 2001, 2013). Refer to Appendix G for further details.

5.4.2 Findings

Table 8 includes the unit root test results of the ERS test, the ZA test and the KPSS test for the level and log-differenced series of the EU ETS spot prices. For the cumulative level series, the ERS test suggests stationarity at conventional statistical significance levels. However, the ZA test, which accounts for any structural breaks within the time series fails to suggest stationarity at any traditional statistical significance levels. For the log-differenced series, despite all tests except for the KPSS test confirming non-stochasticity, the lack of statistically significant test statistics from the KPSS test suggests a unit root might be present in the data series.

Once the cumulative EU ETS spot price series is divided into phase-wise series, the evidence of stochasticity is more prominent in Phase I and Phase II. For Phase III and Phase IV, despite the presence of unit root in the level series (Table 8 and Table G.1) suggesting persistent shocks over time, the test statistics follow a diminishing trend over time. Also, every test confirms stationarity at a statistically significant level for the log-differenced series. This aligns with the

Series	ERS		ZA		KPSS	
	Level series	Log-diff. series	Level series	Log-diff. series	Level series	Log-diff. series
Cumulative	-2.32**	-24.79***	-3.55	-25.02***	3.50***	0.04
Phase I	3.31	-31.24***	-3.36	-32.22***	8.88***	0.89***
Phase II	-0.27	-36.19***	-4.54*	-36.33***	7.70***	0.27*
Phase III	0.11	-34.48***	-4.45*	-34.59***	5.35***	0.14*
Phase IV	0.03	-29.02***	-3.93	-29.19***	0.07***	0.24*

Table 8: The ERS, the ZA, and the KPSS unit root tests result for both the level series and the log-differenced series of EU ETS spot prices. Statistically significant negative values for the ADF, and the ZA tests signify an absence of unit root while statistically significant positive statistics for the KPSS test do the same. Cases where the presence of a unit root could not be rejected are highlighted in red. Statistical significance at 10% is denoted with *, at 5% is denoted with ** and at 1% is denoted with ***.

upward price trajectory observed for Phase III and Phase IV (Figure 3).

The presence of unit roots and non-stationarity in the EU ETS spot prices suggests that external shocks are causing the carbon pricing signals to fluctuate over time. However, over the years, especially in Phase III and Phase IV of the EU ETS, the carbon pricing signals have stabilised and are more aligned with the goals of the corresponding policies, which are to shift to a low-carbon economy. The findings also support World Bank (2024)'s conclusions that, although trading mechanisms are functioning well, the carbon prices have not been trending upward. This trend has been reversed for EU ETS in recent years. Sitarz et al. (2024) highlights the role of effective policies in driving the EU ETS prices upward in recent years and serves as an example for policymakers worldwide. Notably, this upward trend in price over time has been possible due to the policymakers' actions (IEA, 2020).

6 Conclusion

The failure of attempts to impose a carbon tax in Europe gave rise to the EU ETS (Laing et al., 2013). A key factor in the development of the EU ETS has been its planned phase-wise implementation (Figure 1), which made it possible to address many of its early shortcomings in subsequent phases (e.g., The substantial reforms in Phase III including the centralisation of *cap-setting* and switching to auctioning in the power sector were drawn straight out of previous lessons as highlighted by Laing et al. (2013)).

Despite completing 18 years since its inception in 2005 and the extensive literature based on it, the EU ETS still draws attention from academics worldwide. The central question in any discourse on the EU ETS revolves around its efficacy in emission reduction and attaining the EU's climate goals. This study aims to trace the evolution of the EU ETS over the past 18 years, assessing its influence on driving a reduction of emissions over time. The following are the main takeaways drawn from this study:

- **Influence on emissions.** Prices in the EU ETS have a significant effect on verified emissions, especially in Phases III and IV. This indicates the success of the subsequent policy changes within the EU ETS environment in influencing emissions.

- **Short-term efficacy.** An increase in EU ETS prices is likely to lead to a reduction in verified emissions within the next year highlighting its efficacy in driving emission reductions in the short term. Longer-term causal relations, however, did not receive statistical support, suggesting that EU ETS carbon price adjustments had no long-term impact on verified emissions beyond the immediately following one-year lag.

- **Macroeconomic indicators.** The interaction of the EU ETS with other macroeconomic variables, particularly GDP growth and wholesale energy prices significantly impact emissions and adjusts over various lags. The statistically significant interactions of these factors with the EU ETS prices emphasise the necessity to consider these economic factors while analysing the ETS mechanism and its efficacy.

- **Carbon price signals.** Carbon pricing signals generated by the EU ETS market have strengthened over the years. The "periodic unstable prices" still haunt the EU ETS system. This also explains the presence of unit roots in each phase (Section 5.4). Despite the initial volatility and persisting unit roots in earlier phases, Phase III and IV of the EU ETS demonstrate a trend towards stabilisation, following an upward trajectory in allowance prices and generating stronger carbon pricing signals.

Limitations & future research. As Pahle and Quemin (2020) point out, the EU ETS's efficacy on emission reduction is dependent on several other aspects that go beyond the ETS market structure. While this study attempts to capture certain key factors like the interactions between the macroeconomic indicators and wholesale energy prices with the EU ETS prices, other external factors like global coal, gas and fuel prices also bear a significant influence on the ETS market but remain beyond the scope of this study. Preliminary findings on media coverage (Appendix H) show that media coverage has a substantial negative impact on the EU ETS spot prices in the short-term, driving temporary shocks and fall in the EU ETS spot prices, which is counter-intuitive and begs for further research and exploration. Prior theoretical frameworks have implied the relative importance of different non-ETS policies (Grubb et al., 2023), global climate accords (Newell et al., 2014), and market sentiments based on news coverage pronouncedly affecting the EU ETS market environment. Future empirical investigations of these implications, in conjunction with the market phenomena explored in this study will enrich the ongoing discourse on the EU ETS's efficacy in terms of emission reduction.

References

Alberola, E., Chevallier, J. and Chèze, B. (2008), 'Price drivers and structural breaks in European carbon prices 2005–2007', *Energy policy* **36**(2), 787–797.

Alberola, E., Chevallier, J. and Cheze, B. (2009*a*), 'European Carbon Price Fundamentals in 2005) 2007: the Effects of Energy Markets', *Temperatures and Sectorial Production, forthcoming in Journal of Policy Modeling* .

Alberola, E., Chevallier, J. and Cheze, B. (2009*b*), 'The EU Emission Trading Scheme: Disentangling the Effects of Industrial Production and CO_2 Emission on Carbon Prices, forthcoming in Journal of International Economics'.

Anderson, B. and Di Maria, C. (2011), 'Abatement and Allocation in the Pilot Phase of the EU ETS', *Environmental and Resource Economics* **48**, 83–103.

Asdourian, E. and Wessel, D. (2011), 'What is the social cost of carbon?', *Brookings* .

Backman, I. (2021), 'Stanford explainer: Social cost of carbon', Stanford Report.
URL: *https://news.stanford.edu/stories/2021/06/professors-explain-social-cost-carbon*

Bel, G. and Joseph, S. (2015), 'Emission abatement: Untangling the impacts of the EU ETS and the economic crisis', *Energy Economics* **49**, 531–539.

Benesty, J., Chen, J., Huang, Y. and Cohen, I. (2009), Pearson correlation coefficient, *in* 'Noise reduction in speech processing', Springer, pp. 37–40.

Benz, E. and Trück, S. (2009), 'Modeling the price dynamics of CO_2 emission allowances', *Energy Economics* **31**(1), 4–15.

Black, S. J. (2018), 'Carbon Markets Under the Kyoto Protocol: Lessons Learned for Building an International Carbon Market Under the Paris Agreement'.

Bordignon, M. and Gamannossi degl'Innocenti, D. (2023), 'Third time's a charm? Assessing the impact of the third phase of the EU ETS on CO_2 emissions and performance', *Sustainability* **15**(8), 6394.

Boyce, J. K. (2018), 'Carbon pricing: effectiveness and equity', *Ecological Economics* **150**, 52–61.

Boykoff, M., Ballantyne, A., Chandler, P., Fernández-Reyes, R., Hawley, E., Jiménez Gómez, I., Lyytimäki, J., McAllister, L., Mervaala, E., Mocatta, G., Nacu-Schmidt, A., Oonk, D., Osborne-Gowey, J., Pearman, O., Petersen, L., Simonsen, A. and Ytterstad, A. (2024), 'European Newspaper Coverage of Climate Change or Global Warming, 2004-2024', Media and Climate Change Observatory Data Sets. Cooperative Institute for Research in Environmental Sciences, University of Colorado.
URL: *https://scholar.colorado.edu/concern/datasets/2v23vw19t*

Bredin, D. and Muckley, C. (2009*a*), 'An Analysis of the EU Emission Trading Scheme'.

Bredin, D. and Muckley, C. (2009*b*), 'Is There a Stochastic Trend in European Union Emission Trading Scheme Prices?', *Sosyoekonomi* **12**(12).

Cartwright, P. A., Kamerschen, D. R. and Huang, M.-Y. (1989), 'Price correlation and Granger causality tests for market definition', *Review of Industrial Organization* **4**, 79–98.

Chevallier, J. (2009), 'Carbon futures and macroeconomic risk factors: A view from the EU ETS', *Energy Economics* **31**(4), 614–625.

Christiano, L. J. (1992), 'Searching for a Break in GNP', *Journal of Business & Economic Statistics* **10**(3), 237–250.

Chung, C. Y., Jeong, M. and Young, J. (2018), 'The price determinants of the EU allowance in the EU emissions trading scheme', *Sustainability* **10**(11), 4009.

Convery, F. J. and Redmond, L. (2007), 'Market and price developments in the European Union emissions trading scheme'.

Cover, T. M. (1999), *Elements of information theory*, John Wiley & Sons.

Daskalakis, G., Psychoyios, D. and Markellos, R. N. (2009), 'Modeling CO_2 emission allowance prices and derivatives: Evidence from the European trading scheme', *Journal of Banking & Finance* **33**(7), 1230–1241.

Dechezleprêtre, A., Nachtigall, D. and Venmans, F. (2023), 'The joint impact of the European Union emissions trading system on carbon emissions and economic performance', *Journal of Environmental Economics and Management* **118**, 102758.

Dickey, D. A. and Fuller, W. A. (1979), 'Distributions of the Estimators for Autoregressive Time Series with a Unit Root', *Journal of the American Statistical Association* **74**(366), 427–481.

Dickey, D. A. and Fuller, W. A. (1981), 'Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root', *Econometrica* **49**(4), 1057–1072.

Dimitrov, R. S. (2016), 'The Paris Agreement on Climate Change: Behind Closed Doors', *Global Environmental Politics* **16**(3), 1–11.
URL: *https://doi.org/10.1162/GLEP_a_00361*

Ellerman, A. D. and Buchner, B. K. (2007), 'The European Union emissions trading scheme: origins, allocation, and early results'.

Elliot, G., Rothenberg, T. J. and Stock, J. H. (1996), 'Efficient Tests for an Autoregressive Unit Root', *Econometrica* **64**(4), 813–836.

Engle, R. F. (1982), 'Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation', *Econometrica: Journal of the econometric society* pp. 987–1007.

European Commission (2015*a*), *EU ETS Handbook*, European Commission, Brussels, Belgium.

European Commission (2015*b*), Study on the Impacts on Low Carbon Actions and Investments of the Installations Falling Under the EU Emissions Trading System (EU ETS), Technical report, European Commission.

European Commission (2016), 'The European Union Emissions Trading System (EU ETS)', https://climate.ec.europa.eu/system/files/2016-12/factsheet_ets_en.pdf.

European Commission (2023), 'EU Emissions Trading System (EU ETS)'.
URL: *https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets_en*

Galán-Valdivieso, F., Villar-Rubio, E. and Huete-Morales, M.-D. (2018), 'The erratic behaviour of the EU ETS on the path towards consolidation and price stability', *International Environmental Agreements: Politics, Law and Economics* **18**, 689–706.

Gargallo, P., Lample, L., Miguel, J. A. and Salvador, M. (2021), 'Co-movements between EU ETS and the energy markets: A VAR-DCC-GARCH approach', *Mathematics* **9**(15), 1787.

Geweke, J., Meese, R. and Dent, W. (1983), 'Comparing alternative tests of causality in temporal systems: Analytic results and experimental evidence', *Journal of econometrics* **21**(2), 161–194.

Granger, C. W. (1969), 'Investigating causal relations by econometric models and cross-spectral methods', *Econometrica: journal of the Econometric Society* pp. 424–438.

Gronwald, M., Ketterer, J. and Trück, S. (2011), 'The relationship between carbon, commodity and financial markets: A copula analysis', *Economic record* **87**, 105–124.

Grubb, M. (2004), The Economics of the Kyoto Protocol, *in* 'The Economics of Climate Change', Routledge, pp. 92–134.

Grubb, M., Poncia, A., Drummond, P., Neuhoff, K. and Hourcade, J.-C. (2023), 'Policy complementarity and the paradox of carbon pricing', *Oxford Review of Economic Policy* **39**(4), 711–730.

Guilkey, D. K. and Salemi, M. K. (1982), 'Small sample properties of three tests for Granger-causal ordering in a bivariate stochastic system', *The Review of Economics and Statistics* pp. 668–680.

Günther, C., Pahle, M., Govorukha, K., Osorio, S. and Fotiou, T. (2024), 'Carbon prices on the rise? Shedding light on the emerging EU ETS 2', *Shedding light on the emerging EU ETS2 (April 26, 2024)* .

Hammoudeh, S., Nguyen, D. K. and Sousa, R. M. (2014), 'What explain the short-term dynamics of the prices of CO_2 emissions?', *Energy Economics* **46**, 122–135.

Hintermann, B. (2010), 'Allowance price drivers in the first phase of the EU ETS', *Journal of Environmental Economics and Management* **59**(1), 43–56.

Hintermann, B. (2011), 'Market power, permit allocation and efficiency in emission permit markets', *Environmental and Resource Economics* **49**, 327–349.

Holzman, F. D. (1960), 'Inflation: Cost-push and demand-pull', *The American Economic Review* **50**(1), 20–42.

ICAP (2015), *What Is Emission Trading?*, International Carbon Action Partnership, London, UK.

ICAP (2024*a*), *EU Emissions Trading System (EU ETS)*, International Carbon Action Partnership, London, UK.
URL: *https://icapcarbonaction.com/en/ets/eu-emissions-trading-system-eu-ets*

ICAP (2024*b*), *EU Emissions Trading System for buildings and road transport*, International Carbon Action Partnership, London, UK.
URL: *https://icapcarbonaction.com/en/ets/eu-emissions-trading-system-buildings-and-road-transport-eu-ets-2*

IEA (2020), 'Implementing Effective Emissions Trading Systems', https://www.iea.org/reports/implementing-effective-emissions-trading-systems.

Jarque, C. M. and Bera, A. K. (1980), 'Efficient tests for normality, homoscedasticity and serial independence of regression residuals', *Economics letters* **6**(3), 255–259.

Jiao, L., Liao, Y. and Zhou, Q. (2018), 'Predicting carbon market risk using information from macroeconomic fundamentals', *Energy Economics* **73**, 212–227.

Keppler, J. H. and Mansanet-Bataller, M. (2010), 'Causalities between CO_2, electricity, and other energy variables during phase I and phase II of the EU ETS', *Energy policy* **38**(7), 3329–3341.

Kholdy, S. and Sohrabian, A. (1990), 'Exchange rates and prices: evidence from Granger causality tests', *Journal of Post Keynesian Economics* **13**(1), 71–78.

Kirkegaard, J. F. (2023), 'Russia's invasion of Ukraine has cemented the European Union's commitment to carbon pricing', *Peterson Institute for International Economics Policy Brief* pp. 23–13.

Koch, N., Fuss, S., Grosjean, G. and Edenhofer, O. (2014), 'Causes of the EU ETS price drop: Recession, CDM, renewable policies or a bit of everything? —New evidence', *Energy Policy* **73**, 676–685.

Kooshna, K. A. (2023), Essays on Carbon Pricing and Carbon Markets, PhD thesis, Université de Lille; Université catholique de Louvain.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P. and Shin, Y. (1992), 'Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root', *Journal of Econometrics* **54**(1-3), 159–178.

Laing, T., Sato, M., Grubb, M., Comberti, C. et al. (2013), *Assessing the effectiveness of the EU Emissions Trading System*, Vol. 126, Grantham Research Institute on Climate Change and the Environment London.

Lee, J. and Strazicich, M. C. (2001), 'Break point estimation and spurious rejections with endogenous unit root tests', *Oxford Bulletin of Economics and Statistics* **63**(5), 535–558.

Lee, J. and Strazicich, M. C. (2013), 'Minimum LM unit root test with one structural break', *Economics bulletin* **33**(4), 2483–2492.

Li, P., Zhang, H., Yuan, Y. and Hao, A. (2021), 'Time-varying impacts of carbon price drivers in the EU ETS: A TVP-VAR analysis', *Frontiers in Environmental Science* **9**, 651791.

Mirzaee Ghazani, M. and Jafari, M. A. (2021), 'The efficiency of CO_2 market in the phase III EU ETS: analyzing in the context of a dynamic approach', *Environmental Science and Pollution Research* **28**(43), 61080–61095.

Newell, R. G., Pizer, W. A. and Raimi, D. (2014), 'Carbon market lessons and global policy outlook', *Science* **343**(6177), 1316–1317.

Pahle, M. and Quemin, S. (2020), 'EU ETS: The market stability reserve should focus on carbon prices, not allowance volumes', *Energypost. eu (16 June 2020)* .

Paolella, M. S. and Taschini, L. (2008), 'An econometric analysis of emission allowance prices', *Journal of Banking & Finance* **32**(10), 2022–2032.

Perron, P. (1989), 'The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis', *Econometrica: journal of the Econometric Society* pp. 1361–1401.

Phillips, P. C. B. and Perron, P. (1988), 'Testing for a Unit Root in Time Series Regression', *Biometrika* **75**(2), 335–346.

Pohlmann, M. (2009), The European Union Emissions Trading Scheme, *in* 'Legal Aspects of Carbon Trading: Kyoto, Copenhagen, and beyond', Oxford University Press.
URL: *https://doi.org/10.1093/acprof:oso/9780199565931.003.0016*

Schakenbach, J., Vollaro, R. and Forte, R. (2006), 'Fundamentals of successful monitoring, reporting, and verification under a cap-and-trade program', *Journal of the Air & Waste Management Association* **56**(11), 1576–1583.

Schwarz, G. (1978), 'Estimating the dimension of a model', *The annals of statistics* pp. 461–464.

Shannon, C. E. (1948), 'A mathematical theory of communication', *The Bell system technical journal* **27**(3), 379–423.

Simon, F. (2020), 'EU lists sectors eligible for carbon compensation perks'.
URL: *https://www.euractiv.com/section/energy/news/eu-lists-sectors-eligible-for-carbon-compensation-perks/*

Sitarz, J., Pahle, M., Osorio, S., Luderer, G. and Pietzcker, R. (2024), 'EU carbon prices signal high policy credibility and farsighted actors', *Nature Energy* pp. 1–12.

Song, Y. and Liu, Y. (2024), 'Empirical analysis of the relationship between carbon trading price and stock price of high carbon emitting firms based on VAR model—evidence from Chinese listed companies', *Environmental Science and Pollution Research* **31**(1), 1146–1157.

Sousa, R., Aguiar-Conraria, L. and Soares, M. J. (2014), 'Carbon financial markets: A time-frequency analysis of CO_2 prices', *Physica A: Statistical Mechanics and Its Applications* **414**, 118–127.

Stavins, R. (2016), The Paris Agreement lays a good foundation for Climate progress, *in* 'The Environmental Forum', Vol. 33, p. 13.

Stavins, R. N. (2008), 'Addressing climate change with a comprehensive US cap-and-trade system', *Oxford Review of Economic Policy* pp. 298–321.

Toda, H. Y. and Yamamoto, T. (1995), 'Statistical inference in vector autoregressions with possibly integrated processes', *Journal of econometrics* **66**(1-2), 225–250.

UNFCCC (1997), 'Kyoto protocol', *UNFCCC Website.* pp. 230–240.
URL: *http://unfccc.int/kyoto_protocol/items/2830.php*

Veyrat-Charvillon, N. and Standaert, F.-X. (2009), Mutual information analysis: how, when and why?, *in* 'International Workshop on Cryptographic Hardware and Embedded Systems', Springer, pp. 429–443.

Wang, Z., Wang, F. and Wang, Y. (2022), 'Grandfathering or benchmarking: Which is more viable for the manufacturer's low-carbon activities?', *Frontiers in Environmental Science* **10**, 991827.

World Bank (2024), 'State and Trends of Carbon Pricing 2024: Positive Progress on Carbon Pricing', https://blogs.worldbank.org/en/climatechange/state-and-trends-of-carbon-pricing-2024--positive-progress-on-ca.

Ye, J. and Xue, M. (2021), 'Influences of sentiment from news articles on EU carbon prices', *Energy Economics* **101**, 105393.

Zivot, E. and Andrews, D. W. K. (1992), 'Further Evidence on the Great Crash, the Oil Price Shock, and the Unit Root Hypothesis', *Journal of Business, Economics and Statistics* **10**(10), 251–270.

Appendix A Glossary

χ^2 Chi-squared. 6, 23

ρ Pearson's Correlation Coefficient. 6, 22

ADF Augmented Dickey-Fuller. 7, 29–31, 52

ARCH Auto-Regressive Conditional Heteroskedasticity. 18, 19, 45

ERS Elliot, Rothenberg, and Stock. 7, 20, 29–31

ETS Emission Trading System. 3, 6–19, 21–32, 40–55

EU European Union. 3, 6–19, 21–32, 40–50, 52–55

GDP Gross Domestic Product. 9, 13, 18, 26–28, 32, 45–51

JB Jarque-Bera. 19, 45

KPSS Kwiatkowski, Phillips, Schmidt, and Shin. 7, 30, 31

LR Likelihood Ratio. 6, 23

LS Lee-Strazicich. 7, 30, 52

OLS Ordinary Least Squares. 3, 7, 9, 27, 47–50

P F-test Parameter F-test. 6, 23

PP Phillip-Perron. 7, 30, 52

SE Standard Error. 48, 51, 54

SSR Sum of Squared Residuals. 6, 23

SVAR Structural Vector Auto-Regressive. 3, 6, 7, 26–28, 51

VAR Vector Auto-Regressive. 8, 13, 20, 53, 54

VE Verified Emissions. 6, 24, 25

ZA Zivot-Andrews. 7, 30, 31

Appendix B EU ETS market structure

The EU ETS covers emissions from more than 10,000 installations and EU-operating airlines by the end of 2023. Taken together, it accounts for about 38% of all emissions in the EU (ICAP, 2024*a*). By the end of 2022, more than 8,640 installations and 390 aircraft operators were covered under the EU ETS. Following are the various aspects of the EU ETS market structure (Sourced from ICAP (2024*a*)):

- **Countries covered.** Since 2021, the United Kingdom is no longer a participant in the EU ETS, with the exception of Northern Ireland's power generators. Following the countries where the EU ETS operates:

1. Austria	2. Belgium	3. Bulgaria	4. Croatia	5. Cyprus
6. Czech Republic	7. Denmark	8. Estonia	9. Finland	10. France
11. Germany	12. Greece	13. Hungary	14. Iceland	15. Ireland
16. Italy	17. Latvia	18. Liechtenstein	19. Lithuania	20. Luxembourg
21. Malta	22. Netherlands	23. Norway	24. Poland	25. Portugal
26. Romania	27. Slovakia	28. Slovenia	29. Spain	30. Sweden

- **Cross-border integration.** The EU ETS has been linked with the Swiss ETS since 2020. The registries of the two systems are connected directly making allowance transfers across accounts in different systems possible for regulated entities.

- **Market model.** The market operates in a *Cap-and-trade* model. The ETS's total allowable emissions are restricted by a *cap*. By 2030, emissions are expected to have decreased by 62% from 2005 levels.

  - **Phase I & II.** The national allocation plans of each Member State were combined to determine the cap for these two phases, which was determined in a "bottom-up" manner. Phase I started with a cap of 2,096 $MtCO_2e$, while Phase II began with a cap of 2,049 $MtCO_2e$.

  - **Phase III.** Based on emissions monitoring, a single EU-wide cap was determined and set at 2,084 $MtCO_2e$ in 2013. It was lowered yearly by a linear reduction factor (LRF) of 1.74%. This led to a cap reduction of about 38 million allowances per year, culminating in a cap of 1,816 $MtCO_2e$ by the end of 2020.

  - **Phase III (Aviation).** In 2012, the aviation sector was included in the EU ETS, with a cap that was established for all flights into and out of the EEA. The aviation cap for 2012 was 221 million $MtCO_2e$. Aviation allowances issued and put into circulation between 2013 and 2016 were lowered to 38 million each year. The EU ETS's "stop-the-clock" limited scope for this sector, was functional until 2023.

  - **Phase IV.** A single cap applied to the entire EU, subject to an annual LRF. The LRF was fixed at 2.2% annually (based on baseline emissions from 2008 to 2012) for the years 2021 to 2023, 4.3% for the years 2024 to 2027, and 4.4% starting in 2028. A two-step reduction in the cap is also planned, with 90 million allowances in 2024 and 27 million allowances in 2026. Member states are permitted to withhold allowances from their auction share if they implement further policies that lead to the shutdown of electricity production capacity. No more than the installation's average verified emissions over the five years before closure may be cancelled in terms of allowances.

- **Allocation method.** Carbon allowances were allocated based on a combination of benchmarking, grandparenting [30] and auctioning.
- **Sectors covered.** Power, Industry, Maritime and Aviation (domestic).
- **Policy tools.** Following are the various policy tools devised under the EU ETS:
  - **Linear Reduction Factor (LRF).** It sets the yearly decrease in the overall amount of marketable emission allowances. The LRF was implemented to guarantee a consistent decrease in greenhouse gas emissions. It sets a yearly reduction cap on total emissions based on a predetermined percentage. As a result, the supply of allowances becomes increasingly scarcer, increasing their cost.
  - **Market Stability Reserve (MSR).** It was created in 2015 to address the excess of emission allowances in the EU ETS and strengthen the system's resistance to external shocks in the long term. It automatically adjusts the supply of allowances by reinstating them during periods of scarcity and withdrawing some from the market when there is an excess. As a result, allowance prices are kept high enough to encourage emission reductions without experiencing undue volatility that may erode investor trust. It modifies auction quantities based on predetermined thresholds of the total number of circulating allowances (TNAC). Each year, the EU Commission releases the TNAC communication.
    - **Triggers.** 24% of the allowance volume is taken out of future auctions and placed into the MSR over 12 months if the TNAC is more than 1,096 million. To reduce threshold impacts, a lesser portion of allowances is taken out of auction volumes and put in the MSR if the TNAC is between 833 and 1,096 million. A total of 100 million allowances are freed from the MSR and put up for auction if the TNAC is less than 400 million allowances.
    - **Allowance cancellations.** Starting in 2023, yearly cancellations of MSR permits over a specific threshold will occur. The 2022 auction volume was used as the appropriate criterion for 2023. The applicable level is set at 400 million as of 2024. By December 2022, there were more than 3 billion allowances in the MSR. There were 486 million allowances up for auction in 2022. As a result, in January 2023, 2,515 million allowances were cancelled.

[30] In **Benchmarking**, carbon allowances are allocated following industry-specific benchmarks for total output and emission intensity and in **Grandparenting**, allocation of emission allowances is based on a company's historical emissions during a specific base year or period (Wang et al., 2022).

- **Carbon leakage list.** The EU ETS industries and sectors that are significantly vulnerable to carbon leakage [31] are listed on this list. While still being subject to emissions restrictions, sectors on this list receive additional free allowances to help manage the risk and help them remain competitive. To make sure it accurately represents current environmental and economic situations, the list is reviewed and updated regularly based on factors including trade exposure and carbon intensity. The following standards are used to evaluate carbon leakage with a composite indicator of trade intensity and emissions intensity:

$$\text{Trade Intensity} \times \text{Emissions Intensity} > 0.2 \tag{11}$$

$$\text{Trade Intensity} \times \text{Emissions Intensity} > 0.15 \text{ but } < 0.2 \tag{12}$$

For this case, qualitative assessment will follow based on abatement potential, market characteristics, and profit margins. Emissions intensity is determined by:

$$\frac{\text{Direct Emissions} + (\text{Electricity Consumption} \times \text{Electricity Emission Factor})}{\text{Gross Value Added}} \tag{13}$$

Trade exposure is determined by:

$$\frac{(\text{Imports} + \text{Exports})}{(\text{Imports} + \text{Production})} \tag{14}$$

- **Carbon Border Adjustment Mechanism (CBAM).** It aims to impose a carbon price on imports of specific goods from non-EU nations with laxer climate regulations to stop carbon leakage. By levelling the playing field by imposing the same carbon price on imported goods as on those produced within the EU, CBAM guarantees the competitiveness of EU industries. It is anticipated that CBAM will be progressively implemented, beginning with the industries most vulnerable to carbon leakage.
- **New Entrant Reserve (NER).** It reserves a pool of emission permits expressly for new market entrants or for facilities already in place that greatly extend their operations. It ensures that businesses don't suffer from a shortage of allowances when they expand their output or enter new markets. By encouraging innovation and investment in cutting-edge, cost-effective technology, the NER is aimed at the upkeep of fair competition within the EU ETS. At the start of Phase IV, the NER's initial volume was 331.3 million allowances. This contained 200 million MSR allowances and unallocated Phase III allowances.

• **Revenue usage.** The revenue generated is used in climate mitigation, and encouraging low-carbon innovations among others. The budgets of Member States receive the majority

[31] **Carbon leakage** refers to the phenomenon where businesses move their operations to nations with laxer climate regulations and compliance costs.

of the proceeds from the auctioning of allowances under the EU ETS. Member states were directed to allocate a minimum of 50% of their money generated until mid-2023 towards energy and climate-related initiatives. All proceeds received after that date must be used by the member states to further their energy and climate goals. To make up for the higher electricity costs they incur as a result of the EU ETS, Member States may utilise the money they get from the EU ETS to fund state assistance to specific businesses that rely heavily on electricity. A scheme's total expenditure can't be more than 25% of a Member State's ETS earnings. The Innovation and Modernisation Funds, two funds created in Phase IV are financed in part by auctioning off a portion of EU ETS credits.

  - **Innovation fund.** This fund promotes the development of renewable energy, energy storage, and the use and storage of carbon capture. It also supports the practical demonstration of novel low-carbon technologies and industrial solutions to decarbonise Europe's energy-intensive industries.
  - **Modernisation Fund.** This fund encourages investments in Member States with lower incomes to enhance energy efficiency, modernise energy systems, and facilitate a fair and equitable transition to climate neutrality. It is one of the EU ETS's solidarity measures, addressing the disparities in Member States' decarbonisation journeys from various starting points.

- **Banking & borrowing.** Banking of allowances has been allowed since the beginning of Phase II in 2008, while borrowing is not allowed under EU ETS.
- **Carbon offset.** Provisions for carbon offset under EU ETS has evolved over the phases:
  - **Phase I.** The use of the Clean Development Mechanism (CDM) and Joint Implementation (JI) credits was allowed without limitation under Phase I.
  - **Phase II & III.** Under Phase II and Phase III, carbon offset was allowed within certain limits (both qualitative and quantitative).
  - **Phase IV.** Offset of carbon credit is not allowed under Phase IV.
- **Market instruments.** EU ETS carbon allowances are classified as financial instruments.
  - **Primary market.** Every day, EEX holds uniform price auctions with single rounds and sealed bids. Germany conducts national auctions through the EEX and has chosen not to use the common auctioning platform. Although Poland has also chosen to withdraw, it is still active in the shared auction at the EEX for the time being.
  - **Secondary market.** Trading occurs over the counter as well as on exchanges for spot, futures, options, and forward contracts. Futures are traded on ICE, ENDEX, and Nasdaq in addition to the EEX.

Appendix C Proposed EU ETS 2

The EU ETS 2 is a proposed scheme under the European Commission's "Fit for 55" package. Significant changes to the EU ETS framework were included in the package, along with a suggestion to expand carbon trading to additional industries. Details regarding the proposed EU ETS 2 are sourced from ICAP (2024*b*).

- **Year of implementation.** The EU ETS 2 is scheduled to go completely operational in 2027 (or, in the event of abnormally high energy costs, in 2028). The monitoring and reporting of emissions from the covered sectors will begin in 2025 as an interim measure.
- **Sectors covered.** The proposed EU ETS 2 will cover transport and buildings. Emissions from fuels used in road transport, buildings, and other sectors (mostly small industries not covered by the current EU ETS) will be subject to this new, distinct emissions trading scheme, EU ETS 2.
- **Market model.** The proposed EU ETS 2 will follow a *Cap-and-trade* model. Since it would cover emissions upstream, fuel suppliers rather than end users will be responsible for surrendering allowances. By 2030, emissions are expected to have decreased by 42% from 2005 levels owing to the EU ETS 2 cap.
- **Allowance allocation.** The EU ETS 2 allowances will only be sold by auction. A portion of EU ETS 2 allowances will be donated to the Social Climate Fund through auction. Based on the average distribution of emissions in the covered sectors from 2016 to 2018, all remaining EU ETS allowances will be distributed among Member States for auction. To enable a seamless system launch, an extra auction volume will be front-loaded in 2027.
- **Market Stability Reserve (MSR).** To maintain market liquidity, 30% of allowances will be put up for auction during 2027. 600 million carbon allowances will be initially provided to the MSR during the launch of this ETS.
  - **Triggers.** To address excessive price increases, additional allowances may be released from the EU ETS 2's MSR during the first three years of the programme if the price of allowances reaches certain thresholds. Under certain guidelines and restrictions, allowances may also be released from this reserve if their cost rises too quickly.
- **Revenue usage.** National Social Climate Plans will include a compilation of all investments and initiatives. The EU ETS's 50 million allowances as well as the EU ETS 2's allowance auction will be combined into the Social Climate Fund. Member States will face a 25% mandatory contribution to their Social Climate Plans. It will be mandatory for Member States to allocate their residual EU ETS 2 earnings towards social and climate action initiatives.

Appendix D Descriptive statistics

Table D.1 depicts the summary statistics of verified emissions in EU ETS, the yearly GDP growth rate in EU, the yearly inflation rate in EU, and the yearly average wholesale energy prices in EU from 2005 to 2023. Every series demonstrates statistically significant deviations from normality and heteroskedasticity.

Figure D.1 illustrates the EU ETS spot prices daily log returns from March 09, 2005, to December 31, 2023. Significant deviations are observed during the 2008 financial crisis in Phase II (as discussed in Section 3).

Figure D.2 depicts the year-wise EU ETS verified emissions from 2005 to 2023. Figure D.3 depicts the yearly GDP growth and inflation rate from 2005-2023 in EU. Figure D.4 shows the wholesale energy prices in EU from 2005-2023.

Statistics	**Emissions**	**GDP Growth**	**Inflation**	**Energy prices**
Mean	15631	1.32	2.11	101.98
Variance	48148	7.05	4.51	302.70
Skewness	-0.65	-1.18	2.05	0.77
Exc. Kurtosis	-0.20	1.54	4.72	0.68
JB	1.39 **	6.25**	30.99**	2.24**
ARCH	13.17**	2.43**	1.05**	12.30**

Table D.1: Summary statistics of various datasets used in this study. Statistical significance at 5% is denoted with **. All values are rounded off to two decimal places.

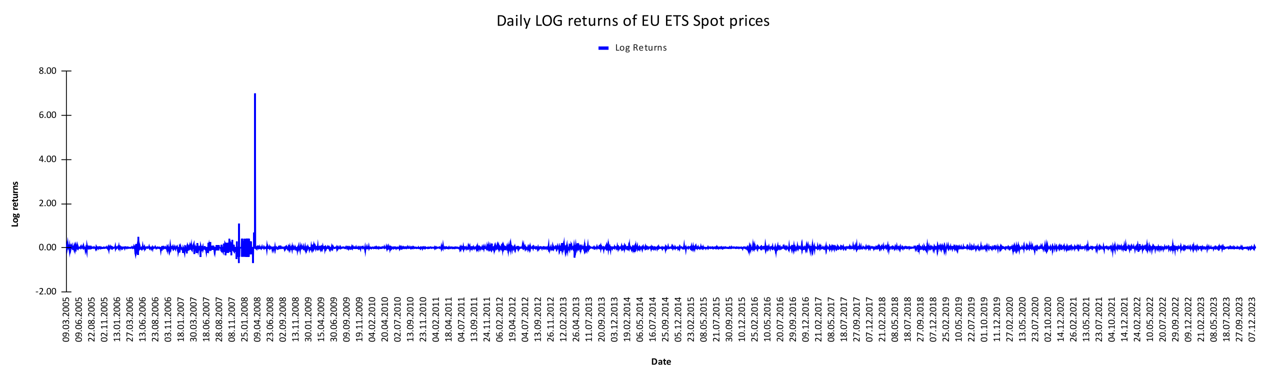

Figure D.1: EU ETS spot prices daily log returns from March 09, 2005, to December 31, 2023. Source: Self-compiled using data from EEX [32].

[32]https://www.eex.com/en/markets/environmental-markets/eu-ets-spot-futures-options
[33]https://www.eea.europa.eu/data-and-maps/dashboards/emissions-trading-viewer-1
[34]https://ec.europa.eu/eurostat/statistics-explained/index.php?title=National_accounts_and_GDP
[35]https://transparency.entsoe.eu/dashboard/show

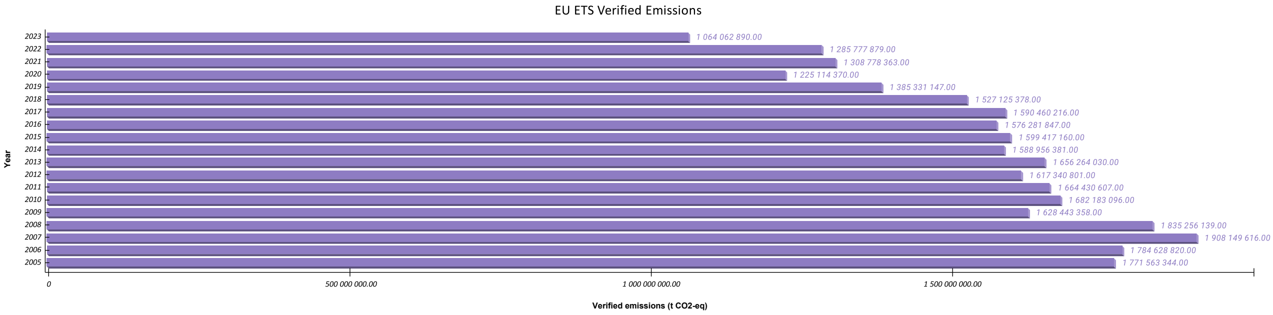

Figure D.2: Year-wise EU ETS verified emissions from 2005 to 2023. Source: Self-compiled using data from EEA [33].

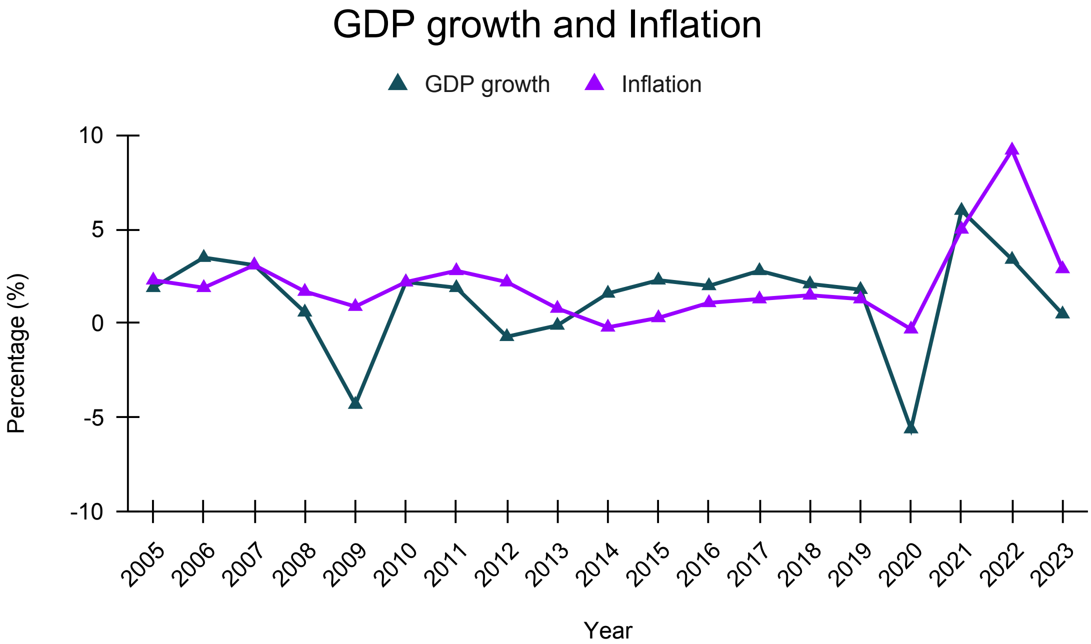

Figure D.3: EU GDP growth & inflation rate from 2005-2023. Source: Self-compiled using data from Eurostat [34].

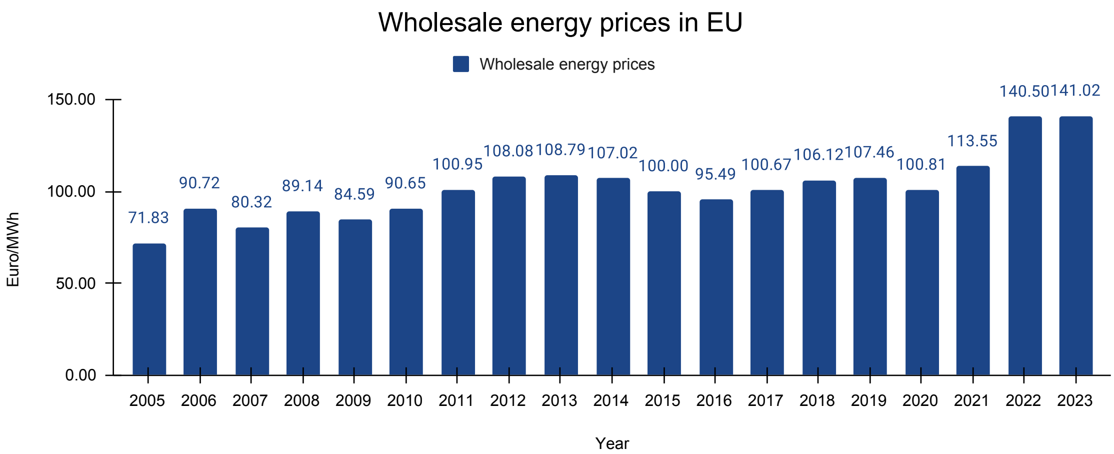

Figure D.4: Wholesale energy prices in EU from 2005-2023. Source: Self-compiled using data from Entsoe [35].

Appendix E OLS analysis

To analyse the impact of carbon prices on verified emissions while considering related factors like wholesale energy prices, GDP growth rate and inflation rates as controlled variables the study employs an OLS regression model (Equation 15). Including wholesale energy prices as a control variable in regression models enhances the validity of analyses, as they are a critical economic indicator that may influence carbon prices (Convery and Redmond, 2007).

Model specifications. For a dependent variable Verified Emissions (VE), independent variable ETS Prices (P), controlled variables GDP growth rate (GDP), inflation rate (IR), and, wholesale energy prices (WEP), the OLS equation is given by:

$$VE = \beta_0 + \beta_1 \cdot P + \beta_2 \cdot (P \times GDP) + \beta_3 \cdot (P \times IR) + \beta_4 \cdot (P \times WEP) + \epsilon_t \tag{15}$$

Here, β_0 is the intercept while the third, fourth and fifth terms are interaction terms capturing the collective effect of controlled variables and EU ETS prices with the emissions.

Findings. Table E.1 depicts the detailed results obtained by the OLS regression analysis. Figure E.1 depicts the regression plots for the cumulative EU ETS price series while Figure E.2 includes the phase-wise regression plots. For the cumulative price series, the model indicates a strong overall fit and high statistical significance. A positive coefficient for EU ETS indicates that with a rise in the spot prices of ETS, there is a rise in emissions which defeats the very purpose behind launching of EU ETS. However, phase-wise segregation draws a better and more desirable picture. The regression coefficient for ETS spot prices shows a diminishing trend as we progress through each phase signifying the efficiency of the policy changes and amendments during each phase. For Phase III, it attains the desirable negative coefficient for the first time. Phase IV depicts a rise again, but given the fact that there are numerous policy changes aimed at reducing the emissions under the EU ETS happening as we speak, it is expected to attain a more desirable effect in the upcoming future. For GDP growth's interaction with EU ETS and their impact on verified emissions, most phases depict a positive coefficient suggesting that growth in GDP is associated with a rise in emissions is expected. The statistically insignificant negative coefficient during Phase II can be attributed to the 2008 financial crisis.

For the interaction between wholesale energy prices and the EU ETS prices and their collective impact on the verified emissions, the findings suggest an inverse relationship for the cumulative dataset. This suggests that higher energy prices likely lead to a fall in emissions. Interestingly, the statistically significant positive coefficient during Phase I indicates higher energy prices are associated with higher levels of emissions. However, given it was during the pilot phase of the EU ETS, the carbon prices were yet to be stabilised.

Particulars		Coefficient	SE	t-values	p-values
Cummulative	**Constant**	2.629***	2.030	12.965	0.000
	EU ETS	9.087	1.500	0.061	0.953
R^2 **= 0.710**	**GDP growth**	1.910	1.380	1.380	0.189
Adjusted R^2 **= 0.627**	**Inflation**	4.772	1.970	0.242	0.812
F-stat. = 8.559	**Wholesale energy**	-1.080***	2.120	-5.092	0.000
Phase I	**Constant**	4.764	3.677	1.295	0.210
	EU ETS	5.232	4.038	0.042	0.850
R^2 **= 0.550**	**GDP growth**	1.663	1.284	1.259	0.154
Adjusted R^2 **= 0.512**	**Inflation**	2.453	1.893	0.217	0.752
F-stat. = 4.926	**Wholesale energy**	2.050***	1.582	2.650	0.000
Phase II	**Constant**	1.907***	1.473	1.574	0.001
	EU ETS	2.729	2.106	0.053	0.750
R^2 **= 0.520**	**GDP growth**	-5.018	-3.875	1.520	0.154
Adjusted R^2 **= 0.500**	**Inflation**	7.968	6.150	1.291	0.200
F-stat. = 3.450	**Wholesale energy**	-4.328***	-3.341	-1.600	0.000
Phase III	**Constant**	1.198	1.120	1.065	0.365
	EU ETS	-7.238	1.180	-0.612	0.584
R^2 **= 0.633**	**GDP growth**	4.684	2.300	2.036	0.135
Adjusted R^2 **= 0.143**	**Inflation**	-4.913	8.960	-0.548	0.622
F-stat. = 1.292	**Wholesale energy**	3.194	1.090	0.292	0.789
Phase IV	**Constant**	3.504***	2.706	1.482	0.003
	EU ETS	1.646	1.271	0.068	0.740
R^2 **= 0.681**	**GDP growth**	7.797*	6.021	0.192	0.090
Adjusted R^2 **= 0.418**	**Inflation**	-2.513	-1.940	-0.281	0.744
F-stat. = 3.900	**Wholesale energy**	7.255***	5.601	-3.210	0.000

Table E.1: Test statistics including the coefficients, standard error, t-values and p-values obtained from OLS regression analysis for each time series. Significant positive values (highlighted in green) indicate a direct relationship and significant negative values (highlighted in red) indicate an inverse relationship. The standard errors show the calculated coefficients' precision, with lower standard errors denoting higher precision estimations. Similarly, higher R^2 suggests a better fit for the model. All values are rounded off to three decimal places. Statistical significance at 10% is denoted with *, at 5% is denoted with ** and at 1% is denoted with ***.

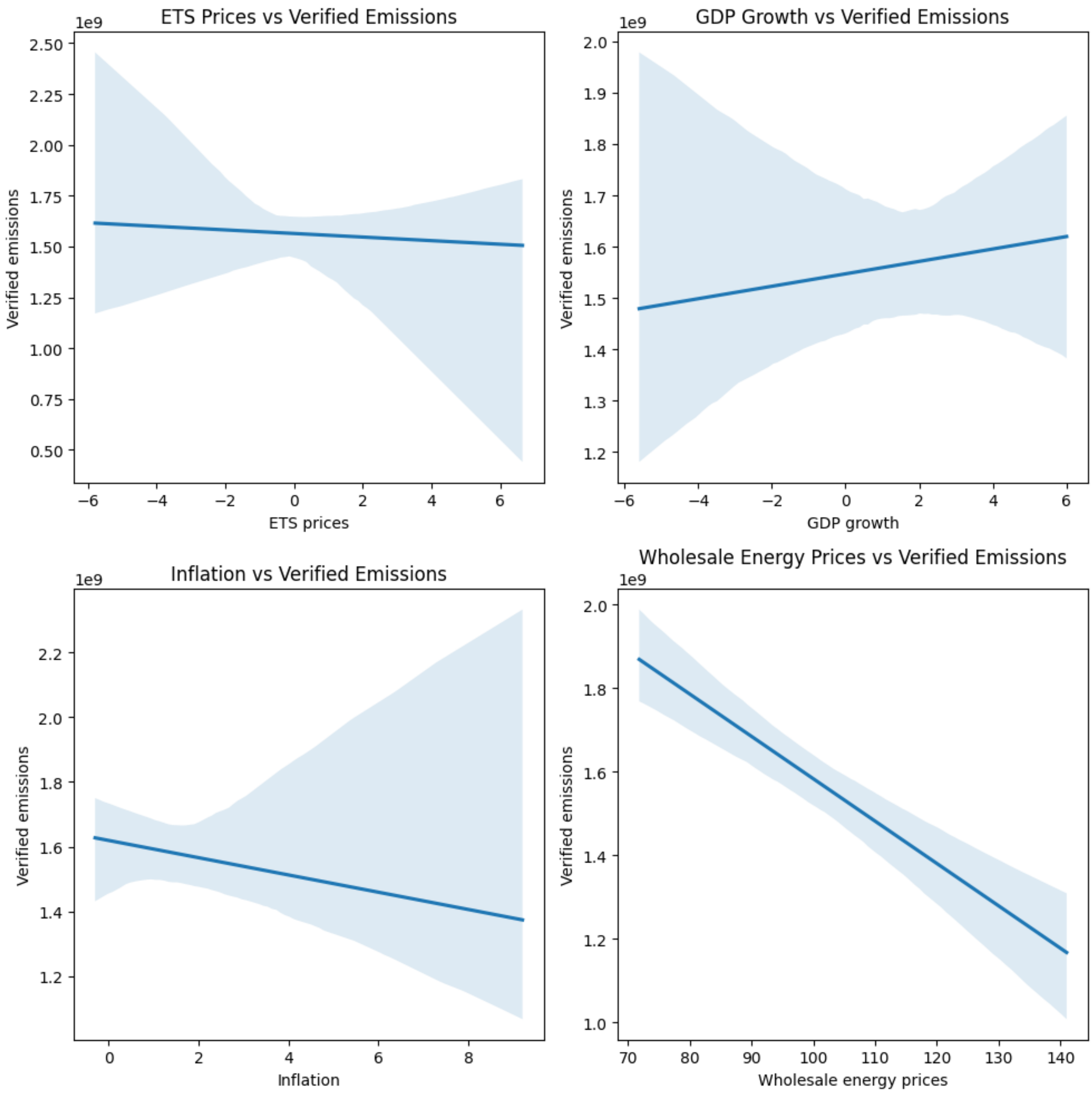

Figure E.1: OLS regression plots for the cumulative EU ETS price series with verified emissions (top-left), the interaction term between EU ETS prices and GDP growth with verified emissions (top-right), the interaction term between EU ETS prices and inflation rate with verified emissions (bottom-left), and the interaction term between EU ETS prices and wholesale energy prices with verified emissions (bottom-right). A narrow confidence interval (like, the bottom-right) indicates a more consistent relationship while a broad confidence interval (like, the top-right) indicates a less consistent relationship. Similarly, a positive slope depicts a positive relationship (like, top-right) and a negative slope depicts an inverse relationship (like, bottom-left). Source: Self-compiled.

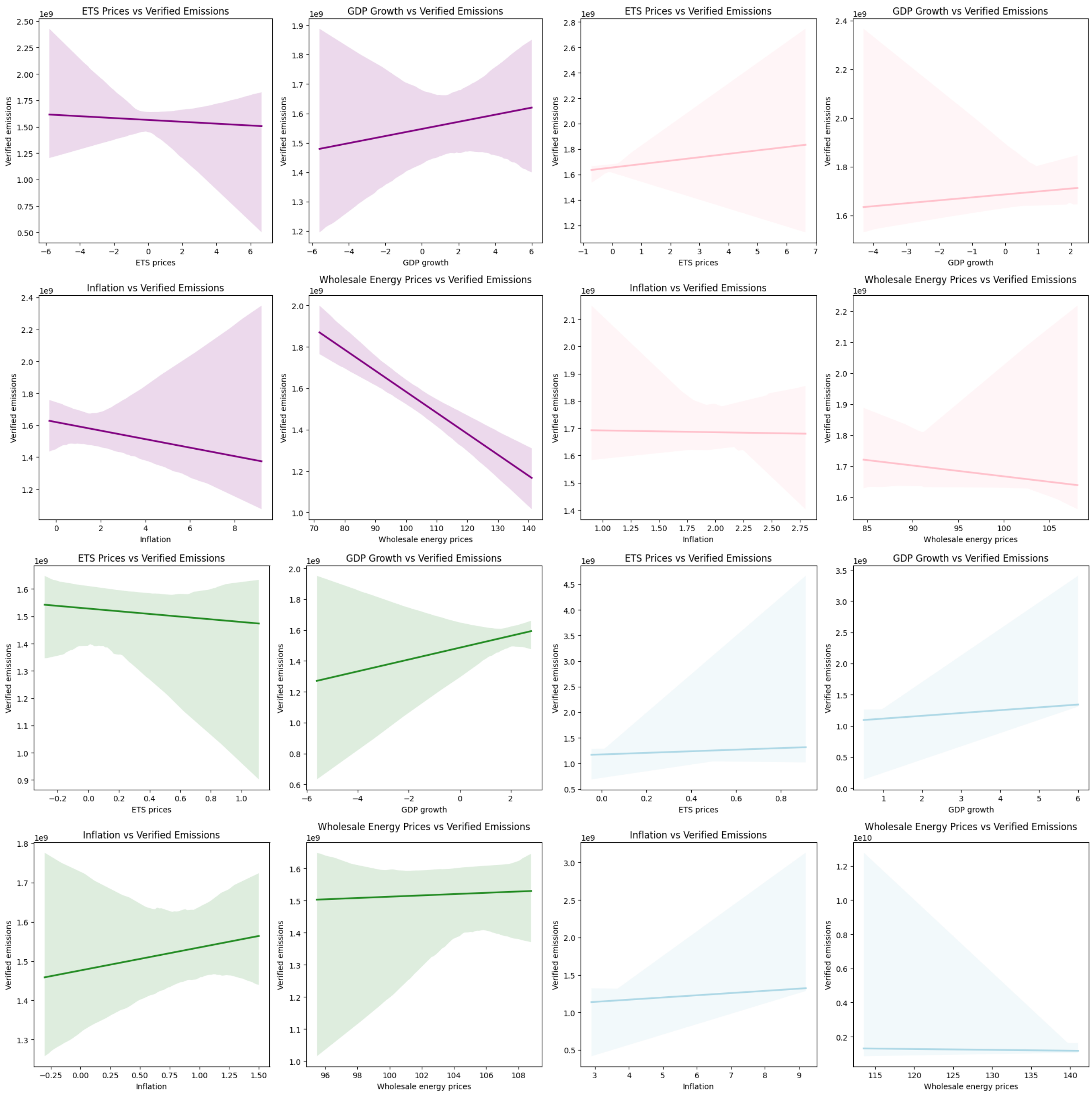

Figure E.2: Phase-wise OLS regression plots. Top-left: Phase I (purple), Top-right: Phase II (pink), Bottom-left: Phase III (pink), and Bottom-right: Phase IV (indigo). For each phase, plot for EU ETS price series with verified emissions (top-left), the interaction term between EU ETS prices and GDP growth with verified emissions (top-right), the interaction term between EU ETS prices and inflation rate with verified emissions (bottom-left), and the interaction term between EU ETS prices and wholesale energy prices with verified emissions (bottom-right). A narrow confidence interval indicates a more consistent relationship while a broad confidence interval indicates a less consistent relationship. Similarly, a positive slope depicts a positive relationship and a negative slope depicts an inverse relationship. Source: Self-compiled.

Appendix F SVAR results

Table F.1 includes the detailed findings including the test statistics, and corresponding standard errors, t-statistics and p-values obtained by the SVAR analysis (Section 5.3).

Particulars		Lag 1				
		Emissn.	**ETS**	**GDP**	**Inflation**	**Energy**
ETS	**Coefficient**	0.000	-0.069	0.214	0.759	-0.351**
	SE	0.000	0.406	0.457	0.538	0.161
	T-stat.	-0.301	-0.171	0.468	1.410	-2.176
	P-value	0.763	0.864	0.640	0.158	0.030
GDP	**Coefficient**	0.000	-0.279	-1.731**	0.317	0.383
	SE	0.000	0.633	0.712	0.839	0.252
	T-stat.	1.987	-0.440	-2.431	0.378	1.520
	P-value	0.047	0.660	0.015	0.706	0.128
Inflation	**Coefficient**	0.000	-0.213	-0.709*	0.990**	0.098
	SE	0.000	0.352	0.395	0.466	0.140
	T-stat.	-0.095	-0.606	-1.794	2.125	0.705
	P-value	0.924	0.545	0.073	0.034	0.481
Energy	**Coefficient**	0.000	-0.698	-3.269*	5.440***	0.946
	SE	0.000	1.597	1.796	2.115	0.635
	T-stat.	0.239	-0.437	-1.821	2.571	1.490
	P-value	0.811	0.662	0.069	0.010	0.136

(a) Lag 1 test statistics.

Particulars		Lag 2				
		Emissn.	**ETS**	**GDP**	**Inflation**	**Energy**
ETS	**Coefficient**	0.000	-0.260	-0.125	0.850	0.343***
	SE	0.000	0.400	0.232	1.461	0.107
	T-stat.	0.102	-0.654	-0.540	0.582	3.213
	P-value	0.919	0.513	0.589	0.560	0.001
GDP	**Coefficient**	0.000	0.155	0.563	-3.613	-0.328**
	SE	0.000	0.620	0.362	2.276	0.166
	T-stat.	-1.361	0.249	1.557	-1.587	-1.974
	P-value	0.173	0.803	0.119	0.112	0.048
Inflation	**Coefficient**	0.000	-0.316	-0.037	-1.930	-0.201**
	SE	0.000	0.345	0.201	1.264	0.092
	T-stat.	-0.360	-0.917	-0.183	-1.526	-2.175
	P-value	0.719	0.359	0.855	0.127	0.030
Energy	**Coefficient**	0.000	-1.374	-0.580	-7.592	-0.185
	SE	0.000	1.564	0.912	5.740	0.420
	T-stat.	-0.320	-0.878	-0.636	-1.323	-0.441
	P-value	0.749	0.380	0.525	0.186	0.659

(b) Lag 2 test statistics.

Table F.1: Test statistics including the coefficients, standard errors, t-statistics, and p-values obtained from the SVAR for Lag 1 (Table F.1a), and for Lag 2 (Table F.1b). Significant positive values (highlighted in green) indicate a direct relationship and significant negative values (highlighted in red) indicate an inverse relationship. The standard errors show the calculated coefficients' precision, with lower standard errors denoting higher precision estimations. All values are rounded off to three decimal places. Statistical significance at 10% is denoted with *, at 5% is denoted with ** and at 1% is denoted with ***.

Appendix G Additional unit root tests

ADF test. The Augmented Dickey-Fuller tests (Dickey and Fuller, 1979, 1981) determine the presence of any permanent or temporary shocks in any time series employing Equation 16 checking the null hypothesis ($\mathcal{H}_0$) of $\gamma = 0$ against the alternative hypothesis ($\mathcal{H}_a$) of $\gamma < 0$.

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{k} \delta_i y_{t-i} + \epsilon_t \tag{16}$$

Here, Δ depicts the first difference, t shows the time trend variable, k depicts the lags incorporated into the model, and ϵ_t depicts the auto-correlations from the residuals. k is determined by minimising the Bayesian Information Criterion (BIC) (Schwarz, 1978).

PP test. Because the Phillips-Perron test (Phillips and Perron, 1988) is non-parametric concerning nuisance parameters, it can handle data that is distributed heterogeneously. Perron (1989) identifies that the ADF tests are biased for non-rejection of the null hypothesis ($\mathcal{H}_0$) of a unit root if structural breaks are present. The alternative proposed by Perron (1989), depicted in Equation 17, provides for a possibility of a structural break under both hypotheses.

$$\Delta y_t = \alpha + \alpha_1 ID_t + \lambda CD_t + \beta_0 TD_t + \beta_1 t + \gamma y_{t-1} + \sum_{i=1}^{k} \delta_i y_{t-i} + \epsilon_t \tag{17}$$

Here, the intercept dummy, ID_t, depicts shifts in the series level, TD_t is the trend regression coefficient dummy, and CD is the crash dummy.

LS test. The Lee-Strazicich test (Lee and Strazicich, 2001, 2013) identifies existence of structural break internally. The LS Lagrange Multiplier unit root test is depicted in Equation 17.

Series	ADF		PP		LS	
	Level series	Log-diff. series	Level series	Log-diff. series	Level series	Log-diff. series
Cumulative	-2.34*	-24.79***	-2.53*	-71.25***	-2.51**	-71.29***
Phase I	2.21	-31.51***	1.97	-31.51***	-0.81	-2.21*
Phase II	-4.71***	-36.19***	-4.71***	-36.19***	-2.63*	-4.71***
Phase III	-0.42	-34.50***	-0.42	-44.57***	0.09	-0.42*
Phase IV	-2.80**	-29.04***	-2.80**	-29.04***	-2.54**	-2.80***

Table G.1: The ADF, PP, and LS tests results for the level and the log-differenced series of EU ETS spot prices. Statistically significant negative values for each test signify an absence of unit root. Cases where the presence of a unit root could not be rejected are highlighted in red. All values are rounded off to two decimal places. Statistical significance at 10% is denoted with *, at 5% is denoted with ** and at 1% is denoted with ***.

Findings. Table G.1 includes the test statistics of the ADF, the PP and the LS tests for both the level series and the log-differenced series. For the cumulative series, all tests suggest stationarity at conventional significance levels for both the level series and the log-differenced. In the case of Phase I and Phase III, all tests confirm the presence of a unit root for the level series and reject the presence of a unit root in the case of the log-differenced series. For Phase II and Phase IV, similar to the cumulative series, every test points to stationarity for both the level series and the log-differenced at conventional statistical significance levels.

Appendix H Preliminary findings for media coverage's impact on carbon prices

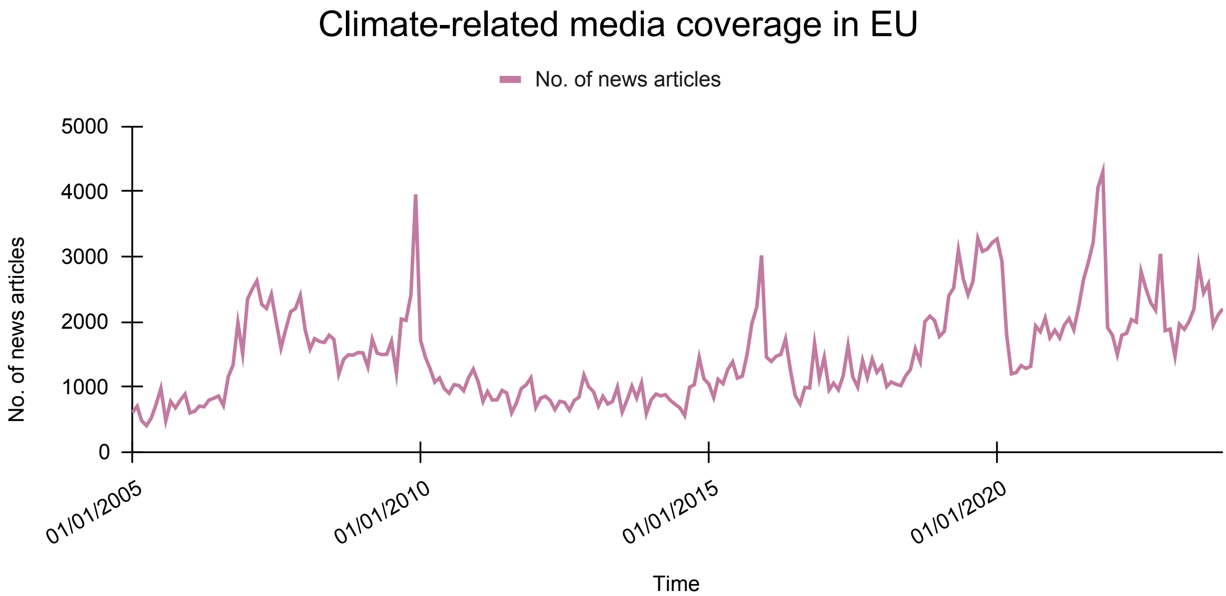

Figure H.1: Newspaper coverage of climate change in EU, 2005-2023. Source: Self-compiled using data from MeCCO [36].

The study incorporated the model extended by Song and Liu (2024) for analysing the impact of media coverage of issues like climate change and carbon pricing within EU on the EU ETS prices. Data for newspaper coverage of climate in EU from 33 leading media houses (Figure H.1) is sourced from MeCCO (Boykoff et al., 2024). To link the EU ETS spot prices to the autoregressive equation of the media coverage, a binary VAR model is employed. It makes it possible to predict both variables in a single system, allowing the variables to be self-consistent with one another.

$$Y_{1t} = \beta_{10} + \sum_{i=1}^{p} \beta_{1i} Y_{1,t-i} + \sum_{i=1}^{p} \gamma_{1i} Y_{2,t-i} + \epsilon_{1i} \tag{18}$$

$$Y_{2t} = \beta_{20} + \sum_{i=1}^{p} \beta_{2i} Y_{1,t-i} + \sum_{i=1}^{p} \gamma_{2i} Y_{2,t-i} + \epsilon_{2i} \tag{19}$$

Equation 18 and Equation 19 depict the model equations employed for the two concerned variables of EU ETS spot prices and media coverage respectively.

Preceding the test, data sets are converted using the differencing approach to confirm the validity of the VAR model, as the presence of unit roots indicates non-stationarity in the data sets (Table 8).

[36] https://scholar.colorado.edu/concern/datasets/2v23vw19t

Particulars		Lag 1		Lag 2	
		ETS	Media Coverage	ETS	Media Coverage
ETS	Coefficient	0.358	-0.001	-0.428	0.001
	SE	0.656	0.000	0.552	0.000
	T-stat.	0.545	-0.139	-0.775	1.328
	P-value	0.586	0.890	0.438	0.184
Media Coverage	Coefficient	-78.920	0.110	-118.710***	1.385***
	SE	371.497	0.476	312.672	0.435
	T-stat.	-0.212	0.231	-3.795	3.181
	P-value	0.832	0.817	0.000	0.001

(a) Lag 1 and Lag 2 test statistics.

Particulars		Lag 3		Lag 4	
		ETS	Media Coverage	ETS	Media Coverage
ETS	Coefficient	0.249	0.001***	0.307	0.000
	SE	0.536	0.000	0.871	0.001
	T-stat.	0.465	2.984	0.352	0.175
	P-value	0.642	0.003	0.724	0.861
Media Coverage	Coefficient	-771.303**	0.138	934.407*	1.094*
	SE	303.789	0.216	493.458	0.584
	T-stat.	-2.539	0.640	1.894	1.872
	P-value	0.011	0.522	0.058	0.061

(b) Lag 3 and Lag 4 test statistics.

Table H.1: Test statistics including the coefficients, standard errors, t-statistics, and p-values obtained from the VAR analysis for Lag 1 and Lag 2 (Table H.1a), and for Lag 3 and Lag 4 (Table H.1b) between EU ETS prices and media coverage of climate change and carbon pricing news. Significant positive values (highlighted in green) indicate a direct relationship and significant negative values (highlighted in red) indicate an inverse relationship. The standard errors show the calculated coefficients' precision, with lower standard errors denoting higher precision estimations. All values are rounded off to three decimal places. Statistical significance at 10% is denoted with *, at 5% is denoted with ** and at 1% is denoted with ***.

Table H.1 includes the detailed test statistics obtained from VAR analysis between EU ETS prices and media coverage of climate change and carbon pricing news across four lags while Figure H.2 depicts the impulse response plots. Statistically significant relationships are observed in the later years (Lag 2 to Lag 4). Media coverage has a significant impact on ETS prices, with a negative influence in Lag 2 and Lag 3 and a positive influence in Lag 4. Significant coefficients indicate media coverage shocks are driving short-term fluctuations in EU ETS spot prices. There is an immediate negative influence on EU ETS spot prices from media coverage of climate change and carbon pricing problems. A negative coefficient (Table H.1) indicates that the prices in the EU ETS market are first suppressed by increased media attention (Lag 2 and Lag 3).

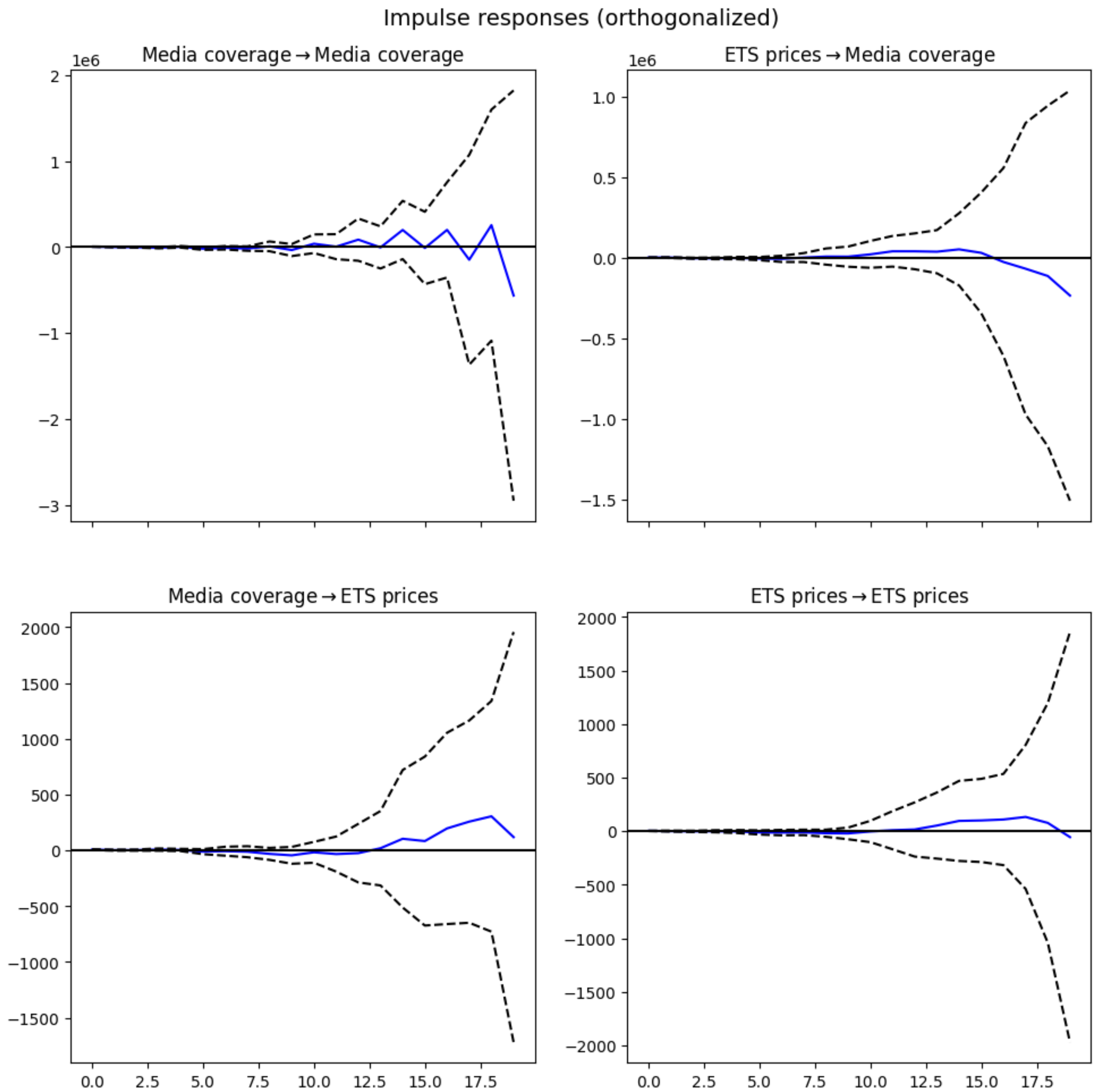

Figure H.2: Orthogonalised impulse response function plots depicting the bidirectional temporal relationship and the persistence of shocks between the EU ETS prices and climate change and carbon pricing related news in EU from 2005-2023. The top-left plot depicts the response of media coverage to its shocks, the top-right plot indicates the effect of a shock in ETS prices on subsequent media coverage, the bottom-left plot illustrates the impact of a shock in media coverage on ETS prices, and the bottom-right plot represents the self-response of ETS prices to external shocks. The estimated reaction functions, which show how each variable responds over time to a shock in another variable, are represented by the blue lines. Black lines show the confidence intervals surrounding the impulse response functions. The range within which the true impulse response is anticipated to fall, with a 95% confidence level, is displayed by the regions between the dashed lines. When the blue line drops below the horizontal zero line, it indicates a negative response (like, top-left). Source: Self-compiled.