ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis

Master of Economics and Business Economics - Financial Economics

“The effect of fundamental demand drivers on EUA price in phase IV”

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Date final version: 1/11/2023

Abstract

This study investigates the determinants of European Union Allowance (EUA) prices during Phase IV of the EU emissions trading system. The analysis examines the impact of electricity, gas, coal prices along with industry variable and renewable energy output. The findings indicate significant influence of electricity and gas prices, with non-significant effect of coal and renewable energy output. Time-varying effects are considered to model the pre, during and post energy crisis of 2022, marked by high gas price due to the Russia-Ukraine conflict. To ensure robustness, Instrumental Variables (IV) and Vector Autoregressive (VAR) model are employed. Overall, this research unveils the varying impact of demand fundamentals on EUA price in Phase IV.

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1 Introduction

Compliance markets aim to push the agenda of energy transition by making the allocation of carbon emissions to economic activities more efficient. In most jurisdictions around the world, carbon allowances can be traded in Emission Trading Schemes (ETS) where excess emissions that are initially allocated to firms can be traded to other firms. European Union ETS (EU ETS) is the most liquid and advanced ETS system in the world accounting for about 90% of the entire global carbon credits turnover (MSCI, 2022). It has continued to inspire the development of emissions trading in other countries and regions. For instance, European Commission (2018) supported Chinese Ministry of Ecology and Environment with technical assistance project focused on building emissions trading system in China. As the number of emissions trading systems around the world is increasing, EU ETS carbon market will be set as the standard for other compliance markets in the world for the years to come.

Building a fundamental understanding on the pricing of European Union Allowance (EUA) that is traded in EU ETS is essential for different stakeholders. Emitters companies such as utilities and energy-intensive industry, are interested to know the dynamics of carbon pricing as it is directly related to their cost of doing business. Gaining deep understanding of the main drivers of carbon price is essential for effective risk management and hedging strategies to reduce cost (Batten et al., 2021). Policy makers must also be aware of the underlying factors that drive the price of carbon to effectively reduce emissions while at the same time minimizing the economic burden to emitters. For instance, within the EU ETS market, policy makers assess industries risk of losing competitiveness by evaluating how carbon credits affect their production costs and their trade exposure (IEA, 2023). Long-term investors and short-term traders are also interested to understand the price drivers of EUA to gain returns from capital appreciation (Swinkels & Yang, 2022).

As an evolving market since its launch in 2005, EUA price drivers had continued to change over time and went through periods of highs and lows. The price moves have been linked to four distinct phases of the EU ETS scheme where industry and policy makers adjusted the market mechanism to maximize the impact of emission reduction. Historically, the fear of an oversupply of allowances and uncertainty of demand and supply ratio caused a sharp drop in prices in Phase II and III as market participants adjust their expectation in response to policy changes or economic uncertainty. The increasing Linear Reduction Factor (LRF) to 2.2% and the doubling rate of MSR in phase IV stabilizes the supply of EUA, which makes demand-side fundamentals drivers become much more relevant (Cornago, 2022). As such, the key empirical question focuses on how the demand drivers affect the dynamics of carbon prices in phase IV. This paper contributes to the broader academic literatures by answering this question and adding to the existing literatures that explored the fundamental drivers of EUA price in phase I (Alberola et al., 2008), phase II (Chevallier 2011; Aaatola et al., 2013) and phase III (Batten et al.,2021; Eslahi et al., 2022). To the best of my knowledge, this paper will be the first one to provide empirical evidence of fundamental demand drivers of EUA price in phase IV.

This paper employs Ordinary Least Square (OLS) regression to assess the effect of demand fundamentals consisting of energy price (electricity, gas and coal), industry variable and renewable energy output. A survey (Pahle & Sitarz, 2022) found that the power sector will continue to be the primary driver of EUA price, while industrial sector starts to gain more important role. The EU ETS system has been revised in Phase IV to only focus in giving free allowance to sectors that have the highest risk of relocating their production outside of the EU. In alignment with this new policy changes, this paper introduces industry variables as the potential drivers of EUA price in addition to traditional factors such as energy prices. This study will be the first few papers that explores industry variables as fundamental drivers of carbon price. Furthermore, following the aftermath of Russia's invasion in February 2022, the global energy landscape especially in Europe has changed dramatically. The energy security crisis that emerged in Europe act as additional push for EU to accelerate the transition towards climate neutral economy and expand renewable power sources (Soren, 2023). Additionally, the release of REPowerEU plan in May 2022, which aims to completely phase out EU's reliance on fossil fuel by 2027 reaffirmed European Commissions (2023) commitment in accelerating the transition agenda. This study acknowledges this trend by analyzing the impact of renewable energy output on EUA price and becomes the first few paper to do so. Furthermore, to account for high-energy price environment in 2022, this study explores the potential of time-varying effects of the explanatory variables by conducting separate regression for sub-periods of before, during and post energy crisis. To ensure the reliability and robustness of the results while addressing the simultaneous bias between electricity price and EUA price, this study employs two econometrics model: Two-Stage least squares (TSLS) regression to calculate Instrumental Variable (IV) estimate and Vector Autoregressive (VAR) model. Overall, this paper will answer the following key research question:

"How fundamental demand drivers affect EUA price in phase IV?"

2 Literature Review

The literature review is structured in the following way: the different types of carbon credit and jurisdictions are introduced. Then, the evolution of EU ETS from phase I, II, III and IV will be discussed. This is followed by the analysis of the supply and demand drivers of EUA price.

2.1 Carbon Credit

Climate change driven by excessive carbon emissions has become the ultimate concern among today's society. Under the 2015 Paris Agreement, nearly 200 countries have pledged to support the goal of limiting the rise in average temperatures to 2.0 degree and ideally reaching 1.5 degree target (UNFCC, 2015). This requires the reduction of global greenhouse-gas emissions by 50 percent by 2030 while reach net zero emission target by 2050. In the transition towards a low-carbon sustainable economy, enterprises play a crucial role and with the increase of regulation, more firms are aligning themselves with this agenda. This can be seen with the one-third of the world's largest companies are now committed to net zero target, yet many of them could not fully eliminate their emissions from their own operations due to the nature of their business (Accenture, 2022). Taking the example of utility firms which core business still heavily relies on the production of fossil fuels, the challenge is especially tough to achieve net-zero emissions by 2050. Other companies may also have trouble reducing emissions using today's technologies even though the costs of those technologies might go down in time. For such firms, the only solution is to use carbon credits to offset emissions as they cannot get rid of it by any other means. According to the McKinsey (2021), the demand for carbon credits could increase by a factor of 15 by 2030 and up to 100 by 2050. Overall, the market for carbon credits could be worth of $50 billion in 2030.

Carbon credits attempt to reduce the global carbon footprint with the notion that market mechanisms ensure that society most efficiently allocates emissions production. Economists have suggested to reduce negative externality of climate change driven by greenhouse gas emissions by putting a price on emission. There are three different types of carbon prices: carbon tax, cap-and-trade systems and carbon offsets. A carbon tax is an additional tax levied on goods that generate carbon emissions thus increasing the price for consumers. This incentivized firms to shift towards alternatives with lower or no carbon emissions to gain competitive advantage in pricing. Andersson (2019) conducted a quasi-experimental study to find causal effect of carbon taxes on emissions and found that the carbon tax levied in Sweden led to an increase in innovation in renewable energy and the reduction of carbon emissions by 11 percent. Countries can also set up cap-and-trade systems where they limit the allowance of greenhouse gas emissions and allow firms to trade the excess emissions in the compliance market. Currently, there are four primary markets of Emission Trading System: European ETS, the United Kingdom ETS, the California Carbon Allowance and the Regional Greenhouse Gas Initiative allowance. There is also a new upcoming compliance market such as Korean and Indonesian ETS. In terms of the scope of emissions coverage, European Union ETS is currently the biggest market covering around 7.3% of global carbon emissions in 2021 and 45% of the EU's greenhouse gas emissions (European Commission, 2022). EU ETS is the biggest cap-and-trade trading system in the world. It limits emissions from 11,000 installations and was originally put in place to regulate CO2 emissions from heat generation, energy intensive industry and aviation sectors of the European Economic Area (EEA). The scope of emissions caught by EU ETS scheme will expand gradually between 2024 and 2026 to cover emissions of nitrous oxides and methane while at the same time emissions for the shipping industry (Max, 2022).

Since 2005, once firms reported their CO2 emissions each year, Member States allocate allowance in which some are provided for free. One allowance entitles the holder to emit one tonne of CO2 from the previous year and for those who do not have enough allowances to cover their emissions, they have to buy the difference at auction market. European Union sets a decreasing cap per sector thus the amount of allotted allowances is lowered every year. The idea is to encourage firms cutting their CO2 emissions and become green as it becomes cheaper to pollute less than to buy the allowances. A minimum fine of 100 euros is imposed once the firms emit CO2 without offsetting an allowance in due time (European Commission, 2021). Carbon taxes and cap-and-trade systems are both made to price-in the negative externalities of greenhouse gas emissions, thus preventing activities with low economic value to emit emissions. EU regulation requires that 50% of auction revenues are used to tackle climate change in the EU by investing in energy and climate related projects (EU Monitor, 2022).

There are also projects that aim to sequester carbon from the atmosphere like deforestation, planting trees and sustainable farming that generate carbon offsets. This carbon offset can be used by firms to voluntarily offset net carbon emissions that currently cannot be avoided while doing business. For instance, firms can make use of voluntary carbon offsets to compensate for scope 3 emission such as corporate travel by their employees (Poolen, 2021). Although the demand for voluntary carbon offsets has grown significantly in recent years, high-quality carbon offsets are scarce because accounting and verification methodologies vary. Moreover, there is still ongoing debate among climate economists whether offsets create the wrong incentives. The option to offset emissions allows polluters to keep polluting and buying a potentially low-quality, cheap carbon offset to greenwash business practices. Miltenberger et al. (2021) argued that the option to compensate emissions leads to corporate executives reducing their effort in the transition into more sustainable business practices. On the contrary, Yang et al. (2020) argued that greenwashing can be mitigated through greater transparency from VCM credit purchasers and operators. More and more companies nowadays disclose their public reporting of GHG accounting due to public pressure, shareholder initiatives, investment mandate and fines. From the supplier's perspective, they encounter uncertain demand when dealing with the sale of their carbon offsets. Additionally, the market as a whole is characterized by lack of liquidity, limited access to financing and low risk management services (McKinsey, 2021). Thus, it will take time for the development of an efficient and large-scale voluntary carbon market.

Due to ongoing uncertainty regarding the pricing of voluntary carbon credit, this paper only focuses on the compliance carbon market that primarily results from cap-and-trade systems traded in ETS. However, there is high possibility that good quality projects that produce carbon credits can have quasi-compliance status and traded in ETS around the world in the future. Thus, it is important for firms or investors that engage in voluntary carbon offsets to know the expected value associated with compliance carbon market. Ruehl (2023) recently published an article that high-quality of carbon credits would be acceptable for offsetting Singapore’s carbon emissions and traded in the compliance ETS market. This is an additional motivation for me to conduct this study as I am building a startup to facilitate the trades for voluntary carbon market (VCM).

2.2 Evolution of EU ETS Market

This section discusses how the market of EU ETS has developed over the years and how the policy changes affect the supply side of EUA price. The summary below was compiled from thirteen years of report papers from 2005- 2023 published by European Commission to explain the EU ETS market development and changes in policy. Additionally, paper from Kerstine & Julian (2023) that explains the initial struggle, past reforms and the latest changes in EU ETS market is utilized to derive how the policy changes overtime.

Phase I (2005-2007) was a 3-year trial and error plan to let market participants familiarize themselves with the features and functioning of a cap-and-trade system. Phase I covered only CO_2 emissions from power generators and energy-intensive industries in which all the allowances were given to emitters for free. In the case of non-compliance, penalty fees of 40 euros per tonne were imposed. During the early stages of the system, it was up to each country to allocate free allowance in a decentralized manner. Each member of National Allocation Plan (NAP) determined the amount of allowances provided to each installation which had to be submitted to the European Commission for approval. As there was no previous historical verified emission data, most Member States distributed allowances based on estimated emissions. This resulted in over-allocation of allowances thus led to the significant drop of the EUAs prices from 29 to 13 euros per tonne.

Phase II (2018-2012) was the start of policy adaptations and the initial commitment period of the Kyoto Protocol to meet binding emission reduction target. Compared to phase I, the non-compliance penalty fee increased to 100 euros per tonne. Other important changes including lower EU ETS cap, additional state member participants, bigger GHGs emissions covered, and the fall of free allocation to 90 percent. The Member States also introduced emission reduction credits (CER) that was verified by Clean Development Mechanism (CDM) from various projects such as energy, afforestation and reforestation. There are around 1.4 tonnes of emissions offset by CER for compliance reason. Most importantly, there was more available and verified data in Phase II compared to Phase I, which improved the functioning of EU ETS. Yet, the 2008 economic crisis had crippled different business sectors with significant reduction in production capacity. Following the recession, the price of EU allowance in the EU ETS feel from almost 30 euros in mid-2008 to less than 5 euros in mid-2013.

Phase III (2013-2020) introduced significant changes to the system such as the establishment of centralized system via a single Union Registry and single EU-wide cap on allowances. Member States were no longer required to prepare NAPs as the cap is set to decrease in Linear Reduction factor (LRF) of 1.74 percent. In the early years of phase III, there were also impact of overlapping policies such as the new policies regarding 20% share in renewable energy and 20% improvement in energy efficiency, which drove more emission reductions than expected in EUA, which led to lower demand. This combined with oversupply of approximately 515 mtCO2 led to a downward trend in EUA price from 2008 to 2016. To tackle this issue, the EU regulators implemented two main policy measures, which are backloading and the Market Stability Reserve (MSR). Backloading was first introduced in 2014 and it is a tool to rebalance the supply and demand of allowances in the short term such as reducing auction volumes by 400 million in 2014, 200 million in 2016 and postponement of 900 million allowances. However, backloading was not very effective and only act as temporary solution to tighten the market resulting to a slight increase in EUA price from 2013 to 2015. Only after 2019, carbon price became attractive when MSR began its operations as the long-term solution to improve the system's resilience to shocks such as economic crisis by adjusting the volume allowances to be auctioned and ensuring predictability for placing allowances in the reserve.

Phase IV (2021-2030) is expected to significantly improve EUA price delivery. The European Commission presented the Fit for 55 climate and energy policy to cut emissions by 55 percent by 2030 relative to 1990 levels. The package required EU ETS cap on emission not only from heavy industry and electricity generation, but also a price on carbon emission for road transport and buildings. The other main changes from phase III was to increase the LRF to 2.2 percent and the doubling rate of MSR. Moreover, in order to eliminate the possibility of greenwashing projects in the mandatory market, Certified Emission Reductions (CER) in the EU ETS will no longer be permitted.

2.3 Supply Drivers (Phase IV)

The price of carbon credits is determined by supply and demand. Throughout Phase I to III, the supply of EUA is multifaceted with a lot of changes in carbon policy, yet getting tight in Phase IV due to further dropping of LRF. From 2023 onwards, if the number of allowances exceed the auction volume of the previous year, it will be considered invalid thus permanently reducing the EU ETS cap (European Commission, 2021).

Past literatures (Fan et al., 2017 and Federico et al., 2018) found that policy adjustments caused structural changes in carbon price. The fear of an oversupply of allowances and uncertainty of demand and supply ratio caused a sharp drop in prices in Phase II and III as market participants adjust their expectation. For instance, Fan et al. (2017) used event study of policy changes as methodology to calculate the abnormal returns of EUA price while Federico et al. (2018) employed GARCH models to describe the behavior associated with fluctuations in the carbon rights market as the main drivers of carbon prices. The continuation of MSR in Phase IV address the imbalance between supply and demand for emission allowances, thus making past literatures that modelled fluctuations in carbon policy to be less valid. For each year, the European commission publishes total number of allowances in circulation, which can be exclusive indicator on whether allowances will be placed or release from the reserves. If the allowance exceeds the threshold of 833 million, 24% of the total number of allowances in circulation (TNAC) will be placed in the MSR by decreasing auction volume (European Commissions, 2023b). If the TNAC falls below 400 million minimum threshold, then portion of allowances from the MSR will be released for auction. From 2023 onwards, any allowances held in MSR above the previous year's auction volume will be invalid. Vertis Environmental Finance (2023) predicted that EUA supply to have a positive long-term effect on the price as further volume reductions in the auctions from 2027 to 2030 is required to achieve the 40% reduction target. Overall, since the volume of the EU ETS auction can be adjusted, the market would not be worried of oversupply potential, thus reducing long-term volatility in EUA price.

2.4 Demand Drivers (Phase IV)

In general, the demand for EUA is determined by power and industrial output as it covers emissions offset for power generation, civil aviation and energy-intensive industries such as chemical, cement and steel (Harriet, 2021). Within the power generation sector, there was a notable rise in the gross electricity production in the European Union (EU) from 2.6k terawatt-hours (TWh) in the year 2000 to its peak of 2.9k TWh in 2008 (European Council, 2022). There was a significant surge of electricity consumption in the 1990s, but has stabilized over the last decade. According to European Commission (2021), emissions stemming from electricity generation accounted for more than half of the total 1.3 billion tonnes of emissions covered under the EU ETS, down from two-thirds when the trading system began.

The electricity price denotes the end product prices that utility company can impose, thereby determining its overall revenue. When increase in demand pushes the electricity price up, utilities companies are incentivized to increase their electricity production. This leads to an increase in carbon emissions as more fossil fuels are burned in the process of generating additional electricity thus create upward pressure on carbon price. Past literatures (Alberola et al., 2008; Aaatola et al., 2013; Batten at al., 2021; and Eslahi et al., 2022) studied the predictive impact of electricity prices on carbon credit price. Alberola et al (2008) found a significant positive impact in Phase I, Aatola et al (2013) in Phase II, Batten et al (2021) in Phase III. While, Eslahi et al (2022) also found that electricity demand as the most important driver for estimating EUA prices from Phase I to III of EU ETS. This study will explore whether electricity price remains a significant driver of EUA price in Phase IV so the first hypothesis will be:

Hypothesis 1:
Electricity prices has a positive effect on EUA price

For many industries involved in the electricity production, many still faces low or zero carbon alternatives. This is due to relatively higher average cost of renewable energy sources compared to fossil fuels, or the financial burden associated with refurbishing existing infrastructure and establishing new energy plants. The primary source of fossil fuel for electricity generation was natural gas, which accounts for 19.6% of the total production, followed by coal and oil at 15.8% and 1.6% respectively. From the perspective of the substitution effect, utilities firms especially in Germany, the Netherlands, Spain and Italy demonstrate willingness to switch among the different type of energy markets to reduce production costs and carbon emissions. In Phase IV, power generators are not granted any free allowance by the European Commission and required to procure allowances for every carbon emission that exceeds the cap limit (Alessandro, 2023).

There is substitution effect between coal and gas price due to the technology and physical ability of power generators in Europe to switch between their fuel inputs (Obermayer, 2012). Thus, coal and gas could be regarded as substitutes. During the period following the financial crisis of 2008, power plants frequently made the strategic choice to switch between natural gas and coal to fuel their productions. This switching behavior is driven by the potential cost reduction that occurs when the price of one of these fuels decreases. Natural gas is known to be more effective than coal in terms of energy conversion efficiency and environmental emissions, but also comes with higher marginal cost. When the price for natural gas increases, power generators make the strategic choice to switch their fuel to coal to reduce cost. This shifts triggers an increase in demand for carbon offset due to higher emissions when burning coal compared to natural gas, consequently increase carbon prices.

Hypothesis 2:
Natural gas price has a positive effect on EUA price

On the other hand, when price for coal rises, power generators also make the strategic choice to switch to natural gas to reduce costs. Natural gas emits less emissions which leads to lower demand for carbon offset thus decrease the price for carbon offset. Furthermore, as natural gas generates significantly less carbon than coal, utilities firms could choose gas as the fuel to produce energy and sell the excess of carbon allowances. This leads to further surplus in carbon allowance exerting downward price pressure on carbon. Overall, for fuel switching to occur, it is necessary for both economic and technology preconditions to be met. Past literatures (Alberola et al., 2008; Aaatola et al., 2013; Batten at al., 2021) from Phase I to III had investigated the switching effect of coal and gas price on carbon price. Alberola et al (2008) found both significant positive impact of gas price and negative impact of coal price on EUA price in Phase I, while Aatola et al (2013) observed similar effects in Phase II. For phase III, Batten et al (2021) denoted a significance negative impact of coal price on EUA price. However, the study also found insignificant positive impact of gas on EUA price. This paper will investigate further the relevance of gas and coal prices in determining EUA price in Phase IV and the second hypothesis will be:

Hypothesis 3:
Coal price has a negative effect on EUA price

Phase III was also the time where the risk of carbon leakage became a significant risk. Carbon leakage is the situation where industrial companies tend to transfer production to other countries with fewer emissions regulation and lower costs for carbon offset. This phenomenon affected European firms, which export intensively to non-EU countries. The high EUA carbon price increases their production costs by at least 5% of the gross value-added thus reducing competitive pricing advantage. In phase III, only the industry sectors that were exposed to significant risk of carbon leakage such as steel and metals were eligible to receive free allocations at 100% while most of the sectors received 80% in 2013 and 30% in 2020.

In Phase IV, the European Commission imposed another revision to stop giving free allowance to most of the industrial sectors to fasten the energy transition. The flexibility to adjust the auctioning level based on firms' production capacity allows European Commissions to allocate free emission to few firms with the highest risk of carbon leakage. The less concentrated of free allocation to industrial emitters implies that these industries will play a vital role in driving the demand for EUA in Phase IV. In 2021, the industrial sector was responsible for emitting 616 mT tonnes of emissions. Cement, steel and oil refineries are the largest emitters collectively producing 27% of all emissions covered under EU ETS (Ember, 2021). Past literatures (Chevallier 2011; Aaatola et al., 2013) had investigated the effect of industry variable on carbon price. Chevallier (2011) used the EU 27 seasonally adjusted industrial production index to represent industry variable and found that it has significant positive impacts on carbon futures in Phase II. Aatola et al. (2013) used steel, paper and mineral price index to represent industry variable. The study observed significant positive impact of both paper and mineral price index on EUA price during phase II. However, the impact of steel price index on EUA prices is found to be statistically insignificant. This paper will explore the relevance of industry variable in determining EUA price in Phase IV and the third hypothesis will be:

Hypothesis 4:
Industry variable has a positive effect on EUA price

Following the invasion of Ukraine that led to the EU's reliance on Russian fossil fuels, there were an increasing public support for transitioning to green energy in Europe as a way to reduce energy dependency. The revenue generated by European Commissions from auctioning EUA in EU ETS to offset carbon, which is estimated to reach 20B euros by 2026, will be partially dedicated towards Innovation Fund. This fund will be allocated to assist the power sector and heavy-emitting industries in their effort to implement innovations in renewable resources. Furthermore, renewable energy sources such as wind, solar and hydro achieved a significant milestone in 2022 by contributing to 40% of the total electricity generation in the European Union (European Council, 2022). This marks the first step where renewable energy has surpassed the share of electricity generated from fossil fuel, which accounted for 38.6%. There are limited past literature (Eslahi et al., 2022) that explore the impact of higher renewable energy output on carbon prices. Eslahi et al. (2022) used solar radiation index, total precipitation index and wind speed Index to represent the renewable energy output in the energy mix and found that among the three indices, solar radiation proves to be the most important feature for predicting EUA prices, followed by wind speed and water precipitation. However, the paper does not explore the causal relationship between the renewable energy indices with EUA price. This study will be the first few one that explore the causal relationship of renewable energy output with EUA price. In phase IV, we could expect that high EU renewable energy contribution in the energy mix will lead to lower demand for carbon credits as utilities firms are expected to reduce its fossil fuels usage to generate electricity. This leads to lower prices of carbon credits and thus fourth hypothesis will be:

Hypothesis 5:
Renewable energy output has a negative effect on EUA price

3 Data & Methodology

This section provide the applied methodologies to test the hypotheses. Furthermore, the rationale behind the selected variables and the comprehensive analysis of the summary statistics are presented.

3.1 Methodology

In analyzing price dynamics of carbon prices, past literatures have different approach in deploying econometrics modelling. One strand of literatures (Arouri et al., 2012; Lutz et al., 2013; Zhang et al., 2016; Liu et al., 2021) explored EUAs volatility dynamics and forecasting using GARCH-type models. For instance, Zhang et al. (2016) used dynamic conditional correlation (DCC) GARCH models to investigate time-varying volatility spillover effect between carbon and energy market. While they did not find any discernible impact of crude oil price on carbon pricing, they found positive volatility spillover effect of coal and natural gas prices on carbon prices. However, volatility dynamics and forecasting are part of additional analysis beyond the scope of this paper.

Another strand of literature analyzed the potential demand drivers of carbon price and highlighted the complexity of carbon market pricing mechanism. Before the implementation of a fixed MSR policy, carbon pricing is affected by instable exogenous environment such as climate negotiations and other special events related to national politics on top of the traditional role of supply and demand. To capture the effect of external factors outside the market mechanism, past literatures covering phase I to III such as (Alexeeva, 2011; Bredin & Muckley, 2011; Tang et al., 2013; Chung et al., 2018) explored the long-run dynamic models of carbon market by deploying time-varying cointegration test and Vector Error Correction Model (VECM) model. For instance, Brendin et al. (2011) found that there is evolving long-run relationship as none of the cointegrating vector are significant in Phase I which is consistent with the pilot nature of the first phase and uncertainty compared to Phase II. VECM is the time-series model that includes cointegration adjustment function, which removes the short-term error and includes long-term equilibrium information (Chung et al., 2018). The aim of this paper is to understand the short-term price movement in Phase IV and thus VECM model is beyond the scope of this paper.

3.1.1 OLS Regression

Alberola et al. (2008) employed a multivariate linear ordinary least squares (OLS) model to identify demand drivers of EU ETS in Phase I. Similarly, Aaatola et al. (2013) used OLS model to examine the carbon market in Phase II and draw the comparison with the earlier findings of Alberola et al. (2008) in Phase I. Furthermore, Batten et al. (2021) investigated the price determinants of EU ETS in Phase III using OLS model and further compared their findings with those from phase I and II. The question arises whether those price determinants still apply in Phase IV with the latest implementation of MSR and different market dynamics. In order to address this question, an empirical model is constructed following the methodology conducted by earlier literatures from Alberola et al. (2008) and Batten et al. (2021). The previous model of the spot price of carbon (Pt) is constructed as follows:

$$Pt = \propto_i + \beta_i P_{t-1} + \gamma_i\, break_1 \;+\; \varphi_i\, break_2 \;+ \delta_i\, brent_t \;+\; \epsilon_i\, ngas_t \;+\; \theta_i\, coal_t \;+\; \sigma_i\, elect_t \\ +\; \mu_i\, clean\ dark_t \;+\; \pi_i\, clean\ spark_t \;+\; \rho_i\, temp_t \;+\; \varepsilon_{\ t}$$

The variables used in Alberola et al. (2008) and Batten et al. (2021) includes lagged value of the dependent variable (P_t), two structural breaks ($break_1$ and $break_2$), returns on Brent crude oil price ($brent$), natural gas price ($ngas$), coal price ($coal$), electricity price ($elect$), clean dark spread ($clean\ dark$), clean spark spread ($clean\ spark$), and weather variables ($temp$). In this study, the existing model has been adapted to address the present circumstances in Phase IV. First, the above model assumed that the spot price depends on its one day lagged value. However, this study uses EUA Dec'23 future contracts as dependent variable instead of spot price. The accumulation of EUA Dec'23 future contracts by traders and carbon credit buyers are assumed to be forward looking based on current available information at time t. Thus, (P_{t-1}) variable is removed from the model. Second, as mentioned in the previous section, carbon credit buyers do not expect the changes in policy to occur in Phase IV, thus structural breaks in price will not be part of the model so $break_1$ and $break_2$ variables are removed from the model. Third, clean dark spread and spark spread variables shows the net profit received by utilities firms, namely the wholesale electricity prices minus the costs of gas, coal and carbon. It have been excluded from the analysis as high correlation with electricity, gas and coal prices are expected which could cause multicollinearity bias in testing the hypothesis. Fourth, temperature variable does not directly affect the carbon prices and it only did so through electricity variables. The removal of the temperature from the model is justified as this paper only analyzed the demand factors that are directly impact carbon prices. Fifth, oil price has no direct impact on carbon price because it is mainly used as transportation fuel. Since EU ETS do not cover the emissions from the transport sector, oil price is excluded from the model. Lastly, demand drivers that are becoming more relevant in the current phase IV such as renewable energy penetration ($renew$) and industrial production (ind) are added on top of the previous equation. Thus, the modified regression for this study will be:

$$Pt = \propto_i + \ \sigma_i \, elect_t + \epsilon_i \, ngas_t \ + \theta_i \, coal_t \ + \ \varphi_i \, renew_t \ + \vartheta_i ind_t \ + \varepsilon_{\ t}$$

3.1.2 TSLS Regression (Instrumental Variable Approach)

The impact of end product prices such as electricity and industry production on carbon prices are generally positive due to the fact that the increase in price lead to higher production and thus carbon emissions. However, most past literatures (Alberola et al., 2008; Batten et al., 2021; Eslahi et al., 2022) that investigate the impact of electricity prices and demand on carbon prices did not take into account the existing endogeneity problem. This means that the price of electricity drives carbon price while at the same time price of carbon could also drives electricity price. In perfectly competitive market, producers bid energy prices into the market and the price is set by the highest marginal costs of power producers which is either gas or coal price. The imposition of carbon price increases power generators' marginal costs associated with coal and gas production. Under the assumption of perfect competition in electricity power generation, it is expected that an increase in emissions costs will be pass on to electricity consumers, leading to higher electricity prices.

Arcos et al. (2023) estimated the short-term impact of carbon price on electricity market in Spanish for the year 2018 and found that the increase of 10 EUR/tCO2 will lead to an increase by approximately 1 EUR/MWh. While Kosch et al. (2022) provide the latest empirical assessment of the impact of rising gas and carbon prices on European electricity prices. The paper retrieved hourly data of power market from 14 European countries from the years of 2018 to 2021 and found that an increase of 1 EUR/tCO2 leads to an increase in electricity price by 0.5 to 1 EUR/MWh. From the findings of these two papers, we can conclude that due to relatively higher price of carbon emissions in Phase IV compared to Phase III, a marginal increase in carbon price contributes to a larger increase in electricity price. This implies that in Phase IV, the impact of carbon prices become increasingly significant in driving electricity price and thus this study aims to address the issue of simultaneous bias using Instrumental Variables (IV) methodology.

There are limited past literatures (Schumacher et al., 2012; Haxhimusa et al., 2021) that used IV methodology to address electricity as endogenous variable in driving EU ETS price. For instance, Haxhimusa et al. (2021) employed exogenous instrumental variable of COVID-19 infections that indicates the slowing down of economic activity, resulting in reduced demand for electricity production. The study then examined the implication of the decreased in electricity demand on 34% reduction of CO2 emissions per hour. On the other hand, Schumacher et al. (2012) used STOXX Euro 600 Index as Instrumental Variable as proxy of economic activity in Europe, which represents the demand for electricity. Two-stage least-squares (TSLS) econometrics technique is then performed to estimate linear models containing the IVs. The following equation illustrates the two stage regression performed in this study:

$$elect_t = \propto_i + \ \sigma_i \, IV1_t + \epsilon_i \, IV2_t \ + \ \theta_i \, IV3_t \ + \cdots + \ \varepsilon_{\ t} \ (first \ stage \ )$$

$$Pt = \propto_i + \ \sigma_i \, \hat{e}lect_t + \epsilon_i \, ngas_t \ + \ \theta_i \, coal_t \ \ + \ \ \varphi_i \, renew_t \ + \ \vartheta_i ind_t \ + \ u_{\ t} \ (second \ stage)$$

TSLS uses instrumental variable $(IV1_t \ , IV2_t \ , \ IV3_t, \ldots)$ that is uncorrelated with the error terms $(u_{\ t})$ to create a new variable $(\hat{e}lect_t)$ replacing the endogenous variable $(elect_t)$ in the first stage. In the second stage, the estimated values $(\hat{e}lect_t)$ from the first stage is used instead of the endogenous predictors $(elect_t)$ to compute an OLS model for the response variable (Pt).

3.1.3 Selecting Instrumental Variables

Obtaining suitable and good instruments for instrumental variables is a challenging task as it involves stringent assumptions and careful considerations. Two validity conditions must be met for variables to qualify as valid IVs. First, the instrument must be strongly correlated with the endogenous variable. In assessing the correlation of the chosen instrumental variables with endogenous variable, this study will use economic relevance as criterion that can be used to determine the appropriateness of these variables as instruments. The second condition for validity entails the requirement that instruments must meet exogeneity conditions, ensuring that they do not correlate with the error term. The exogeneity condition of instrumental variables also includes exclusion restriction theory, which states that instrumental variable can only impact dependent variable through its direct relationship with the endogenous variable. Economic relevance will be used as argument and guidance to select good and valid instrumental variables that adhere to the exclusion restriction theory. In this study, five instrumental variables have been selected based on previous literature and the current economic situation as factors that influence the supply and demand for electricity. These IVs variables include Liquified Natural Gas (LNG) flow, oil price, Temperature, equity index and exchange rate.

3.1.3.1 LNG Flow

Throughout history, European countries have predominantly sourced their natural gas through pipeline deliveries from Russia. Yet, higher costs associated with storing and transporting of natural gas is higher than its liquid form which lead to an increase in liquefied natural gas (LNG) demand (Zakeri et al., 2022). According to Cedigaz (2022), an international association for natural gas, Europe's import of LNG surged by 71% following the disruption of traditional natural gas sources via Russian pipelines from the aftermath of Russia's invasion of Ukraine. To fill the depleted natural gas storage and meet the energy demands, the EU imported a huge volume of LNG from other countries, in particular the US which boosted its LNG export by 137% to Europe in 2022 (Reuters, 2022). This increase in LNG flow to Europe contributed to stabilizing the energy supply for electricity production, consequently playing important role in stabilizing electricity prices. From this economic argument, LNG flow could be considered as relevant instrumental variable that is strongly correlated with electricity price as endogenous variable. LNG flow also satisfy the exclusion restriction that it does not have any direct effect on carbon prices and only does so via electricity prices. The high volume of LNG flow to Europe is not a short-term occurrence limited to 2022 due to natural gas supply disruption, but it also extends well into the next decade. For instance, the Netherlands has stopped importing any energy from Russia with the exception of LNG and there will be huge expansion in new LNG terminals to further increase the capacity for importing LNG (NL Ministry of Economics Affairs, 2023). This signifies that utilizing LNG Flow as instrument variable in predicting carbon prices will always be relevant in Phase IV from 2021 to 2030.

3.1.3.2 Oil Price

Oil price has direct impact on electricity price as it is one of the energy source for electricity production. However, electricity production from oil-based power plants only counts for 1.6% of the total electricity generation in Europe by 2022 (European Council, 2022). While oil's contribution to electricity production is minimal, it still plays a crucial role as transportation fuel for coal production, which is one of the main sources of energy in electricity generation in Europe. Therefore, the increase in oil prices lead to an increase in operating expenses in coal production and consequently driving up the overall costs in the electricity generation process for coal-based power plant (Phuong et al., 2021; Cevik et al., 2022). Additionally, the price of crude oil could be a good indicator of economic conditions given that an increase in oil consumption aligns with rapid economic expansion (Farhad et al., 2015). Strong economic growth is associated with greater energy consumption leading to heightened demand for electricity and consequently an upward pressure on its price. From these two economic relevance, oil prices could be considered as relevant instrumental variable that is strongly correlated with electricity price as endogenous variable. Most importantly, oil price does not directly affect carbon prices as emissions emitted by oil consumption in transport sectors falls beyond the scope of EU ETS. According to European Commission (2023), new separate emissions trading system (EU ETS II) will be launched in a close system to cover fuel combustion in buildings and road transport but is not expected to become operational until at least the year of 2027. Thus, oil price meet the exclusion restriction criteria as it only affects carbon price through electricity price.

3.1.3.3 Temperature

According to Bredin & Muckley (2011), the changes in weather conditions have an indirect impact on EUA prices especially in the short-term. For instance, during severe winter period, there is higher electricity demand to generate heating from heat pump. Similarly, during a long summer, there is also higher demand for electricity to generate air conditioner for cooling, thus increase its price. The increase price of electricity during seasonal consumption peaks, driven by weather-related factors lead to an increase in power generation by dirty sources such as gas or coal to fulfill heightened demand. This occurs as renewable energy sources are often flow-limited during peak energy consumption as there is a limit to what can be capture over time. For instance, renewable resources such as wind are often only available when the wind is blowing strongly and we could not generate more wind than what already exists (Palmetto, 2022). Consequently, there is greater need of carbon credit to offset emissions, which ultimately increase its price. This economic argument implies strong correlation between temperature as instrumental variable and electricity as endogenous variable, while also satisfy the exclusion restriction criteria as temperature only affects carbon price through its impact on electricity price.

3.1.3.4 Equity Index

Tang et al. (2018) discovered that when the economy experiences growth, its productivity increases causing higher output and greater resource utilization. As a result, this leads to elevated energy consumption, which drives upward pressure on electricity prices. The rise in the production levels during economic growth also elevated carbon emissions, thereby driving carbon price upwards. This study uses stock index, which often become a leading indicator for economic growth. Stock price are the outcome of discounted future dividends so it is a forward-looking indicator of future economic growth, which makes it a strong instrumental variable in determining electricity prices. Moreover, it also satisfy the exclusion criteria as stock index only influence carbon prices through its signal on electricity consumption.

3.1.3.5 Foreign Exchange Rate (FX)

Yu et al. (2014) analyzed the indirect effect of exchange rate effect on carbon credit price. The paper concluded that exchange rate represents economic activity through its influence on international trade. A country with a weak currency relative to the currency of their trading partner will experience a strong export demand for its goods. This stimulates an increase in the demand of power consumption to produce more goods thus increasing electricity prices. Furthermore, coal commodity, one of the main source of electricity generation is typically transacted and imported to Europe in US dollar. For instance, when the Euro appreciates against US dollar, the costs of purchasing coal becomes cheaper which reduce the marginal cost of coal power plants thus lowering electricity price. These economic rationales make exchange rate to be a strong IV instruments that influence electricity prices while adhering to the exclusion criteria by not having direct influence on carbon prices. The following equation illustrates the two regression with the chosen instrumental variables:

$$elect_t = \propto_i + \sigma_i \, LNGFlow_t + \epsilon_i \, OilPrice_t + \theta_i \, Temperature_t + \varphi_i \, EquityIndex_t + \vartheta_i FX_t + \varepsilon_t \; (first\ stage)$$

$$Pt = \propto_i + \sigma_i \, \hat{e}lect_t + \epsilon_i \, ngas_t + \theta_i \, coal_t + \varphi_i \, renew_t + \vartheta_i ind_t + u_t \; (second\ stage)$$

3.2 Data

Time series data consisting EUA December 2023 future price and its demand fundamentals are extracted from Bloomberg database. Daily data for all variables are obtained from 1st January 2021, the start of phase IV to 31th August 2023, the latest data observed. The EUA Dec'23 future (MOZ23 Comdty) is the most liquid financial asset and has experienced a tremendous growth over the past years. The average daily trading volume increased from 77k in 2021 to 183k in 2022 until its peak at 271k in 2023. To understand carbon price movement, this paper does not use EUA spot price due to its relatively limited volume compared to future contracts. When there is a growing attention on carbon credit market in Phase IV, future EUA price fulfills the purpose of a hedging tool for carbon credit buyers. When utility companies expect higher EUA price in the future, they are likely to increase their hedging speed by locking in a portion of EUA future at current low prices to save cost. This is especially true when there is expectation of higher corporate profit margin in the near future, which requires utilities firms to emit more CO2 in producing electricity and offset allowance to keep up with the increased in industrial demand. Thus, this paper uses EUA 23 futures instead of spot price to provide a better analysis of the changes in industrial expectations.

Energy commodity prices are important drivers of the carbon markets mainly due to the electric power generators, which take up more than half of the total European CO2 emissions covered under the EU ETS. For physical energy commodities, they have the general characteristics that are difficult to store thus traded on futures markets, where the delivery purchase and hedging activities are conducted on a month or year ahead basis. For instance, gas is almost impossible to store in large volumes and usually delivered through pipelines. For electricity prices, since there is no single prices in Europe that will be representative of power prices in EU, Germany electricity price is chosen in this study. The data (ELGB1MON) obtained is OTC Germany baseload electricity forward prices for physical delivery in high voltage grid which is quoted in Euro per Megawatt hour (EUR/MWh). Germany, which is the largest economy in Europe has the highest electricity demand of 556 TWh accounting for almost 20% of total EU demand (Jones, 2022). In 2022, Germany alone accounts for 25% of the EU's total CO2 emissions from fossil fuel combustion for energy use, followed by Italy and Poland each with 12% (Eurostat, 2022). For natural gas price, Netherlands TTF Natural Gas one month forward (TTFG1MON Index) quoted in EUR/MWh is used. It is the physical forward prices for natural gas delivered to Title Transfer Facility (TTF), a virtual trading point within Gasunie Transport Services' national gas transport network. The TTF is the most liquid gas hub in the EU and is a widely serves as proxy for overall European gas price (ICE, 2022). While for coal price, API2 Rotterdam Coal one month futures (XA1 Comdty) data is used as the Europe-wide coal price benchmark for steam coal. Data transformation is performed from the quoted API2 price in USD/MT to EUR/MT. According to Covert Units (2023), 1 tonnes of coal is equivalent to 8.141 MWh of electricity.

To represent industry sectors, MSCI Europe Materials Index (MXEUOMT Index) which represents the large and mid-cap companies across 15 developed countries across Europe is used. Cement, steel and metals are the largest emitters collectively producing 27% of all emissions covered under EU ETS (Ember, 2021). The index portfolio consists of 25.88% diversified metals & mining, 25% specialty chemicals, 13% construction materials and others like paper and plastic packaging material (MSCI, 2023), thus it is a good representation of the largest emitters of carbon in EU ETS. While for the renewable energy penetration that is getting more relevant in Phase IV, daily data from Europe Wind Generation Index (ENTSO-E) which represents European power generation by wind per megawatt is utilized. This followed by other sources of renewable energy that are being analyzed in this paper such as Europe Water Reservoir Generation Index (EPWREUWR) and Europe Solar Generation Index (EPWREUSL).

To construct the Instrumental Variable (IVs) for endogenous variable (electricity), daily data of oil price, LNG flow, Temperature, Euro Stoxx 600 Index and USD/EUR exchange rate are obtained from Bloomberg database. First, Liquefied natural gas (LNG) flow to Northern Europe (EGTPNTLE) denoted by million standard cubic meter per day (MCM/d) are used to represent the daily volume of LNG flow to EU. Second, average daily temperature in Germany (WER1DL00 Index) is also used as the benchmark of the average temperature in EU as it is centrally located. Third, ICE Brent Crude Oil Futures (CL1 Comdty) in USD/bbl, which is the deliverable contract based on physical delivery traded in ICE Future Europe Commodities is used as the global benchmark for navigating the impact of global crude oil markets on German electricity price dynamics. The oil price is transformed from USD/bbl into EUR/bbl using daily exchange rate. Finally, the USD/EUR exchange rate is chosen as variable to assess economic impact on electricity prices.

4 Results

4.1 Descriptive Statistics

To understand the dynamics of the variables movement overtime, this study plots the graphs of each variables included in the main OLS regression.

Figure 1: EUA Futures Dec 23 Daily Price

Fig 1 shows the fluctuation of the EUA Dec 23 future price in Phase IV. Overall, the trend of the price has been moving up from the beginning of 2021 until the latest data taken in August 31st 2023. As discussed in the literature review, European Commissions had decide to increase the Linear Reduction Factor (LRF) to 2.2 percent and double the rate of Market Stability Reserve (MSR) in Phase IV to stabilize EUA supply thus its price. From this fixed policy, we can expect this fluctuating increase trend in EUA price to prolong in the long-term until at least 2030. In the past, during the recovery from 2008 great recession, the price of EUA dropped from 30 euros in mid-2008 to less than 5 euros in mid-2013. The mechanisms to adjust EUA overall supply will safeguard against similar decline in EUA price even in the event of potential future recessions.

This paper studies the EUA short-term price movements that is mainly driven by its demand, thus it is important to gain insights from the fluctuations in EUA price especially during the year 2022. From fig 1, we could observe an anomaly of 35% dropped in EUA price from 90 euros in 25th of February 2022 to 60 euros within 5 days timeframe. The price then slowly recovered to 80 euros one week later in 15th March 2022. According to Sorhus (2022), EU carbon analyst at Refinitiv, the Russian invasion of Ukraine impacted the overall financial markets including the EUA price. The huge drop in price was mainly due to the sell-off of EUA positions by utilities firms and investors to cover margin calls due to sudden spike in energy prices, mainly gas and electricity prices. From fig 2, we could observe the high volatility in gas and electricity prices after the Russia invasion of Ukraine in 24th of February 2022. Russia has decided to stop gas supply to number of EU countries, which was highly dependent on Russia's energy sources, causing a supply shock that pushed up the price of gas to record high of 345 euros/MWh in March 2022 (European Council, 2023).

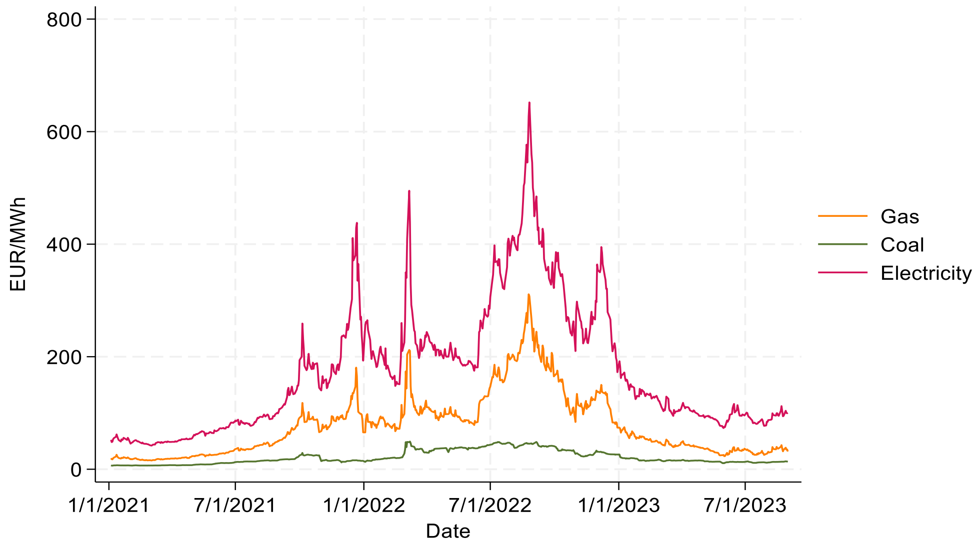

Figure 2: Energy (Gas, Coal, Elec) Daily Price

High gas prices also leads to high electricity prices in Germany as shown in fig 2. With the assumption that there is adequate demand for electricity in the market, the price of electricity is determined based on the marginal costs of the most expensive power plant currently in operation. There is high degree of correlation between electricity prices and the price of the biggest share of power plants in the electricity generation mix. Renewable energy power plants produce electricity at very low marginal costs due to the abundance of its resources. On the contrary, coal and natural gas-fired power plants have higher marginal costs as they have to pay for the fossil fuel. In Germany, gas-fired power plants dominate approximately 37% of the electricity generation mix and more than half of the gas supply is sourced from Russia (Oltermann, 2022). Consequently, when Russia reduced its gas exports, this led to substantial supply shock that directly contributed to a significant increase in Germany electricity price as depicted by fig 2. Although the price of gas and electricity are not formally pegged, the choice of this paper to use Germany electricity as the representative of electricity price in Europe establishes a strong correlation between the two. The high correlation of 0.885 between German electricity and gas prices is shown by the correlation matrix in Appendix 2, indicating a strong positive linear relationship between the two variables.

From fig 2, we could also observe another spiked in EU power and gas price with a record high in early August 2022 following the increase in demand for winter gas supplies and expectations of more persistent fall in Russian gas supply (ESMA, 2023). Yet, the price quickly subdued in the late August 2022. Despite the cut in Russian gas pipeline, the EU got their energy supply imported from other countries like the US in the forms of liquefied natural gas (LNG). Those purchase order of LNG by the EU countries during the summer arrived in late August, resulting in gas excess supply (Simon, 2022). According to the data compiled by Gas Infrastructure Europe (2022), the EU's overall storage levels were nearly full and above the 80% target set for countries by the start of November 2022. Additionally, Europe experienced unusually warm winter temperatures in 2022, which significantly lowered the demand for energy consumption for heating (Zeniewski et al., 2023). These two factors caused the gas price to fall by 60% from their peak levels by the end of August 2022. Overall, the average gas and electricity price remains at record levels compared the previous year until it was back to normal in January 2023.

Figure 3: MSCI Europe Materials Index Daily Price

Fig 3 illustrates the upwards trend of MSCI Europe Materials Index in 2021 until its peak in early 2022. This positive trend was mainly driven by the high amount of orders from key buyer industries during economic rebound following the Covid-19 lockdown. Despite some challenges remain such as supply chain bottlenecks and raw material shortage that surpassed industry's robust recovery, the metals and steel industry sector still saw significant improvements in profit margins in 2021 and the first quarter of 2022 (Atradius, 2022). Following a price hike in 2021, the market took another downfall in 2022 due to the economic repercussions of the Russian invasion in Ukraine. This conflict brought greater economic uncertainty and supply issues in the overall manufacturing sector. While many industry sectors managed to pass on a large share of high energy price to the customers, this came at the expense of weakening demand. This lead to lower revenues for industrial sectors which was reflected on the downtrend of materials equity index starting in the second quarter of 2022. As of 2023, there has been modest price recovery from the lowest point observed in mid 2022, although the price have not yet reached the levels seen in 2021 (fig 3).

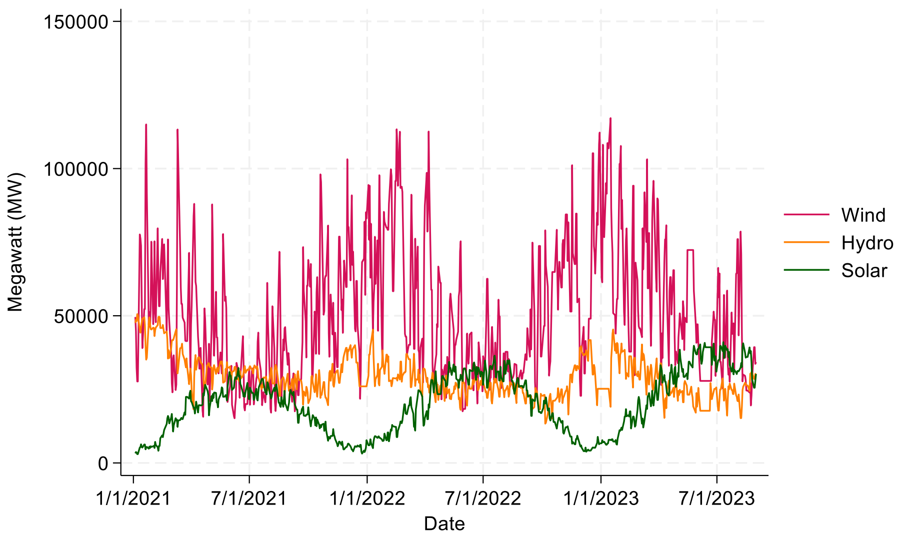

Figure 4: Renewable Energy Output

Fig 4 depicts the megawatt-scale renewable energy generation output by wind, hydro and solar sources. We could observe that hydro and wind output follow similar seasonal pattern over the long-term. Both exhibit an upward trend starting in August, reaching their peak in January and then a downward trend the beginning of March as winter period ends. The natural variability in water availability plays a significant role in determining the seasonal pattern observed in hydropower output (Wen, 2022). During dry summer season, there is low precipitation of water to generate power due to the increase in evaporation rate and less rainfall. While during the wet spring-winter season, there is relatively high hydro inflows for power generation. Similarly, for wind power energy output, there is more output during winter than summer season. The trend occurs in major wind energy-producing leading countries like Germany and China because of the specific winter climate condition, which is characterized by mild temperatures and strong wind conditions (Mahmud, 2022). According to Wind Europe (2017), which quantify the wind power output, wind turbines project in Europe can anticipate higher 30-45% wind production in winter compared to summer due to the seasonal variations of wind.

On the other hand, solar energy output exhibits a seasonal pattern but follows the reverse pattern of wind and hydro energy output. There is a downward trend starting in August, reaching their lowest in January and then an upward trend the beginning of March as summer period starts. There are more solar power produced in the summer than any other time due to the longer availability of sunlight with longer daylight and clearer skies (Solar Energy, 2023). According to Aztech Solar (2022), solar panels will produce on average of 2-15% less energy compared to the summer in Europe.

From fig 4, we could also observe that there is more fluctuations and greater variance in wind output in daily basis compared to hydro and solar. This is due to unpredictable, variable conditions such as wind speed, direction, temperature and humidity that are vital for powering wind turbines to generate electricity. For instance, turbulence and gusts can cause sudden changes in wind speed, posing an imminent challenge to sustain a steady energy output in a daily basis (Andersen, 2022).

4.2 Stationarity Test

Before computing the OLS model, it is necessary for all variables to be stationary to prevent spurious results when running the regression. Appendix 1 represents the summary statistics of the dependent and independent variables in level forms. For normal distribution, skewness should be close to zero while kurtosis should be around 3. We could observe some variables do not follow normal distribution by looking at the skewness and kurtosis. For instance, gas price has skewness of 1.257 which is greater than 1 indicating a right-skewed distribution with longer right tail. It also has kurtosis of 4.356, which is greater than 3 indicating fatter tails than normal distribution.

Table 1: ADF Test (Level)

Series	**Constant**	**Trend**
EUA23	-2.291	-2.822
Electricity	-2.054	-1.927
Gas	-2.030	-1.907
Coal	-1.558	-1.297
Industry	-2.568	-3.243
Wind	-9.850***	-9.868***
Hydro	-7.002***	-7.858***
Solar	-3.181*	-3.372*
Oil	-2.035	-2.254
Temp	-4.327***	-4.279***
LNGFlow	-3.172*	-3.564**
Stoxx600	-2.693	-2.652
USDEUR	-1.646	-1.336

*Note.**p < 0.10, **p < 0.05, *** p <0.001

For formal test, the Augmented Dickey-Fuller (1979) test is utilized to test for the presence of a unit root with the null hypothesis suggesting the presence of unit root. Table 1 shows that variables such as Wind, Hydro, Solar, Temp and LNG Flow have significant test statistics. This means the variables are already stationary as we reject the null hypothesis. For easy interpretation, Wind, Hydro and Solar variables were converted into logarithmic form.

Table 2: ADF Test (Log-Differenced)

Series	**Constant**	**Trend**
EUA23	-27.839***	-27.899***
Electricity	-25.800***	-25.860***
Gas	-26.889***	-26.977***
Coal	-24.926***	-25.033***
Industry	-26.081***	-26.079***
Oil	-25.475***	-25.512***
Stoxx600	-26.716***	-26.708***
USDEUR	-26.235***	-26.263***

*Note.**p < 0.10, **p < 0.05, *** p <0.001

On the other hand, ADF test statistics for EUA, Electricity, Gas, Coal, Industry, Oil, Stoxx600 and USD/EUR are not significant. Thus, we fail to reject the null hypothesis, indicating those variables is non-stationary. To address the non-stationarity of these variables, we apply the first log-differenced: $x_t = \ln (x_t/x_{t-1})$ which is also used by Alberola et al. (2008) and Batten at al.(2021) papers. Table 2 denotes significance ADF test statistics after the first log-difference transformations have been applied, indicating a stationary data.

4.3 Multicollinearity Check

Before conducting the OLS analysis, we also needs to assess multicollinearity, which occurs when there is high degree of linear relationship among two or more independent variables. Addressing multicollinearity is crucial because it can distort the model coefficients, which make it difficult to interpret the role of each independent variable. As discussed in the descriptive statistics section, gas and electricity prices have high degree of correlation of 0.885 as shown in Appendix 2. Even after the transforming the non-stationary dataset into first log-differenced form, the correlation coefficient remains high at 0.734 as presented in Appendix 3.

4.4 OLS Model

4.4.1 Full-period OLS Models

To test the hypothesis of this study, multivariate time series regression is presented in table 3. Model 1 represents the full model as explained in the methodology section. While model 1.1 and model 1.2 is computed to evaluate the robustness of the full model when the presence of multicollinearity between gas and electricity prices was observed. Several approaches such as removing one of the highly correlated variables, combining them into a single variable or conducting separate regression analysis for each of the highly correlated variable can be employed to address multicollinearity (Frost, 2023). This study opts to perform a separate regression analysis, where gas and electricity prices were removed from the full model as presented in model 1.1 and 1.2 respectively. This decision is based on the observation that gas and electricity prices are not formally pegged to each other, implying that each of these variables may offer distinct explanations for causation as discussed in the hypothesis.

One of the key assumptions of best linear unbiased estimator for OLS regression is homoscedasticity, where the residuals are distributed with equal variance at each level of the independent variable. Breusch Pagan test (1979) is used in this study to check homoscedasticity assumption by fitting a new regression model using the squared residuals as the dependent variable. From the BP test in appendix 4, the p-value of the Chi-Square test statistics for model 1, 1.1 and 1.2 are all less than 10% significance level, thus the null hypothesis is rejected indicating the presence of heteroscedasticity of non-constant variance in the error terms. Furthermore, OLS regression also assumes no autocorrelation where error terms are not correlated overtime. To check for autocorrelation, this study employs Breusch-Godfrey test (1978) that is more statistically powerful than the more popular Durbin Watson's test as it has the capability to detect autocorrelation beyond the first order autoregressive models. From the

LM test in appendix 4, the p-value for model 1 and 1.1 are more than 10% significance level, thus we fail to reject the null hypothesis indicating no autocorrelation in the regression model. To account for heteroscedasticity and unobserved autocorrelation, the models are run on Newey-West standard errors.

Table 3: Full Period OLS Regressions

	Model 1	Model 1.1	Model 1.2
Electricity	0.065*	0.068***	
	(0.033)	(0.025)	
Gas	0.003		0.045**
	(0.025)		(0.019)
Coal	-0.004	-0.003	-0.003
	(0.038)	(0.039)	(0.038)
Industry	0.345	0.344***	0.345***
	(0.090)	(0.090)	(0.090)
Wind	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
Hydro	-0.001	-0.001	-0.001
	(0.006)	(0.006)	(0.006)
Solar	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)
Constant	0.058	0.058	0.060
	(0.091)	(0.091)	(0.092)
Observations	693	693	693
Adjusted R^2	0.043	0.038	0.036
F-Statistics	0.000	0.000	0.000

Standard error in parantheses

* p<0.01, ** p<0.05, *** p<0.001

The first hypothesis predicts a positive effect of electricity price on EUA price. The results in model 1 confirm the first hypothesis with a significantly positive electricity prices coefficient (0.065) at the 10% confidence level. The coefficient implies that on average, an increase of 1% in electricity price return results in 0.065% increase in EUA price return. This relationship is confirmed in model 1.1 where the exclusion of gas prices results in an even more significant positive coefficient of electricity price (0.068) at 1% confidence level. The result is consistent with past papers (Alberola et al., 2008; Aatola et al., 2013; Batten et al., 2021; Eslahi et al., 2022) that covers Phase I to III. Most importantly, this finding contributes to new empirical evidence highlighting the significance of electricity price in determining EUA price in Phase IV.

The second hypothesis predicts that gas price has positive effect on EUA price. Model 1 does not align with the second hypothesis with insignificant positive gas coefficient (0.003) at 10% significance level. However, the finding is debunked with model 1.2 that excluded electricity price and found a significant positive coefficient of gas (0.045) at 5% significance level. This is an evidence that multicollinearity exists between gas and electricity price, which reduced the precision of the estimated coefficients and weakened the statistical power of the regression model. Hence, we exclude model 1 from further analysis in this study and only consider model 1.1 and 1.2 to test the hypothesis. The coefficient of gas price from model 1.2 implies that on average, an increase of 1% in gas price return results in 0.045% increase in EUA price return. The result is consistent with Alberola et al. (2008) and Aatola et al. (2013) that found significant positive impact of gas price on EUA price due to fuel-switching behavior to coal in Phase I and II respectively. However, it contradicts the finding of Batten et al. (2021) that found insignificant gas impact on EUA price in Phase III.

The third hypothesis predicts that coal price has negative effect on EUA price. The result in model 1.1 and 1.2 shows insignificant negative coefficient (-0.003) at 10% significance level. This finding contradicts all the past literatures (Alberola et al., 2008; Aatola et al., 2013; Batten et al., 2021) which found significant negative impact of coal prices on EUA price due to fuel-switching behavior from coal to gas. The negative sign of the coefficient suggests a negative relationship between coal price and EUA prices but it is not sufficient to conclude causal relationship with insignificant t-statistics, thus we still reject the third hypothesis. The reason could be that fuel-switching behavior from coal to natural gas is limited following the disruption of gas supply to European after the Russian invasion of Ukraine in 24th of February 2022.

The fourth hypothesis predicts that industry variable has positive effect on EUA price. Model 1.1 and 1.2 confirms the fourth hypothesis with a significantly positive coefficient (0.344) of industry variable, which is represented by MSCI Europe Material Index at 1% significance level. This finding implies that on average, an increase of 1% in MSCI Europe Material Index return results in 0.344% increase in EUA price return. The result is consistent with past papers (Chevallier 2011; Aatola et al., 2013) that found significant positive impact of industrial variable on EUA price during phase II. This finding contributes to new empirical evidence highlighting the significance of industrial variable in determining EUA price in Phase IV.

The fifth hypothesis predicts that renewable energy output has negative effect on EUA price. Model 1.1 and 1.2 do not support the fourth hypothesis with insignificant negative coefficient for wind (-0.001), hydro (-0.001) and solar (-0.003) at 10% significance level. The negative sign of the coefficient suggests a negative relationship between renewable energy output and EUA prices but it is not sufficient to conclude causal relationship with insignificant t-statistics, thus we still reject the fifth hypothesis.

4.4.2 Sub-periods OLS Models

Past literatures (Alberola et al., 2008; Batten et al., 2021) took into account the potential of time-varying effects of demand fundamentals on EUA price by conducting regression analysis on different sub-periods. For instance, Batten et al., (2021) considered the impact of the 2014 oil price collapse by dividing the regressions analysis into sub-periods before and after the collapse. Their study revealed that the price of electricity becomes a significant driver of EUA price only after the oil price collapse and found more accurate prediction in the period following this collapse. As discussed in the descriptive statistics section, the EUA price experienced an anomaly drop by 35% following the Russia invasion of Ukraine in 24th February 2022. This event also marked the high volatility in gas and Germany electricity prices due to energy crisis as Russia had decided to stop the gas supply to number of EU countries. The fluctuations in gas and electricity prices began to subside as of November 2022 due to the combination of excess supply of LNG fuel and lower demand of energy in an unusual warmer winter.

This study explores the potential of time-varying effects of the explanatory variables on EUA price by conducting separate regression for sub-periods that cover the periods before (pre), during and post energy crisis. The sub-periods are structured as follows: The pre energy crisis commences on 1st January 2021 until 24th of February 2022. This is followed by the energy crisis period from 25th of February 2022 until 31st August 2022. Subsequently, the post energy crisis period starts from 1st November 2022 until 31st August 2023. Furthermore, two separate regressions for gas and electricity prices are conducted within each sub-periods to address the issue of multicollinearity. Table 4 shows the results of the sub-periods regression.

Table 4: Sub-periods OLS Regressions

	Pre energy crisis	Pre energy crisis	During energy crisis	During energy crisis	Post energy crisis	Post energy crisis
	Model 2	Model 2.1	Model 3	Model 3.1	Model 4	Model 4.1
Electricity	0.128***		-0.099*		0.099***	
	(0.033)		(0.069)		(0.038)	
Gas		0.115***		-0.069*		0.050**
		(0.335)		(0.040)		(0.026)
Coal	-0.084***	-0.078***	-0.071	-0.073	0.053*	0.066*
	(0.030)	(0.028)	(0.080)	(0.072)	(0.037)	(0.037)
Industry	0.548***	0.553***	0.213	0.219	0.182*	0.200*
	(0.139)	(0.137)	(0.216)	(0.206)	(0.132)	(0.135)
Wind	-0.002	-0.002	-0.004	-0.002	-0.002	-0.003
	(0.004)	(0.004)	(0.009)	(0.009)	(0.004)	(0.004)
Hydro	-0.006	-0.006	-0.008	-0.004	0.001	0.001
	(0.008)	(0.008)	(0.038)	(0.041)	(0.007)	(0.008)
Solar	-0.004	-0.004	0.001	0.003	-0.004	-0.004
	(0.004)	(0.004)	(0.015)	(0.014)	(0.003)	(0.003)
Constant	0.095	0.082	0.105	0.035	0.052	0.057
	(0.135)	(0.132)	(0.585)	(0.606)	(0.110)	(0.114)
N	298	298	134	134	261	261
Adj R-squared	0.176	0.143	0.049	0.038	0.074	0.072
F-Stat	0.000	0.000	0.052	0.090	0.000	0.010

Standard error in parantheses

* p<0.01, ** p<0.05, *** p<0.001

4.4.3 *Pre-crisis and Post-crisis Analysis*

Both model 2 (pre-crisis) and model 4 (post-crisis) shows significantly positive electricity price coefficient (0.128) and (0.099) at 1% significance level. This implies that on average, an increase of 1% in electricity price return results in 0.128% increase in EUA price return during the pre-energy crisis period and 0.099% increase during the post-energy crisis period. This finding align with the full-period model 1.1 and support the first hypothesis. Similarly, model 2.1 (pre-crisis) and model 4.1 (post-crisis) shows significantly positive gas price coefficient (0.115) and (0.050) at 5% significance level. This implies that on average, an increase of 1% in gas price return results in 0.115% increase in EUA price return during the pre-energy crisis period and 0.050% increase during the post-energy crisis period. This finding is also align with the full-period model 1.2 and support the second hypothesis.

Overall, the positive economic impact of electricity price and gas price are the largest during pre-energy crisis period, as indicated by the larger coefficient magnitudes in comparison to the full model and the post- energy crisis model. During pre-energy crisis in 2021, gas generation decreased by 5% across the EU with coal increasing by 20% as it became more economically favorable leading to higher EUA price (Ember, 2021). This fact supports the significance of gas coefficient that explains the fuel switching behavior from gas to coal on EUA price, as stated in the second hypothesis. Hence, this study finds that electricity and gas price to have greater economic power in explaining EUA price in the pre-energy crisis period in Phase IV. On the contrary, during post-energy crisis period, the EU has significantly reduced its reliance on natural gas to power its electricity generation. This is evident by REPowerEU plan's in 2022 to end EU's dependency on fossil fuels by 2027 (European Commissions, 2023). Furthermore, the emergence of energy security concerns further accelerated EU's shift towards a carbon-neutral economy and the massive expansion of renewable energy sources (Amelang, 2023). This means that higher electricity prices from the increased in power consumption has diminishing role in driving higher demand for carbon credits during the pre-energy crisis. This is due to higher penetration of renewable energy sources in the energy mix in Europe that will be able to effectively meet the increasing needs of power consumption. Hence, this study predicts electricity and gas price to have less economic power in explaining EUA price in the post-energy crisis period in Phase IV.

Both model 2 and 2.1 (pre crisis) shows a robust and significantly negative coal price coefficient (-0.084) and (-0.078) at 1% significance level when removing gas and electricity price. This implies that on average, an increase of 1% in coal price return results in (0.078% to

0.084%) decrease in EUA price return during the pre-energy crisis period. This finding contradicts the earlier results in the full-period model 1.1 and 1.2 that found insignificant negative coefficient of coal. The result thus confirms the third hypothesis and aligns with past literatures (Alberola et al., 2008; Aatola et al., 2013; Batten et al., 2021) which found significant negative impact of coal prices on EUA price due to fuel-switching behavior from coal to gas. On the contrary, Model 4 and 4.1 (post crisis) shows a robust and significantly positive coal price coefficient (0.053) and (0.066) at 10% significance level when removing gas and electricity price. This indicates that on average, an increase of 1% in coal price return results in (0.053 to 0.066%) increase in EUA price return during the post-energy crisis period. This finding contradicts the third hypothesis, past literatures and the full-period model. The reason could be that due to the relatively high gas price in post-energy crisis in 2023 compared to pre-energy crisis in 2021, it is still more profitable to run coal than gas. Most importantly, there is still limited supply of natural gas to Europe due to ongoing conflict between Russia and Ukraine so there is less opportunity for power producers in Europe especially Germany to switch from coal to gas. Thus, despite less efficient energy conversion efficiency and higher environmental emissions, coal is still the choice for power producers in the post-energy crisis period. This is evident as Germany approved to reactivate on-reserve coal power plants and extended their lifespans from October 2023 until March 2024 to replace the scare natural gas of 2023's winter and avoid shortages despite new LNG terminal that eased the gas bottlenecks last winter (Reuters, 2023). Hence, fuel-switching arguments from coal to gas as discussed in the third hypothesis does not hold in the post-energy period. Instead, a rise in coal price indicates higher demand of coal, which increased carbon offset demand, thus increase its price.

Both model 2 and 2.1 (pre crisis) shows a robust and significantly positive Industry variable coefficient (0.548) and (0.553) at 1% significance level when removing gas and electricity price. This implies that on average, an increase of 1% in industry variable results in (0.548% to 0.553%) increase in EUA price return during the pre-energy crisis period. Similarly, both model 4 and 4.1 (post crisis) shows a robust and significantly positive Industry variable coefficient (0.182) and (0.200). This implies that on average, an increase of 1% in industry variable results in (0.182% to 0.200%). The finding of industry variable, which is represented by MSCI Europe Material Index in pre and post energy crisis supports the earlier results in the full-period model 1.1 and 1.2 and confirms the fourth hypothesis.

All the models from before and after the energy crisis show insignificant coefficient of renewable energy output (wind, hydro and solar) with varying result. The magnitude of the coefficient (0.001 to 0.008) is too small in predicting EUA price thus we reject the fifth hypothesis. As discussed in the descriptive statistics section, renewable energy output may have predictive power only in the long term as it follows seasonal pattern influenced by the weather conditions such as winter and summer. Yet, in the short term, the variability of the output is not strong enough to predict short-term movements in EUA prices, particularly in the case of wind power daily output, which is known for its unpredictable nature

4.4.4 During-crisis Analysis

Model 3 (during crisis), however, show significantly negative electricity price coefficient (-0.099) at 10% significance level. This means that on average, an increase of 1% in electricity price return results in 0.099% decrease in EUA price return during the energy crisis period. This finding contradicts the first hypothesis and past literatures (Alberola et al., 2008; Aatola et al., 2013; Batten et al., 2021; Eslahi et al., 2022) that found significant positive impact of electricity prices on EUA price from Phase I to III. We could also observed this phenomenon happens to the relationship between gas price and EUA price. Model 3.1 (during crisis) shows significantly negative gas price coefficient (-0.069) at 10% significance level. This means that on average, an increase of 1% in gas price return results in 0.069% decrease in EUA price return during the energy crisis period. This finding contradicts the second hypothesis and the result from the full period model 1.2.

During energy crisis, the correlation between electricity and gas price became stronger compared to the pre energy crisis. This is due to the fact that in the presence of sufficient demand, electricity prices are predominantly influenced by the highest marginal costs incurred by power producers in the market. During energy crisis, natural gas price increased to become the most expensive fuel for power producers due to supply shock, subsequently causing significant surge in Germany electricity prices. This also means that the surge in electricity and gas price were not driven by the increased demand of power consumption. Consequently, high price of electricity and gas does not lead to higher carbon price. According to Zeniewski et al. (2023), the high energy price environment in 2022 led to the emergence of fuel poverty in Europe as both the industrial and residential sectors actively curbed their energy consumption due to inability to afford higher energy costs, while simultaneously accelerating the efforts to improve their energy efficiency. Hence, the increased prices of gas and electricity price lead to lower overall demand for energy during the energy crisis period, resulting in reduced demand for carbon credits and subsequently decrease its price. None of the other explanatory variables such as coal price, industry variable and renewable energy output helps to explain EUA price during the energy crisis period in model 3 and 3.1 as shown by the insignificant coefficients at 10% significance level. Overall, the OLS regression only explains a small portion of variation (3.8% to 4.9%) in EUA prices during the crisis period which is evident from the adjusted R^2 statistics, which is the lowest compared to the periods before and post energy crisis.

4.5 Robustness Checks

4.5.1 TSLS Regression (IV Approach)

As discussed in the methodology section, the interaction between the price of electricity and the price of carbon in Europe exhibits a simultaneous bias relationship, which might cause bias to the OLS regression. In order to address the simultaneous bias while checking the robustness of OLS model, this study will perform employ Instrumental Variable (IV) approach in the regression for the post-energy crisis period which spans from 1st November 2022 until 31st August 2023. The post energy period is chosen due to the relevance of the results for Phase IV, which extends until the year of 2030.

In total, four IV regression models are constructed to assess the validity and strength of the IV variables. Model 5 incorporates all the proposed instrumental variables discussed in the methodology and data section, including ICE Brent Crude Oil future price, liquefied natural gas (LNG) flow to Northern Europe, average daily temperature in Germany, Euro Stoxx 600 equity index and USD/EUR exchange rate. In model 6, oil price and LNG flow are considered, while model 7 includes temperature, Stoxx 600 and USD/EUR. Finally, model 8 combines oil price and Stoxx 600. Table 5 shows the TSLS instrumental variables regression result.

Table 5: TSLS (Instrumental Variables) Regression

	Model 5	Model 6	Model 7	Model 8
Electricity	0.256**	0.246**	0.287	0.233*
	(0.124)	(0.124)	(0.617)	(0.125)
Coal	0.067*	0.067*	0.068	0.066*
	(0.041)	(0.040)	(0.045)	(0.040)
Industry	0.185*	0.184*	0.188	0.183*
	(0.126)	(0.125)	(0.141)	(0.123)

Wind	-0.002	-0.002	-0.001	-0.001
	(0.004)	(0.004)	(0.009)	(0.004)
Hydro	0.000	0.000	0.001	0.001
	(0.007)	(0.004)	(0.009)	(0.007)
Solar	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.004)	(0.003)
Constant	0.033	0.033	0.032	0.033
	(0.118)	(0.117)	(0.122)	(0.116)
N	261	261	261	261
Instruments	Oil, LNG Flow, Temp Stoxx600, USDEUR	Oil, LNG Flow	Temp, Stoxx600, USDEUR	Oil, Stoxx600

Standard error in parantheses

* p<0.01, ** p<0.05, *** p<0.001

To check for the strength of the correlation between instrumental variables and the endogenous variables of electricity price, this paper will conduct weak instrument test by Cragg-Donald Wald (1993) to calculate the conditional first-stage F-statistics. To check the null hypothesis that IV instruments are weak, Stock and Yogo (2005) pre-calculated the critical values to ensure the bias of the error from OLS is less than 5, 10, 20 or 30% IV relative bias. If the F statistics exceeds one the critical values, then there is enough evidence to reject the null hypothesis, indicating the presence of strong and relevant IV instruments. Appendix 5 shows that the F-statistics of model 5, 6 and 8 exceeds at least one of the critical value defined by Stock and Yogo (2005), while this is not the case for model 7. This result implies that model 5,6 and 8 has strong instrument variables with high degree of correlation with electricity prices. On the other hand, model 7 consists weak instrument variables with low degree of correlation with electricity prices. From these finding, we can infer that excluding oil price and LNG flow in model 7 leads to weak instruments, which can lead to unreliable statistical inferences. Hence, it is evident that oil price and LNG flow are strong instruments that should be included in any model to prevent biased coefficient estimates.

Furthermore, under identification test by Kleibergen & Paap (2006) is carried out to assess whether the instruments are sufficiently strong to address the endogeneity problem effectively. The null hypothesis indicates that the model is under-identified. Appendix 5 shows that the p-value of model 5, 6 and 8 is less than 10% significance level, thus the null hypothesis is rejected indicating well-identified models. On the contrary, the p-value of model 7 is larger than 10% significance level, thus we fail to reject the null hypothesis that the model is under-identified. This means that model 7 needs additional valid instrumental variables to address the under-identified problem. These results further support the importance of oil price and LNG flow as instrumental variables to make sure that the model is well-identified.

Lastly, this study performs an over-identification test to assess the exogeneity of the instrumental variables by employing Sargan-Hansen J statistics. The null hypothesis is that instrumental variable is exogenous as it does not introduce bias through correlation with the error term. Appendix 5 shows that the p-value of all models is bigger than 10% significance level, thus we cannot reject the null hypothesis implying that the instrumental variables used in all models are exogenous as it did not correlate with the error term. Overall, model 5,6 and 8 successfully passed all the three tests, affirming strong and valid instrumental variables. Consequently, these models will be analyzed for robustness check.

The IV regressions indicate significantly positive coefficients of electricity price ranging from (0.233 to 0.256) at 5 to 10% significance level. This result aligns with the first hypothesis and the OLS estimate in model 4.1 that found significant positive coefficient (0.099) of electricity price on EUA price during the post-energy crisis, implying robustness of the OLS result. However, the magnitude of the IV estimates differ slightly from the OLS estimates. The positive coefficient of electricity is larger in the IV estimations with almost three times coefficient value compared to the OLS estimate. This happens as IV treatment reveals the true causal relationship between electricity price as explanatory variable and EUA price as dependent variable. Larger coefficient on the endogenous variable reflects a more accurate and unbiased estimation of the true relationship. Furthermore, this finding underlines the importance role of electricity price in determining EUA price as emissions from electricity generation accounted for more than half of the emissions covered under EU ETS (European Commission, 2021). However, while larger coefficient of may indicates the IV model is effective in addressing endogeneity, it is important to note that IV approach also results in less precise estimates and larger standard errors.

The IV regressions also indicates significantly positive coefficients of coal price ranging from (0.066 to 0.068) at 10% significance level. This result aligns with the OLS estimate in model 4.1 that found significant positive coefficient (0.053) of coal price on EUA price during the post-energy crisis, implying the robustness of the OLS result. The magnitude of IV estimates of coal price are slightly larger than OLS model 4.1. Similarly, IV regressions also denotes significantly positive coefficients of industrial variable ranging from (0.183 to 0.185) at 10% significance level. Again, this result aligns with the OLS estimate in model 4.1 that found significant positive industrial variable (0.182) of industrial variable on EUA price during the post-energy crisis, suggesting robustness of the OLS result. The magnitude of IV estimates of industrial variable is almost the same as OLS model 4.1. Lastly, the results obtained for renewable energy output from IV regressions align with OLS model, as neither of them reveals statistically significant variables.

4.5.2 VAR Model Approach

Thus far, the study had shown consistent and reliable results regarding the impact of demand fundamentals on EUA prices as observed in the OLS and IV regression models. To strengthen the validity of the results, Vector Autoregressive (VAR) model is employed as a robustness test in addition to the IV regression models. VAR model deals with multivariate time series data and treats each of the variable in the system as both the outcome and explanatory variable. VAR models allows the modelling of endogenous interactions among the variables in the system including with its own lagged thus making it suitable for modelling variables with reverse causality problem such as electricity and EUA price. For instance, there is no need to specify which variables are exogenous and which endogenous as all variables are by definition endogenous (Kotze, 2021).

This study will perform VAR model to check for the validity of OLS regression in the post-energy crisis period, which spans from 1st November 2022 until 31st August 2023. Again, the post energy period is chosen due to the relevance of the results for Phase IV, which extends until the year of 2030. This paper run a VAR model with the three variables from model 4 that has significant impact on EUA price during the post-energy crisis, consisting of electricity price, coal price and industry variable. Gas price is also significant variable in determining EUA price yet it is excluded in the VAR model due to multicollinearity bias arising from its high correlation with electricity price. Moreover, stationarity in the dataset is crucial assumption to derive at VAR representation with constant coefficient, so this paper uses the relevant variables that have been transformed by the first-log differenced.

To select the number of lags in the VAR models, lag order selection test is conducted in Appendix 6 using final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (BIC) and Hannan and Quinn information criterion (HGIC) on the first five lags of the variables. The lag order 1 consistently yields the lowest values across all the selection test results, implying the best model fit for the VAR regression. Appendix 7 shows the VAR regression table with lag order 1 consisting of EUA price, electricity price, coal price and industry variable. To interpret the coefficient of VAR regression, however, is not straightforward. To assess the effect of demand fundamentals and achieve results that is comparable to the previous OLS and IV models, impulse response analysis will be conducted. Impulse response analyze how EUA price in EU ETS market was affected by the impact of shocks from electricity price, coal price and industrial variable overtime. This study will present a graph for each of the shock impacts, illustrating the Generalized Impulse Response Function (GIRF). GIRF measures the response of EUA price return at one time shock of the explanatory variable while holding other variables constant. The standard deviation shock on EUA price return will be within the confidence interval of 95%. The vertical axis of the graph represents the response of EUA price return in euros, while the horizontal axis displays the time lag with one day interval. The blue line illustrates the extent of the response of EUA price return to the shock on the explanatory variables. While the varying shades in grey signify the magnitude off the difference between positive and negative response.

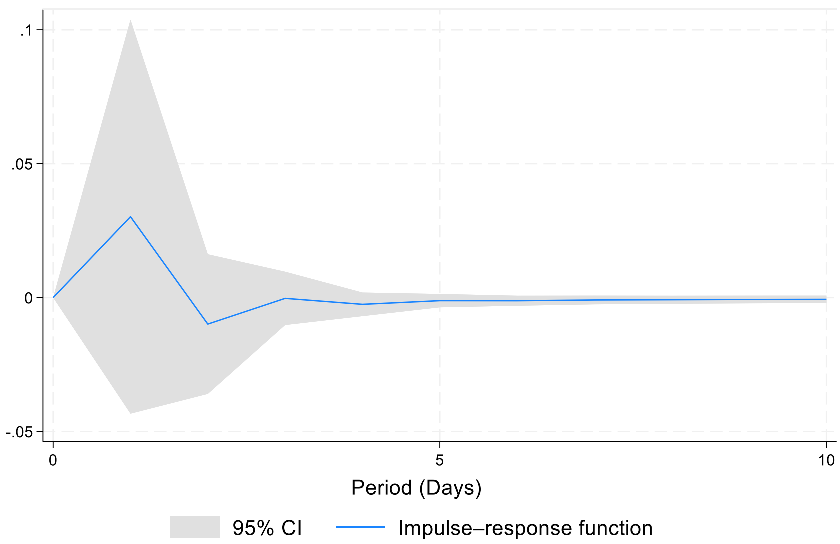

Figure 5: Response of EUA price to Electricity Price

Fig 5 shows the GIRF graph of the response of EUA price return to a standard deviation shock of electricity price return. A positive standard deviation change in electricity price return results in an initial increase of 0.025% in EUA price return in 2 days period, going back to normal in the next day and remain unchanged after 4 days. The positive response of EUA price return to the positive shock of electricity price during the pre-energy crisis aligns with the result estimated in the earlier OLS and IV regressions, thus confirming the first hypothesis. This shows the robustness of the earlier OLS and IV regression models. However, the observed magnitude of the impact of electricity price return shock on EUA price return are relatively smaller than the OLS and IV estimates from earlier results. This discrepancy could be attributed to the distinct nature of VAR model which entails a dynamic analysis. As a result, the causal relationships may not be as direct, and the definition of impulses might influence the outcome. Hence, VAR model will only be used to investigate the consistency and robustness of the directional impacts of the earlier OLS and IV regressions results, instead of assessing the intuition behind the magnitude of the impact.

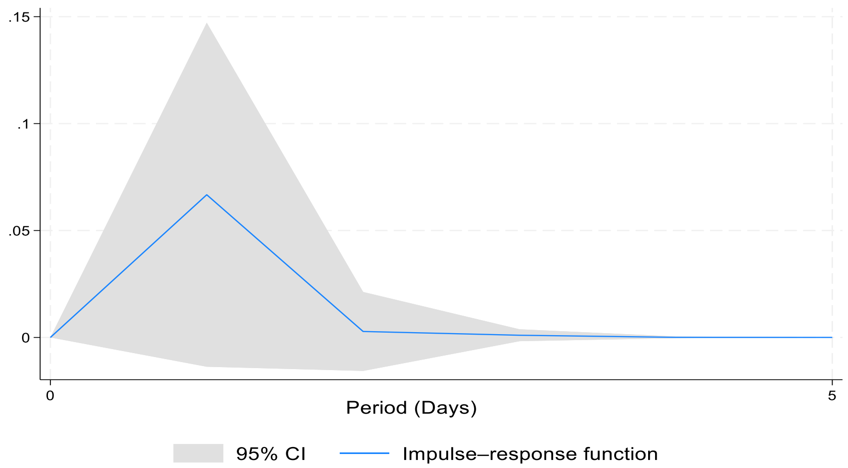

Figure 6: Response of EUA price to Coal Price

Fig 6 shows the GIRF graph of the response of EUA price return to a standard deviation shock of coal price return. A positive standard deviation change in coal price return results in an initial increase of 0.060% in EUA price return in 1 day period, going back to normal in the next day and remain unchanged after 3 days. The positive response of EUA price return to the positive shock of coal price return during the pre-energy crisis aligns with the result estimated in the earlier OLS and IV regressions, thus rejecting the third hypothesis. This implies the robustness of the earlier OLS and IV regression models.

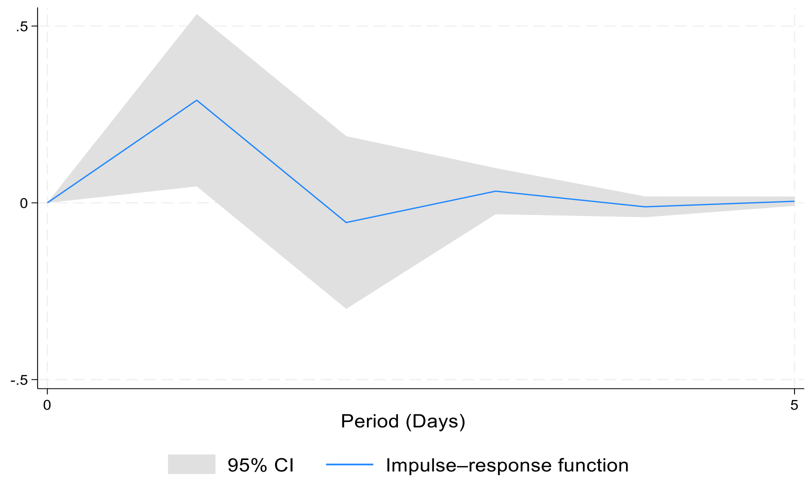

Figure 7: Response of EUA price to Industry Variable Index Price

Fig 7 shows the GIRF graph of the response of EUA price return to a standard deviation shock of industry variable return. A positive standard deviation change in industry variable return results in an initial increase of 0.250% in EUA price return in 1 day period, going back to normal in the next day and remain unchanged after 3 days. The positive response of EUA price return to the positive shock of industry variable return during the pre-energy crisis aligns with the result estimated in the earlier OLS and IV regressions, thus confirming the fourth hypothesis. This implies the robustness of the earlier OLS and IV regression models.

5 Conclusion

This study investigates the demand fundamentals that determine European Union Allowance (EUA) price that is traded in the EU emissions trading system (EU ETS) in phase IV (2021-2030). During Phase I to III, concerns about oversupply of EUA allowances and uncertainty in demand and supply ratio resulted in significant drop in EUA price as market participants adjust their expectation in response to policy changes or economic uncertainty. To address this issue, European Commissions increased the Linear Reduction Factor (LRF) to 2.2 percent and doubled the rate of Market Stability Reserve (MSR), which allows them to adjust the supply side. With fixed supply side policy, fundamental demand drivers became much more relevant in Phase IV.

This paper employed Ordinary Least Square (OLS) regression to test for the full period (01/01/2021 to 31/08/2023) impact of the demand fundamentals consisting of electricity price, gas price, coal price, industry variable and renewable energy output on EUA price. For electricity price, the model found significant positive impact of electricity price on EUA price in Phase IV, which is consistent with past papers (Alberola et al., 2008; Aatola et al., 2013; Batten et al., 2021; Eslahi et al., 2022) that covers Phase I to III. For gas price, the model also found significant positive impact on EUA price due to fuel-switching behavior to coal in Phase IV aligns with Alberola et al. (2008) and Aatola et al. (2013). However, for coal price, it found insignificant negative coefficient on EUA price in Phase IV, which contradicts Alberola et al., 2008; Aatola et al., 2013; Batten et al., 2021. For industrial variables, it found significant positive impact on EUA price in Phase IV in line with Chevallier 2011 and Aatola et al.,2013. For renewable energy output, it found insignificant negative impact on EUA price in Phase IV.

This study also explores the potential of time-varying effects of the explanatory variables on EUA price by conducting separate regression for sub-periods that cover the periods before energy crisis (01/01/2021 to 24/02/2022), during energy crisis (25/02/2022 to 31/08/2022) and post energy crisis (01/11/2022 to 31/08/2023). The energy crisis, marked by exceptionally high gas and electricity price, can be attributed to the aftermath of Russia's invasion of Ukraine, which led to political decision to limit gas supplies from Russia to EU countries. Pre-crisis and post-crisis periods were first analyzed together. For electricity and gas price, the models identified significant positive impact on EUA price in line with the full period model. We could also observed that gas and electricity have less economic power in explaining

EUA price during post-energy crisis period with smaller coefficient magnitude compared to pre-energy crisis period.

For coal price, the models found a more dynamic results. During pre-crisis, the models identified a significant negative coefficient of coal price that aligns with past literatures (Alberola et al.,2008; Aatola et al., 2013; Batten et al., 2021) but contradict the earlier full period model. On the other hand, during post-crisis, the models identified a significant positive coefficient of coal price that contradicts both past literatures and the full model. The consistent coal's profitability over gas in the post-energy crisis period driven by relatively higher gas prices and limited gas supply due to the ongoing Russia-Ukraine conflict, undermine the fuel-switching behavior from coal to gas as proposed by past literatures from Phase I to III. Instead, the increase in coal prices in Phase IV indicates higher demand for coal thus increasing carbon offset, consequently its prices. For industry variable, the models found significant positive coefficient in both the pre and post crisis period that is aligned with past literatures and the full period model. Lastly, for renewable energy output, the model also found insignificant negative impact on EUA price in Phase IV in line with the full period model.

Given the central role of the electricity price in determining EUA price, it is important to address the issue of simultaneous bias between the price of electricity and the EUA price, which might cause bias in OLS regression results. Thus, this study employs Instrumental Variable (IV) approach to fix the simultaneous bias while checking the robustness of the OLS model. The post energy crisis period was chosen due to the relevance of the results for Phase IV which extends until 2030. The methodology section confirms the economic relevance and exclusion restriction for all the chosen IV variables consisting of oil price, LNG flow to Northern Europe, average daily temperature in Germany, Euro Stoxx 600 equity index and USD/EUR exchange rate. Furthermore, weak test, under-identification test and over-identification are conducted to check the validity of the IVs variables. Oil price and LNG flow are found to be strong instruments that should be included in any model to prevent biased coefficient estimates. The IV regression results shows that the coefficient of electricity is larger with almost three times compared to the OLS estimate. This might indicates that IV treatment reveals the true causal relationship between electricity price on EUA price and helps to correct for the endogeneity bias, leading to more accurate and unbiased estimation of the true relationship. Overall, the IV regressions result shows that OLS estimation are robust.

Furthermore, to strengthen the validity of the results, Vector Autoregressive (VAR) model is employed as a robustness test in addition to the IV regression models. VAR models allows the modelling of endogenous interactions among the variables in the system including with its own lagged thus making it suitable for modelling variables with reverse causality problem such as electricity and EUA price. This paper run a VAR model with the three variables from that has significant impact on EUA price during the post-energy crisis, consisting of electricity price, coal price and industry variable with lag order 1. To interpret the coefficient of VAR model, impulse response analysis is conducted to analyze how EUA price in EU ETS market was affected by the impact of shocks from the explanatory variables. Overall, all the graphs of the impulse response function confirms the robustness of the earlier OLS and IV regression models.

Lastly, the paper also analyze the demand drivers of EUA price during the energy crisis period. The models found both significant negative coefficient of both gas and electricity that contradicts all the past literatures (Alberola et al., 2008; Aatola et al., 2013; Batten et al., 2021; Eslahi et al., 2022) from Phase I to III. During the energy crisis, the surges in electricity and gas price were not driven by increased in power consumption but due to the supply shock effect. The high-energy price environment in 2022 caused fuel poverty in Europe, which forced industrial and residential sectors to curb energy consumption due to inability to afford higher energy costs, resulting in reduced demand for carbon credits and subsequently decrease its price. On the other hand, none of the other explanatory variables such as coal price, industry variable and renewable energy output help to explain EUA price during the energy crisis period. Overall, the OLS regression only explains a small portion of variation on EUA price during energy crisis compared to the periods before and post energy crisis.

6 Limitations and Future Research

One of the limitation of this study is the selection of the data used to represent the fundamental demand drivers that influence EUA prices. This study used German electricity to represent power prices in EU due to the absence of single, unified electricity prices across Europe. The While it is true that Germany accounts for 25% of the EU's total CO_2 emissions from fossil fuel combustion, it is important to recognize that the impact of electricity on carbon prices exhibit substantial heterogeneity among countries. This is due to electricity price in Europe is being determined by the highest marginal costs of the biggest energy producers in each country. For instance, electricity price for country like Germany, which rely on gas-fired power plants to produce 37% of its electricity, is moderately affected by the movement of gas price (Oltermann, 2022). Likewise, electricity price in a country like Poland, who uses coal to generate 70% of electricity, is likely to be heavily affected by an increase in the coal price. For further research, one could acquire more comprehensive dataset from various EU countries with different energy mix in their electricity production. With this dataset, a weighted single and unified electricity price could be constructed based on emissions generated. This approach would offer a more robust analysis of the impact of electricity price on EUA price.

Another limitation of this study is using OLS regression to model the impact of high and volatile electricity and gas prices on EUA price during the energy crisis period from 24th February 2022 until 31st of August 2022. During the crisis, EUA price temporarily dropped by 35% following the Russian invasion while at the same time the price of gas went to record high, followed by the high electricity price. This is due to a sudden sell-off of EUA positions by utilities firms and investors to either cover losses in other asset classes or access liquidity to purchase the more expensive gas and electricity (ING, 2022). This significant dropped in EUA price results in a structural break for EUA price. OLS regression assumes that the relationship between variables are constant overtime, which make it unsuitable choice to capture the effect of structural breaks where these relationships change dramatically. For further research, one could use Bai-Perron structural break test to analyze the factors that influences carbon price fluctuations using the Johansen cointegration technique. For instance, Dong et al. (2021) applied the Bai-Perron structural break test to model the outbreak of COVID-19 that caused significant structural changes in the EU carbon price. The paper found that when covid hits, there was a significant drop in carbon price in a short period of time that caused structural break, which quickly rebounded. This is similar to the situation during the crisis period. As discussed in the descriptive statistics section, we could observe an anomaly of 35% dropped in EUA price from 90 euros in 25th of February 2022 to 60 euros within 5 days timeframe, which then slowly recovered to 80 euros one week later in 15th March 2022.

Moreover, other limitation of this study comes from the fact that during crisis, model 3 and 3.1 do not represent the right demand fundamentals that influence EUA price. Most of the explanatory variables that is used in the regression consisting of coal price, industry variable and renewable energy output fail to explain EUA price during the energy crisis period as shown by the insignificant coefficients at 10% significance level. Moreover, the OLS regression only explains a small portion of variation on EUA price with the lowest adjusted R^2 statistics compared to the periods before and post energy crisis. This means there are other explanatory variables that is better to explain EUA price during the energy crisis but not included in the OLS model. For instance, the Russian-Ukraine conflict disrupted industry demand and operations, thus there was lower expectation for industrial productions, which lowered the demand for carbon credit and subsequently its price. As such, lower expectation for industrial productions is therefore one of the relevant factors that influence EUA price during crisis.

As this study used instrumental variables to address the simultaneous bias, we could chose other IVs that are considered as strong instrument like oil price and LNG flow to be included in the model. For instance, non-covered sectors such as real estate and transportation indirectly affect the EUA price through their consumption of power demand, which satisfy exclusion restriction theory.

Further research could also be conducted to improve the predictability of EUA price by identifying other fundamental drivers that influence EUA price besides energy prices, industry variable and renewable energy output. First, one could investigating the impact of delays in grid capacity is essential as such delay could impede the growth of renewable power capacity, subsequently slowing down the transition to renewable sources for heavy industry. This leads to increase demand for EUA price and ultimately reduce its price. Second, one could find the effect of technological breakthrough in emissions reductions technology such as the carbon capture technology that lead to lower emissions thus lower demand for carbon credit and its price.

Lastly, one could observe the behavior of automatic selling of positions triggered by technical trading stop-losses from big investors and asset managers. Historical returns from 2016-2021 show that there were diversification benefits from carbon investing across global markets with low correlation between returns on carbon markets and conventional assets such as stocks, bonds and commodities (Swinkels & Yang, 2022). Long-term speculators who hold their carbon position for longer period of time could accumulate the allowances in bulk and hold them for the long term as they expect higher price in the future. Such activity by long-term speculators such as pension fund who have huge buying power could have huge impact on EUA prices. There is evident of growing market activity to accumulate Exchange Traded Funds (ETF) that invest in carbon credits (Ampudia et al., 2022). This phenomenon suggests that exchange-traded funds and similar investment funds are potentially taking a more prominent role within the EU ETS market.

7 Appendices

Appendix 1: Descriptive Statistics (Level)

Variables	Obs	Mean	Std. Dev.	Min	Max	Skew.	Kurt.
EUA23	694	74.026	17.856	32.190	100.800	-0.713	2.294
Electricity	694	174.688	115.437	42	652	1.146	3.959
Gas	694	77.389	56.641	15.580	311	1.257	4.356
Coal	694	21.154	12.076	6.417	49.278	0.766	2.303
Industry	694	327.352	20.637	274.740	370.180	-0.130	2.227
Wind	694	51074.573	22684.521	15180.470	117000	0.700	2.737
Hydro	694	29177.573	6952.587	13355.090	50564.030	0.750	3.523
Solar	694	20111.245	10153.619	3004	41031.200	0.062	1.909
Oil	694	72.741	16.516	38.864	115.867	0.457	2.576
LNGFlow	694	189.534	77.153	27.742	355.985	-0.382	2.302
Temp	694	10.864	7.061	-7.360	27.710	-0.031	2.115
Stoxx600	694	446.058	23.496	382.890	494.350	-0.473	2.470
USDEUR	694	0.904	0.056	0.811	1.042	0.260	2.232

Appendix 2: Correlation Matrix (Level)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) EUA23	1.000												
(2) Electricity	0.434	1.000											
(3) Gas	0.386	0.885	1.000										
(4) Coal	0.453	0.545	0.577	1.000									
(5) Industry	-0.129	-0.254	-0.266	-0.258	1.000								
(6) Wind	0.127	-0.041	-0.070	-0.116	0.070	1.000							
(7) Hydro	-0.422	-0.256	-0.273	-0.380	0.220	-0.015	1.000						
(8) Solar	0.257	-0.079	-0.042	0.164	-0.269	-0.474	-0.554	1.000					
(9) Oil	0.639	0.667	0.681	0.882	-0.136	-0.047	-0.446	0.265	1.000				
(10) Stoxx600	0.264	-0.264	-0.299	-0.365	0.668	0.059	-0.111	0.009	-0.185	1.000			
(11) USDEUR	0.693	0.720	0.712	0.754	-0.568	0.032	-0.482	0.204	0.748	-0.342	1.000		
(12) LNGFlow	0.620	0.277	0.231	0.275	-0.186	0.245	-0.137	-0.001	0.405	-0.068	0.571	1.000	
(13) Temp	0.120	0.093	0.136	0.261	-0.222	-0.441	-0.584	0.762	0.248	-0.014	0.197	-0.323	1.000

Appendix 3: Correlation Matrix (Log-differenced)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) rEUA	1.000												
(2) rElectricity	0.147	1.000											
(3) rGas	0.104	0.734	1.000										
(4) rCoal	0.032	0.284	0.366	1.000									
(5) rIndustry	0.145	-0.060	-0.083	-0.037	1.000								
(6) ln_Wind	0.006	-0.094	-0.095	-0.061	0.062	1.000							
(7) ln_Hydro	0.044	0.030	0.033	0.066	0.015	-0.035	1.000						
(8) ln_Solar	-0.067	0.034	0.035	0.047	-0.046	-0.444	-0.542	1.000					
(9) rOil	0.047	0.174	0.186	0.199	0.212	0.033	0.019	-0.013	1.000				
(10) rStoxx600	0.206	-0.101	-0.136	-0.065	0.850	0.035	0.015	-0.025	0.123	1.000			
(11) rUSDEUR	-0.142	0.094	0.139	0.126	-0.310	-0.033	0.003	0.037	0.080	-0.287	1.000		
(12) LNGFlow	-0.015	-0.093	-0.079	-0.057	0.013	0.265	-0.127	-0.017	-0.029	0.003	-0.056	1.000	
(13) Temp	-0.041	0.063	0.053	0.011	-0.045	-0.472	-0.553	0.746	-0.051	-0.021	0.023	-0.328	1.000

Appendix 4: OLS Test

Test	Model 1	Model 1.1	Model 1.2	Model 2	Model 2.1	Model 3	Model 3.1	Model 4	Model 4.1
LM test	0.113	0.112	0.116	0.233	0.334	0.257	0.217	0.431	0.709
BP test	0.037	0.029	0.034	0.221	0.808	0.000	0.000	0.174	0.542
AIC	-3025.500	-3027.477	-3019.755	-1371.884	-1339.700	-511.285	-513.710	-1232.506	-1223.632
BIC	-2989.172	-2995.690	-2987.968	-1318.334	-1310.150	-495.000	-493.425	-1207.555	-1198.680
Procedure	NW OLS	NW OLS	NW OLS	NW OLS	NW OLS	NW OLS	NW OLS	NW OLS	NW OLS

Appendix 5: IV Regression Test

IV Test	Model 5	Model 6	Model 7	Model 8
Weak- identification test (Cragg-Donald Wald F Stat)	7.225*	10.460*	3.152	10.263*
Under- identification test (Anderson canon LM Stat)	0.049	0.005	0.925	0.005
Over-identification test (Sargan Stat)	0.716	0.533	0.548	0.762

Appendix 6: VAR Model (Lag-order Selection Test)

Lag	LogL	FPE	AIC	HQIC	SBIC
0	1920.48	7.2e-16	-15.0077	-14.9686	-14.9105
1	2597.25	5.2e-18*	-19.9313*	-19.6185*	-19.1537*
2	2626.34	6.1e-18	-19.7752	-19.1887	-18.317
3	2660.97	6.8e-18	-19.6625	-18.8022	-17.5238
4	2690	8.0e-18	-19.5059	-18.3719	-16.6868
5	2719.76	9.4e-18	-19.355	-17.9473	-15.8554

Appendix 7: VAR Regression

	EUA	Electricity	Coal	Industry
EUA-1	0.010	0.202*	-0.002	0.035
	(0.064)	(0.159)	(0.102)	(0.032)
Electricity	0.008	-0.099	-0.020	0.002
	(0.027)	(0.067)	(0.043)	(0.013)
Coal	0.0667*	0.050	0.106*	-0.017
	(0.041)	(0.102)	(0.065)	(0.021)
Industry	0.262**	0.303	-0.191	0.019
	(0.124)	(0.309)	(0.198)	(0.062)
Constant	0.001	-0.006	-0.004	0.001
	(0.001)	(0.004)	(0.002)	(0.001)
R-Squared	0.027	0.017	0.015	0.008
LM Test (lag 1)	0.501	0.501	0.501	0.501

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