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What is the effect of energy commodities on EU carbon emissions certificates?

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Abstract

This paper investigates the effect of energy commodities on EUA futures using econometric models. Using daily data from 2021 to May 2022, an OLS and VAR model are estimated to capture the influence of energy commodities in the trading phase IV. Based on the VAR model and the Granger causality analysis, coal is the most important short-term driver of EUA futures. In contrast, both coal and oil have a significant influence in the medium term. Secondly, the paper investigates if the impact of energy commodities changes between trading phases III and IV with a regression analysis and a Chow break test. The results of the regression analysis show a significant decline in the impact of energy commodities from phase III to IV. Based on the results of the Chow break test, there was a structural change between trading phases III and IV.

JEL-codes: Q52 Q53 G13

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1. Introduction

Fighting climate change is one of the key policy challenges for the European Union this century. One of the central aspects of an effective climate change policy is the reduction of greenhouse gas emissions. By setting the right incentives, the annual amount of emitted greenhouse gases can be reduced significantly. Following the Kyoto agreement in 1997, the European Union developed an emissions trading scheme to reduce greenhouse gas emissions. The EU emissions trading scheme has since become one of the central pillars of Europe's environmental policy.

The emissions trading scheme was one of the first of its kind and is based on a cap-and-trade mechanism. The EU emissions trading scheme (EU ETS) imposes a cap on greenhouse gas emissions emitted by specific sectors and creates tradeable certificates (EU, 2022). Companies that fall under the scheme need to surrender an allowance certificate at the end of the year for each ton of Co^2 (carbon dioxide) or equivalent greenhouse gas emitted during that year to avoid facing substantial fines. Since its establishment in 2005, the trading scheme has undergone four phases. Throughout each phase, the cap on total emissions has been reduced (EU, 2022).

One of the most important instruments under the EU ETS is the European Union Allowance (EUA) which gives the owner the right to emit one ton of CO^2 or equivalent greenhouse gas. The EUA is traded in spot, futures, and options markets, with the European Energy Exchange (EEX) and Intercontinental Exchange (ICE) as the main trading platforms. Of these markets, the futures market is the most important, making up 88% of total trading volume in carbon allowances (Sandor et al., 2014). The ICE EUA, December futures contract, can be considered a benchmark for the carbon price in the EU (Palao & Pardo, 2021). In order to obtain a better understanding of the market efficiency of the EUA market, it is important to understand which factors drive the EUA price. One of the key factors affecting the price of EUA futures are energy prices (Aatola et al., 2013). This paper aims to investigate the relationship between EUA futures and energy commodities with the following research question:

"What is the effect of energy commodities on EUA futures?"

1.1 Relevance and background

CO^2 emissions certificates are based on a cap-and-trade system. Firstly, a maximum number of available certificates is defined, determining the total allowed emissions in a given calendar year. Then allocated certificates can be traded in spot futures and options markets. This mechanism goes back to the theorem of (Coase, 1960), who describes how individuals reach an optimal solution through negotiation after the allocation of property rights. In a cap and trade scheme, emissions certificates are first allocated by either auction or free allocation. Thus the property rights are clearly defined, fulfilling the first condition of the Coase theorem. Secondly, the marketplaces give companies the ability to trade certificates at relatively low transaction costs. In this way, market participants can find an efficient solution without direct government intervention.

The EU carbon allowance certificates are a relatively new asset class, and the market has significantly changed since it was established. The European emissions trading system started with a pilot phase from 2005 to 2007. The main goal of the first phase was to build up the infrastructure needed for verifying and measuring emissions. Initially, CO2 certificates based on historical emission data were granted to most businesses for free in a process called grandfathering. Phase I covered energy-intensive industries' emissions and power generation (EU, 2022). At the start of Phase II in 2008, the emission cap was reduced by 6.5% compared to the start of the trading scheme (EU, 2022). Furthermore, the proportion of freely allocated certificates was slightly reduced, and the system was expanded to Norway, Iceland, and Liechtenstein.

Trading Phase III started in 2013 and saw the introduction of a single EU-wide emission cap rather than the previous national caps. Moreover, Phase III also switched from free allocation to auctioning as the default allocation method, and more sectors were included. Since 2021 the market for carbon emissions has entered phase IV of the trading scheme. In phase IV, the annual reduction is set to 2.2% of total emissions, currently covering 40% of total emissions (EU, 2022). Moreover, the market stability reserve (MSR) will be used to reduce the surplus in allowances and make the mechanism more resilient against shocks.

The price of EUA futures is determined as a commodity by the supply and demand for the certificates (Sandor et al., 2014). As the supply is fixed for a given year by the predetermined emission cap, the demand side is the only factor affecting the price in the short to medium term. The demand for emission certificates depends on the excepted emissions in each period. These emissions are affected by multiple factors such as macroeconomic conditions, energy prices, and weather events. This paper will focus on the short to medium-term link to energy commodities.

Within the energy commodities, it is important to make to look at the relative emissions of the energy commodities. Natural gas burning causes about half of the Co^2 emissions for the same amount of energy output compared to oil and coal (Hammoudeh et al., 2014). Due to the difference in relative emissions, the impact of price changes in coal and oil is opposite to the impact of price changes in natural gas. With rising coal and oil prices, the quantity demanded will be reduced, leading to lower consumption of these high-emission fossil fuels. At the same time, the consumption of lower emission fuels will increase due to their now relatively lower price. With the substitution of high emission fuels for natural gas, the expected emissions will be reduced, leading to a lower price for emission certificates (Aatola et al., 2013). The opposite is true for natural gas here; an increased price also leads to increased use of higher emission fuels such as oil and gas and thus to an increased price of emission certificates. Thus economic theory would predict a negative impact of coal and oil price increase and a positive impact of natural gas price increases.

This paper aims to expand on the current literature and establish whether the relationships between commodity prices and EUA futures found in the earlier phases of the mechanism are still present today. In this way, the paper will contribute to a better understanding of the price dynamics behind EUA futures. This analysis will help shed light on the market efficiency of the EUA futures market. As the emissions trading scheme is at the core of Europe's climate policy, the efficiency of the carbon allowance market has significant societal implications. An efficient carbon market has a stable relationship with market fundamentals and would provide a reliable base for EU climate policy. Furthermore, this paper will develop an understanding of trading rules' impact on the market mechanism. This will be valuable information for future changes to the emissions trading rules. Moreover, this understanding will also help guide company and investor decisions.

The rest of this paper will be structured as follows; in chapter two, the existing literature on carbon certificates and their price drivers will be reviewed, and the hypothesis will be introduced. Chapter three will explain the data sources, and chapter four will discuss the methodology. Finally, chapter five will lay out the results, and chapter six will discuss the main takeaways of the analysis.

2. Literature review

This chapter will discuss the existing literature about carbon emission certificates. Firstly, section 2.1 will introduce the general concept of emission certificates and examine the literature on early examples like SO^2 (sulfur dioxide) certificates. Afterward, 2.2 will discuss the European carbon certificates and their price drivers in trading phases I and II. Next, section 2.3 will discuss the research on trading phases III and IV. Moreover, section 2.4 will discuss the literature on structural breaks, and section 2.5 will examine the influence on other markets. Finally, section 2.6 will discuss the main takeaways and introduce the hypothesis.

2.1 Early applications of cap and trade systems

To understand the EU ETS market, it is important to examine earlier applications of cap and trade schemes. One of the first applications of a cap-and-trade system was the market for SO^2 emissions in the electricity industry in the United States. In 1990 the US government instituted a cap on aggregate SO^2 emissions from electricity production and created a mechanism where firms could transfer the emission rights to each other. Burtraw (1998) analyses the market performance and economic efficiency of the SO^2 emissions market. He concludes that the benefits of the market greatly outweigh the cost. Furthermore, he points out the significant contribution of the market to reducing SO^2 emissions. Colby (2000) analyzes the impact of cap-and-trade systems based on three different markets. The market for SO^2 shows the most potential for welfare gains, while the markets for water rights and fishery permits suffer from low trading activity. While the research on early applications of cap and trade schemes established the economic benefits, little research has been done on the market dynamics and price drivers of these certificates.

2.2 Price drivers of EUAs in trading phases I and II

As the goal of this paper is to identify the current price drivers behind EUA futures, its useful to examine the research on the early trading phases. The relationship between market fundamentals and EUA futures in trading phases I and II has been well documented. Christiansen et al. (2005), Benz & Trück (2006), Bunn & Fezzi (2007) all find evidence for a relationship between carbon markets and market fundamentals in trading phase I. Christiansen et al. (2005) analyze key price determinates for EUA prices during the first trading phase. Based on market data between 2005 and 2007, the authors investigate the impact of policies, market fundamentals, and market psychology. Firstly, they point out that policies such as the national allocation plan applied in phase I will likely impact EUA prices significantly. Secondly, the paper also highlights the growing importance of market fundamentals such as weather events, fuel prices, and economic growth. Benz & Trück (2006) classify the EU emission certificate as a new commodity. Furthermore, they point out that the EU emissions trading scheme is the largest of its kind covering about 45% of total emissions. Based on empirical analysis, they identify that emission certificate prices show excess kurtosis and asymmetry. They also mention that an adequate pricing model should account for regulatory issues and market fundamentals. Bunn & Fezzi (2007) investigate the relationship between carbon electricity and gas prices from April 2005 to May 2006. The authors construct a structural cointegrated vector autoregressive model to capture the relationship between EUA prices, UK electricity, and UK gas prices. They conclude that gas drives EUA prices while EUA and gas prices drive electricity.

For trading phases I and II, Chevallier (2011), Aatola et al. (2013), and Yu et al. (2015) also establish a link between energy commodities and EUA certificates. Chevallier (2011) looks at the impact of macroeconomic conditions and energy prices on EUA futures prices. Based on a Markov switching vector autoregressive model investigates the link between macroeconomic shocks and EUA prices from 2005 to 2010. The paper establishes that an increase in industrial production leads to an increase in EUA prices. Moreover, this relationship persists after accounting for shocks in energy commodities. Aatola et al. (2013) investigate the price determination of daily EUA futures prices. Based on an OLS, IV, and VAR model, the examines the relationship between market fundamentals and carbon certificates from 2005 to 2010. The authors find that market fundamentals determine about 40% of the EUA futures prices, with electricity prices being the most important determinant. Additionally, gas and coal prices are shown to impact the price of EUA futures significantly. Yu et al. (2015) examines the causality between Crude oil and EUA futures using linear and nonlinear Granger causality tests. The authors state that there is no short-term causality between both markets. On the other hand, the paper finds evidence for a significant linear relationship between the long-term trends.

All in all, it can be said that energy commodities are an important driver of EUA futures in phases I and II. Additionally, macroeconomic conditions (Chevallier, 2011) and electricity prices (Aatola et al., 2013) also play a significant role.

2.3 Research on trading phases III and IV

This section will focus on the literature on EUA futures for trading phases III and IV. The research on trading phases III and IV is less developed than on the earlier trading phases, but it covers more aspects of the EUA market than the earlier research. One of the major changes in Phase III compared to earlier trading phases was the introduction of a market stability reserve (MRS) that absorbs excess allowances to preserve the stability of the EUA prices. Bruninx et al. (2020) show that the introduction of the MRS has greatly strengthened the stability of EUA prices and is one of the key drivers for the increase in EUA prices. Zhu et al. (2019) conducted a multiscale analysis of the drivers of the EUA price in phases II and III. Based on EUA futures prices from 2008 to 2016, the authors analyze the drivers for the carbon price on a short, medium, and long-term time scale. On a short time scale, the authors find a significant impact on electricity and stock markets. On a long-term time scale, both natural gas and oil prices have a significant adverse effect, while the effect of stock indices is also stronger. Ghazani & Jafari (2021) investigate the market efficiency of the EUA futures market in trading phase III. The authors confirm that the adaptive market hypothesis holds for EUA futures in phase III based on two different statistical techniques. Moreover, the paper states that the market has become more mature due to the increased use of auctions and the induction of the market stability reserve. Wang & Zhao (2021) examine global energy and stock markets on the EUA futures markets between 2015 and 2020. Based on structural equation models, the authors find that macroeconomic conditions and energy markets influence the EUA futures market. The paper identifies the CAC40 index, the natural gas price, and Brent crude oil price as the most important direct determinants of EUA price.

The topic of volatility spillover between energy and carbon markets has gained interest in recent research. Zhang & Sun (2016) examine dynamic volatility spillovers between the European carbon market and fossil energy markets. Based on EUA futures, natural gas, Brent crude oil, and coal prices from 2008 to 2014, the paper first constructs a VAR model and then uses the resulting residuals to construct various GARCH models. The authors conclude that there is strong evidence for dynamic volatility spillover between carbon and energy markets. Dai et al. (2021) explore the high-order spillover between the EUA and energy markets. The authors find that spillovers are weak in the short term but more substantial in the long term. Moreover, the paper finds that the switch to a more auction-based system has led ability of the carbon market to transmit information to energy markets.

To conclude, the research existing on trading phases III and IV has given some evidence for an interaction between energy commodities and EUA futures (Zhu et al., 2019) and (Dai et al., 2021). Nevertheless, the price drivers for EUA futures are much less established than for the earlier trading phases. This paper aims to add to the current research on trading phases III and IV by capturing the impact of energy commodities in these phases.

2.4 Structural breaks in the EUA market

Another important aspect in understanding the dynamics behind EUAs are structural changes in the relationship between market fundamentals and EUAs. Structural breaks have been a focus of academic literature on EU carbon throughout its existence. Alberola et al. (2008) analyze trends in the EUA spot price from 2005 to 2007. The authors identify two structural breaks, one in April 2006 and another in October of the same year, based on the chow break test. The authors identify electricity in the markets as the key determinant for EUA prices in the structural break. After the second structural break, the paper finds a significant relationship between market fundamentals, such as crude oil and temperature changes. Hinterman (2010) analyses the price determinants of the EUA allowance prices. The paper identifies a structural break in April 2006 due to a market crash caused by a shift in expectations on aggregate emissions. The author points out a stronger nonlinear relationship to market fundamentals and increased market efficiency after the crash. Based on daily over-the-counter prices, the paper identifies fuel prices, temperature, and precipitation as the most important drivers of the EUA price after the structural break.

Certi et al. (2012) examine the price drivers of the EUA price in trading phases I and II. Using cointegration techniques, the authors conclude that both periods have an equilibrium between carbon prices and market fundamentals. Furthermore, the relationship to market fundamentals is getting stronger in trading phase II. Dai et al. (2021) found evidence for a structural break between EUA and energy markets on September 15, 2016, using a nonparametric approach. While there was a stable bearish for energy and carbon in Phase III before the break, both markets are more volatile and bullish after the breakpoint.

All in all, it can be said that structural breaks are important aspects of the analysis of EUA markets in trading phases I and II. Moreover, Dai et al. (2021) established a structural break in trading phase III. This paper will add to the existing literature by investigating the existence of a structural break between trading phases III and IV.

2.5 Impact of EUAs on other markets

While the main focus of this paper lies on the impact of energy commodities on the EUA market, it is also important to view this relationship in the context of the impact of EUAs on other markets. With the increasing importance of the EUA market, the likelihood of spillovers to other markets has also been increasing. Oestreich & Tsiakas (2015) examine the existence of a carbon risk premium based on German and UK stock market data in trading phases I and II. To capture the carbon risk premium, the authors build a portfolio that goes long in the stock with the highest emissions and short in the ones with the lowest emissions. The authors find a significant carbon risk premium of 15.7% in trading phase I, which they attribute to the free allocation of carbon certificates in the first phase. With the increasing use of auctions in trading period II, the carbon premium becomes negative and insignificant. Dutta et al. (2018) investigated the return and volatility linkages between EUA and clean energy stock prices between 2009 and 2017. Based on a VAR-GARCH model, the authors examine the relationship between EUA spot prices and two clean energy indices. The authors conclude that there is no significant relationship between EU clean energy returns and EUA returns. For volatility, on the other hand, the paper finds a significant linkage between the EUA market and Erix, the European clean energy portfolio, but not to the Us clean energy portfolio Eco.

The Chinese market for carbon emissions is one of the largest trading schemes for greenhouse gas emissions (Wen et al., 2020), making the Chinese carbon market one of the most important comparisons to the European carbon market. Ji et al. (2021) identify regulatory changes, energy, and product prices as key drivers of the Chinese carbon price. This shows that similar factors drive the Chinese carbon price as the EUA price in its early stages (Christiansen et al., 2005). Wen et al. (2020) investigate the link between stock returns and the price of Chinese carbon certificates. The authors identify a significant positive carbon risk premium. Contrary to the declining premium identified by (Oestreich & Tsiakas, 2015) for the European market, (Wen et al., 2020) find that the premium is increasing over time.

2.6 Main takeaways

All in all, it can be said that price drivers for the first two trading phases are well documented. Christiansen et al. (2005), Chevallier (2011), Aatola et al. (2013), and Certi et al. (2012) all find evidence for a relationship between market fundamentals and the EUA price. For trading phases III and IV, the research is much less developed, but there is some evidence for a relationship between carbon prices and market fundamentals (Zhu et al., 2019). This paper aims to contribute to the existing research by empirically investigating the relationship between energy commodities and EUA futures in trading phase IV with the following hypotheses:

H1: Brent crude oil, coal, and natural gas drive the price of EUA futures

H2: Brent crude oil, coal, and natural gas Granger cause EUA futures

Secondly, it can be concluded that structural breaks between market fundamentals and EUA futures are present in the first two trading phases. Alberola et al. (2008), (Dai et al., 2021), and (Hinterman, 2010) found evidence for structural breaks in trading phases I and II. Moreover, Certi et al. (2012) established the presence of a structural break between trading phases I and II. This paper will build on the existing research on structural breaks by exploring the following hypothesis:

H3: The impact of energy commodities on EUA futures changed significantly from trading phase III to IV

3. Data

This chapter will give an overview of the data used in this research. Firstly, the selected commodities and their characteristics will be discussed. Moreover, the data sources and the observation periods will be covered. Finally, the data clean-up and the number of observations will be described.

EUA price *(Euro/megaton)* This paper selects the EUA futures contract traded on the ICE futures Europe commodities exchange. Following Aatola et al. (2013), Zhang & Sun (2016), and Zhu et al. (2019), the active EUA December futures is chosen due to its trading volume and role in price discovery.

Oil price *(Euro/barrel)* The monthly Brent crude oil futures contract traded on the ICE futures Europe commodities exchange is chosen for this research. Following Alberola et al. 2008 and Zhu et al. (2019), this contract is selected due to its role as a reference point for European oil prices.

Coal price *(Euro/megaton)* Following Hinterman (2010) and Zhu et al. (2019), the monthly coal futures contract on the ICE futures Europe commodities exchange was chosen.

Gas price *(Euro/megawatt hour)* Following Hinterman (2010) and Zhu et al. (2019), this research uses the monthly natural gas futures contract negotiated at the title transfer facility in the Netherlands

Table 1: Overview of data series and sources

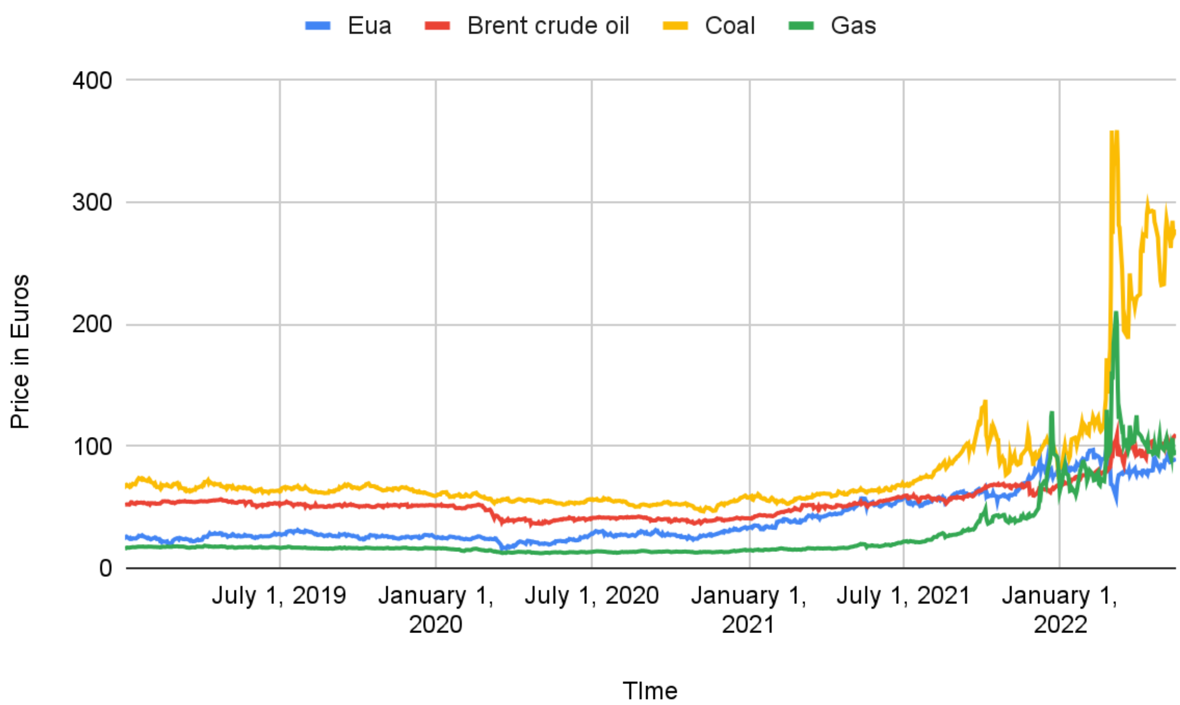
Series	Ticker	Unit	Specification	Source
EUA price	MOA Comdty	(Euro/MT)	EUA futures, active contract	ICE futures Europe commodities
Brent crude oil price	COA Comdty	(Euro/BBL)	Brent crude oil futures, active contract	ICE futures Europe commodities
Coal price	XAA Comdty	(Euro/MT)	Coal, Rotterdam monthly active contract	ICE futures Europe commodities
Gas price	TTFG1MON	(Euro/MWh)	Netherlands TTF natural gas forward month 1	Bloomberg OTC composite

Notes: Carbon and energy commodities, with their respective units, tickers, specifications, and sources

The daily closing prices for the four commodities were extracted from the Bloomberg commodities database. The observation period starts on January 2, 2019, to cover the last two years of trading phase III and ranges until May 16, 2022, to cover the first one and a half years of trading phase IV. Due to missing data points in the EUA time series, all observations on 26.12.2019, 13.04.2020, and 05.04.2021 were excluded from the data set. As the primary analysis relies on daily log differences, classic imputation techniques like the last observation carried forward or the last observation carried backward would have caused a bias towards zero in the relationship between the commodities. This is due to the fact that by imputing either the previous or next value, one of the differences will be equal to zero as the two values are identical. Thus, all observations were dropped to maintain consistency between the time series.

Figure I shows the price development of the EUA and energy commodities from 2019 to May 2022. All commodities show a relatively stable trend until mid-2021, when an increasing trend in all four commodities can be observed. Coal and gas prices increased the most, with EUA prices increasing the least.

Figure I: EUA and energy commodity prices



Notes: EUA and energy commodity prices in Euros from 2019 to May 2022

Table 2: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Max	Min
EUA	868	40.48	21.06	96.93	16.12
Oil	868	54.42	14.66	109.58	36.31
Coal	868	80.13	50.97	359.23	46.54
Gas	868	28.24	28.39	210.80	12.31

Notes: Descriptive statistics for the full sample from 2019 to May 2022

The full sample consists of 3472 observations, with 868 observations for each price series. The mean price of EUA futures is 40.48 Euros, with a maximum price of 96.93 Euros and a minimum of 16.12 Euros. Of the energy commodities, Brent crude oil has the highest average price at 80.13, with gas having the lowest at 28.24 Euros.

4. Methodology

This chapter will lay out the methodology used in this research to test the hypothesis and answer the research question. The methodology is split into two main sections. In the first part, the dataset will be restricted to data from 2021 to May 2022 to empirically investigate the relationship between carbon energy commodity markets in trading Phase IV. The methodology's second part aims to test for a structural break between trading phases III and IV.

4.1 Price determinants in trading phase IV

To establish the relationship between energy commodity futures and EUA futures in trading phase IV, firstly, econometric models will be estimated based on daily market data from January 2021 to May 2022. An OLS and a vector autoregressive (VAR) model will be constructed in the spirit of (Aatola et al., 2013). Firstly, descriptive statistics for the price of EUA futures and energy commodities will be calculated. Afterward, the stationarity of the time series will be assessed using the augmented Dicky-fuller test and the Phillips-perron test. The non-stationary are then variables are transformed into log differenced form. Then the tests are repeated to confirm the stationarity of the log differenced time series. Furthermore, descriptive statistics and a correlation matrix of transformed data are estimated. Then an OLS model will be estimated with *deua* as the dependent variable representing the daily returns of EUA futures. The model will include *dbrent* for the Brent crude oil returns, *dcoal* for coal returns, and *dgas* representing gas *returns*. Newey-west standard errors will be applied to account for autocorrelation and heteroskedasticity:

$$deua = \boldsymbol{\alpha} + \boldsymbol{\beta 1} dbrent + \boldsymbol{\beta 2} dcoal + \boldsymbol{\beta 3} dgas + \boldsymbol{\varepsilon} \qquad (\mathbf{1})$$

Secondly, a VAR model will be constructed to overcome the OLS model's possible endogeneity and improve the results' robustness. The VAR model jointly estimates the EUA futures and the three energy commodities. The optimal order of lags included for each variable was selected based on the Akaike information criterion (AIC), following (Aatola et al., 2013) and (Zhang & Sun, 2016). The VAR model follows the general form of:

$$\mathbf{X} = \mathbf{C} + \mathbf{B}(\mathbf{L})\mathbf{X} + \boldsymbol{\varepsilon} \qquad (\mathbf{2})$$

With X as a vector representing the endogenous variables, C for the constant terms, B for the polynomials representing the lags, and $\boldsymbol{\varepsilon}$ for the error terms. To confirm the stability of the model, the Eigenvalues will be estimated. Moreover, the residuals will be predicted and visualized in a graph. Then an impulse response function analysis based on the selected VAR model will be carried out. The impulse response function will capture the dynamic impact of shocks in one variable on the other variables by plotting the size and sign of the response over time.

Finally, a Granger causality test at three different lag lengths will provide additional insight into the relationship between energy commodities and EUA futures. The Granger causality test is based on the VAR with five, eight, and sixteen lags, respectively. A Granger causality test assesses the predictive value of an independent variable, compared to only using own past values. In this way, each energy commodities' predictive power for EUA futures will be evaluated. The impact of each energy commodity will be captured based on the size and significance of the estimated coefficients from the OLS and VAR models. Moreover, the impulse response function and the Granger causality analysis results will also be considered to establish which commodity is the most critical driver of EUA futures prices.

4.2 Structural change between trading phases III and IV

The second part of the methodology examines whether the relationship between energy commodities and carbon prices significantly changed from trading period III to trading period IV. Firstly, an OLS regression model including a structural change dummy for 04.01.2021 and interaction terms for each commodity is estimated based on log-returns of EUA and energy prices:

$$deua = \boldsymbol{\alpha} + \boldsymbol{\beta 1} dbrent + \boldsymbol{\beta 2} dcoal + \boldsymbol{\beta 3} dgas + ß\mathbf{4} break + ß\mathbf{5} break * dbrent + ß\mathbf{6}\boldsymbol{b}reak * dgas + ß\mathbf{7} break * dcoal + \boldsymbol{\varepsilon} \qquad (\mathbf{3})$$

Then the null hypothesis of no structural change is tested using the Chow break test. The Chow break test assesses whether the linear relationship between the energy commodities was significantly different by estimating a regression model for the full sample and one restricted one. Following (Chow, 1960), the following F-test statistic is estimated:

$$F = \frac{(RSSr - RSSu)/(k+1)}{RSSu/Df} \qquad (4)$$

Where RSSr is the residual sum of squares of the restricted model and RSSu is the residual sum of squares of the unrestricted model. K the number of restrictions and Df the degrees of freedom.

5. Results

This chapter will present the results of the econometric analysis described in the previous chapter and connect them to existing research. First, the results for trading phase IV will be explored, starting with the OLS model (Table 3), followed by the VAR model (Table 4), and the Granger causality tests. The second section will focus on the structural break test regression in table 6 and the results of the Chow break test in table 7.

5.1 Price determinants in trading phase IV

In order to investigate the impact of energy commodities in trading phase IV, we start by estimating an OLS model with Newey-west standard errors. The results of the OLS model are presented in table 3. The table shows the coefficients for and standard errors for the regression of log-returns of EUA futures on the log-returns of three energy commodities. *Dbrent* shows a positive insignificant coefficient, while *dcoal* and *dgas* have insignificant negative coefficients.

Table 3: OLS regression

	Deua
Dbrent	0.039
	(0.080)
Dcoal	-0.020
	(0.070)
Dgas	-0.020
	(0.051)
Constant	0.003*
	(0.00155)
Observations	352

Notes: OLS regression on log returns for the restricted sample from 2021 to May 2022 using Newey-west standard errors, Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

While the OLS model indicates no significant causal relationship, at first sight, the OLS model is unlikely to represent the true causal relationship. The model most likely suffers from endogeneity due to omitted variables such as electricity prices, macroeconomic conditions, and simultaneous causality between the variables. To obtain a more accurate estimate of the true causal relationship between the energy commodities and EUA futures, a VAR model is estimated. Compared to the OLS model, the VAR allows all four variables to be endogenous at the same time. In this way, the relationship between the variables is not assumed to be unidirectional, and more complex feedback relationships can be captured.

Based on the minimization of the AIC criterion, a VAR model with eight lags is chosen (see table A1). After selecting a model with eight lags, the model was estimated using the maximum likelihood technique. In order to obtain valid interpretations from a VAR, the stability condition needs to be satisfied. To test the stability conditions of the VAR model, the eigenvalues were plotted. Figure A1 shows that all eigenvalues lie within the unit circle, and the VAR model fulfills the stability condition.

Table 4 shows the estimates of the VAR(8) model with the coefficients of each variable for their respective lags. For *deua*, its own lags one and five have a significant negative impact, while lag eight of *dbrent* has a significant negative impact. This confirms the earlier findings of (Martin et al., 2020), who identified a negative impact of oil on the EUA market using a VAR model. The negative impact of oil is likely explained by the decrease in oil consumption following an oil price increase leading to lower excepted emissions and thus lower demand for emission certificates. Lag three of *dcoal* have also had a significant negative impact on *deua*. This is in line with the research of (Aatola et al., 2013), who also found a negative impact of coal on EUA prices. As with oil, this negative effect of coal can be explained by an expected decrease in emissions following an increase in coal price.

Dgas, lag six is significant and positive, while lag seven is negative and significant. This goes contrary to existing literature, as both (Martin et al., 2020) and (Aatola et al., 2013) have pointed out a positive effect of gas due to its lower emissions compared to other fossil fuels. One possible explanation for the inconclusive effect of gas in the VAR model could be unique shocks to the gas prices following fears of gas shortages in Europe in 2022. For *dbrent* lags two, three, and five of *deua* have a significant negative impact. This points to a bidirectional relationship between both markets. A similar relationship can be found between *dcoal* and *deua,* where lags two and four *of deua* are significant and negative.

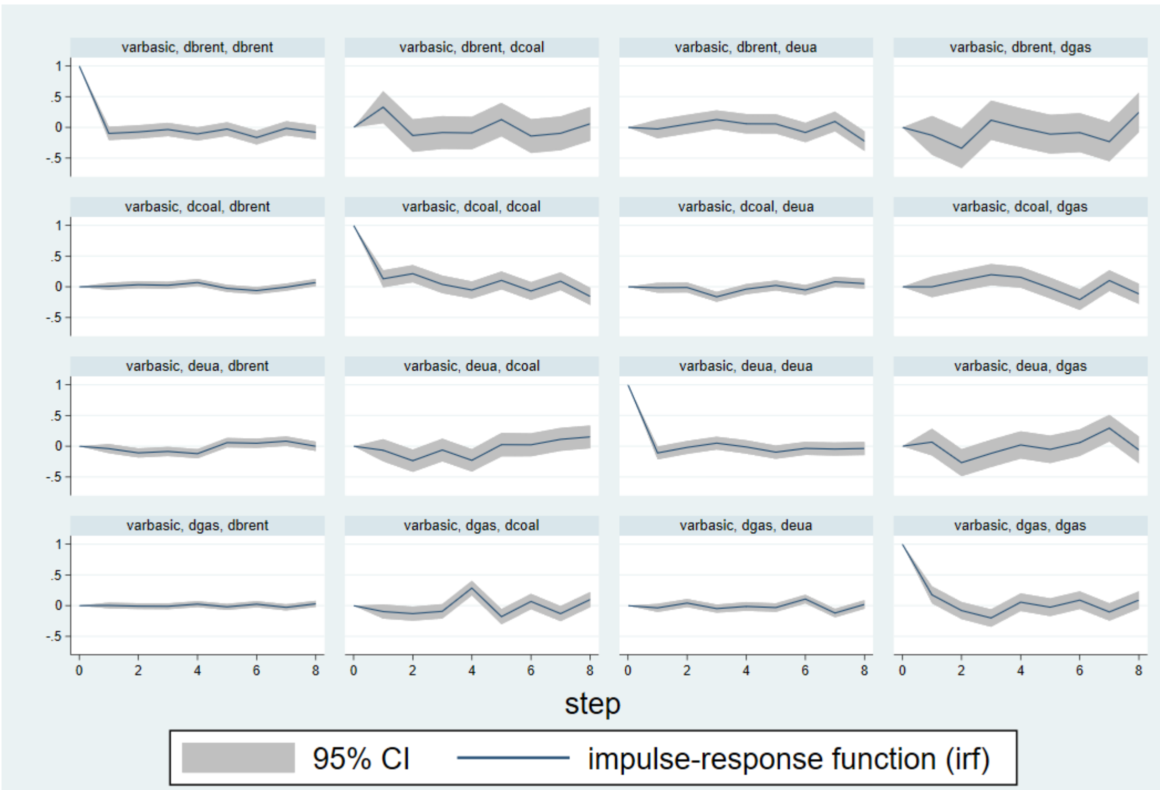
Table 4 : VAR(8) model

VARIABLES	Deua	Dbrent	Dcoal	Dgas
L.deua	-0.108**	-0.039	-0.065	0.064
L2.deua	-0.031	-0.116***	-0.215**	-0.277**
L3.deua	0.028	-0.107***	-0.031	-0.114
L4.deua	0.001	-0.145***	-0.213**	-0.004
L5.deua	-0.128**	0.022	0.003	-0.092
L6.deua	-0.055	0.051	0.083	0.100
L7.deua	-0.075	0.050	0.049	0.277**
L8.deua	-0.015	-0.037	0.109	-0.103
L.dbrent	-0.027	-0.0984*	0.328**	-0.125
L2.dbrent	0.046	-0.087	-0.158	-0.326**
L3.dbrent	0.128	-0.061	-0.170	0.080
L4.dbrent	0.147*	-0.120**	-0.080	-0.136
L5.dbrent	0.047	-0.047	0.251*	-0.134
L6.dbrent	-0.101	-0.127**	-0.089	0.027
L7.dbrent	0.102	-0.018	-0.148	-0.186
L8.dbrent	-0.168**	-0.114**	0.072	0.084
L.dcoal	-0.016	0.008	0.130*	0.001
L2.dcoal	-0.010	0.033	0.193***	0.105
L3.dcoal	-0.155***	0.021	-0.017	0.167*
L4.dcoal	-0.032	0.0571*	-0.082	0.108
L5.dcoal	0.048	-0.049	0.104	-0.089
L6.dcoal	-0.045	-0.080***	-0.065	-0.192**
L7.dcoal	0.065	-0.015	0.014	0.165*
L8.dcoal	0.063	0.094***	-0.181***	-0.189**
L.dgas	-0.035	0.003	-0.095	0.172**
L2.dgas	0.043	-0.009	-0.104*	-0.107
L3.dgas	-0.0590*	-0.008	-0.048	-0.170**
L4.dgas	-0.026	0.030	0.310***	0.147**
L5.dgas	-0.043	-0.024	-0.311***	-0.062
L6.dgas	0.077**	0.024	0.117*	0.075
L7.dgas	-0.078**	-0.043	-0.087	-0.167**
L8.dgas	-0.011	0.006	0.093	0.147**

Notes: VAR (8) model on log returns for the restricted sample from 2021 to May 2022 *** p<0.01, ** p<0.05, * p<0.1

The interpretation of the VAR model is not as straightforward as just looking at the lags and their significance. Thus, it is helpful in also take impulse response functions and the Granger causality test into account. Figure II shows the impulse response functions for each commodity to shocks of the other commodities. *Deua* has a slightly positive response to shocks in *dbrent* that stays relatively stable of the eight periods considered in the graphic. For *dcoal*, the response is initially slightly negative but then turns positive for the later periods. For *dgas*, the impulse response is initially negative, then positive, and the end positive again. Thus, confirming the inconclusive influence of gas on the Eua market seen in the VAR.

Figure II: Impulse response functions per commodity



Notes: Impulse response functions based on the VAR(8) model

Although the OLS model did not provide any significant coefficients, the VAR analysis showed that there is an influence of energy commodities on EUA futures. Coal seems to have the strongest initial negative response, which confirms the findings of (Zhu et al., 2019), who identified coal as the most short-term driver important driver of EUA futures. Brent crude oil has an initial positive response that turns negative after lag 5. From the magnitude of the coefficients and the impulse response function, gas has the smallest impact on EUA futures.

The second hypothesis focused on the Granger causality between energy commodities and EUA futures. Table 6 shows the pairwise Granger causality test for five, eight, and sixteen lags. For five lags, *deua* is Granger caused by *dcoal* only. For eight and sixteen lags, *deua* is Granger caused by both *dbrent* and *dcoal* at a 5% significance level but not by *dgas*. Thus, in the short term, only coal gas has significant predictive power. In the medium-term, Brent crude oil and coal Granger cause EUA futures while gas does not Granger cause EUA futures.

The results from the Granger causality analysis go in the same direction as (Yu et al., 2015), who found that there was no short-term Granger causality for crude oil, but significant Granger causality for the medium term. Zhu et al. (2019) also found that coal was the only short-term driver of EUA futures with a negative significant negative relationship to EUA futures. In the medium term, on the other hand, oil, coal, and gas all had a significant influence. This mostly confirms the findings of this paper, apart from the significant effect of gas.

The Granger causality analysis in Table 6 also shows a significant unidirectional Granger causality from *deua* to *dgas* after eight and sixteen lags. This confirms the findings of (Chung & Young, 2018), who identified a Granger causal relationship between EUA and natural gas in trading phase III. Fuel switching effects can explain this Granger causal relationship. If the EUA price decreases, high carbon emission fuels such as coal and oil become more attractive compared to natural gas, thus decreasing the demand for natural gas. An increase in EUA prices, on the other hand, has the opposite effect and thus leads to increased demand for natural gas.

Table 5: Pairwise Granger causality tests between energy commodities and EUA futures

Dependent variable	Independent variable	Lag(5)	Lag(8)	Lag(16)
Deua	**Dbrent**	0.121	0.034**	0.028**
Deua	**Dcoal**	0***	0.002***	0.005***
Deua	**Dgas**	0.558	0.142	0.251
Dbrent	**Deua**	0***	0***	0***
Dbrent	**Dcoal**	0.01**	0***	0.005
Dbrent	**Dgas**	0.434	0.746	0.363
Dcoal	**Deua**	0.034**	0.064	0.034
Dcoal	**Dbrent**	0.003***	0.037**	0***
Dcoal	**Dgas**	0***	0***	0***
Dgas	**Deua**	0.223	0.015**	0.01**
Dgas	**Dbrent**	0.22	0.45	0.013**
Dgas	**Dcoal**	0.147	0.003***	0***

Notes: Pairwise Granger causality tests P-values for different lag lengths, *** p<0.01, ** p<0.05, * p<0.1

Based on the Granger causality analysis and VAR model results, it can be concluded that Brent crude oil and coal are the most influential energy commodities for EUA futures in trading phase IV. This is in line with the research on earlier trading periods and economic theory. For gas, on the other hand, both the VAR model and the Granger causality analysis did not point towards a significant influence on EUA futures. All in all, it can be said that energy prices still remain an important driver of EUA futures in trading phase IV.

5.2 Structural change between trading phases III and IV

The second part of chapter five covers the investigation of the structural break between trading phases III and IV. Table 6 shows the results of an OLS regression for the full sample period, including dummies for a structural break on 04.01.2021 and their interaction terms with the three energy commodities. All three energy commodities have positive significant coefficients, with *dgas* having the highest one of 0.867. The coefficient of the break itself is positive but insignificant, while the interaction terms with the energy commodities are negative and significant at one percent. This suggests that the relationship between energy commodities has changed significantly after the switch to trading phase IV at the beginning of 2021. All energy commodities have a decreased importance for the returns of the EUA futures. Table 7 shows the joint significance of the structural break terms assessed by the Chow break test. Based on the P value of 0.0 in the Chow break test, one can reject the null hypothesis that there was no structural change in the relationship between the energy commodities and EUA futures.

Table 6: Structural break regression

	Deua	
Dbrent	0.274***	(0.089)
Dcoal	0.321***	(0.111)
Dgas	0.867***	(0.114)
Break	0.002	(0.002)
Break*dbrent	-0.232**	(0.113)
Break*dcoal	-0.344***	(0.116)
Break*dgas	-0.877***	(0.118)
Constant	0.001	(0.001)

Notes: OLS regression on log returns for the full sample from 2019 to May 2022 with break dummies for 04.01.2021
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7: Chow break test

Test	**F statistic**	**P-value**
Chow-break	36.97	**0.00*** **

*Notes: Structural break test on 04.01.2021 for the full sample from 2019 to May 2022**** p<0.01, ** p<0.05, * p<0.1

Based on the results of the regressions and Chow break test, the expectations from hypothesis three hold true. The relationship between energy commodities changed significantly between trading phases III and IV. While all three commodities had significant positive coefficients before the structural break, the interaction terms are all negative and significant, indicating a weaker relationship to energy commodities after the break. Although there is no other research that investigates the structural break between phases III and IV, the concept of structural breaks has been well documented in other trading phases. Alberola et al. (2008), (Dai et al., 2021), and (Hinterman, 2010) all found evidence for structural breaks between market fundamentals and EUA commodities. The structural break on 04.01.2021 that was established in this paper thus further supports the existence of structural breaks between market fundamentals and EUA futures.

Certi et al. (2012) also find evidence for a structural break between two trading phases. The authors conclude that the relationship between market fundamentals and carbon price got stronger in trading phase II compared to phase I. While the sign of the change is the opposite compared to the structural change established in this paper, their research still supports the general idea that trading rules can fundamentally change the price drivers of EUA futures. The changes in the trading rules between trading phases I and II were different in nature compared to the ones between trading phases III and IV. The transition to trading phase II saw an immediate reduction of the emissions cap by 6.5% and a cutback on the freely allocated certificates. Between trading phases III and IV, the changes were more focused on preventing carbon leakage and increasing the annual emissions reduction. Through the new carbon leakage rules, more certificates were allocated to new and growing industries and sectors at the highest risk of relocating production (EU, 2022). This increased free allocation could provide an explanation behind the weakening of the relationship to market fundamentals in trading phase IV.

Another possible explanation for the declining importance of energy commodities from trading phase III to IV could be the increasing use of renewable energy sources. The share of renewable energy sources increasing to 40% in 2020 (Melnyk et al., 2020), leading to lower emissions in electricity production than in previous periods. With the significant expansion of renewable energy sources such as solar, wind, and hydropower, this trend is likely to continue over the following decades. With the decreasing importance of fossil fuels for energy production, the influence on EUA futures will also likely continue to decline.

All in all, it can be said that there was a structural break in the relationship between energy commodities and EUA futures between trading phases III and IV. This builds on the existing literature on structural breaks for EUA futures and proves that the trading rules influence the relationship between market fundamentals and EUA futures. The structural break on 04.01.2021 led to a reduction of the impact of energy commodities on EUA futures in trading phase IV. This could be explained by the new carbon leakage rules that change increase the free allocation of certificates and by the increasing importance of renewable energy sources.

6. **Discussion and conclusion**

This chapter will discuss the main takeaways from the analysis and explore its implications for policymakers and investors. Additionally, the robustness of the results will be examined. Next, the limitations of the paper will be mentioned, and ideas for further research will be outlined. Finally, the research question will be answered, and a conclusion will be drawn.

The first part of the research investigated the influence of energy commodities on EUA futures in the trading phase IV using various econometric techniques. While the OLS model did not reveal any significant influence of energy commodities, both coal and oil showed a significant negative influence in the VAR model. The first hypothesis is that energy commodities influence EUA futures, which can thus be mostly confirmed with the barring the caveat of gas, where the influence was inconclusive in both the IRF analysis and VAR model.

The results of the Granger causality analysis go in a similar direction. In the short term, only coal had a significant impact on EUA futures. In the medium term, however, both oil and coal were significantly granger causal. Therefore, the second hypothesis stating that energy commodities Granger cause EUA futures can be mostly confirmed with the exception of the Granger causal effect of gas. Furthermore, gas was significantly Granger caused by EUA futures in the medium term while not having a significant influence on EUA futures in the medium term. Oil was Granger caused by EUA futures for all lag lengths, while coal had a significant effect for both five and sixteen lags. This provides interesting insight into the influence of EUA futures on energy markets. Through fuel switching effects, the EUA market seems to give incentives to switch to low emissions fuel such as gas or alternative sources when EUA price is high. This should be a signal to policymakers to continue with incentives like the market stability reserve to achieve a high stable carbon price. In this way, the emissions will be reduced, and the climate policy objectives will be easier to achieve. Investors could also make use of this connection between energy and carbon markets in their portfolio optimization. Carbon certificates could offer protection against falling energy prices, while energy commodities could be used as a hedge against increasing carbon prices.

The second part of this paper focuses on establishing a structural break in the relationship between energy commodities and EUA futures between trading phases III and IV. Firstly, an OLS model with structural break dummies was estimated. The interaction terms between the energy commodities and the break dates were significant and negative, indicating a decrease in the impact of energy commodities. This negative impact could have been caused by the increase in freely allocated certificates for at-risk industries. This points to a trade-off for policymakers, as the free allocation, on the one hand, serves to protect domestic production from competition abroad that does face an emissions trading scheme. On the other hand, this free allocation could lead to a loss in efficiency in the emissions trading scheme as these producers would not face the cost of carbon certificates. This provides support for the Eu's plan of facing out most of the free allocated certificates by 2026 (EU, 2022). Secondly, a Chow break test was conducted to test whether there was a structural break on 04.01.2021. The test rejects the null hypothesis that there was a structural break at a 1% significant level. Thus the third hypothesis that there was a structural break between trading phase III can be confirmed.

In order to increase the validity of the results, some robustness checks have been carried out. In a VAR model, the number of lags included follows a trade-off between the loss of information by including too few lags and the over-specification of the model by including too many. Thus it's useful to look at different lag specifications as a comparison. Table A3 for shows the VAR (2) model, in which the only significant coefficient for *deua* is its own first lag. *Deua,* on the other hand, still has a significant negative influence on both *dcoal* and *dgas* with its first lag. In the IRF analysis, the impact of *dcoal* and *dbrent* on deua is very slightly positive in the beginning, while gas seems to have no impact. All in all, it can be said that the VAR(2) fails to capture the complexity of the relationship between energy commodities and Eua futures. Table A4 shows the Var(5) model where the third lag of coal is negative while the fourth lag *dbrent* is positive. The IRF analysis shows a slightly positive impact of *dbrent*, while *dcoal* seems to have a slightly negative impact on deua. The VAR(5) already captures more impact of energy commodities, but the VAR(8) model chosen for the main part of this analysis seems to offer the most accurate picture of the relationship between energy commodities and EUA futures. To improve the robustness of the second part of the analysis, a few alternative structural break tests were carried out. Table A2 shows the results of the Fisher, Wald, likelihood ratio, and Lagrange multiplier test. All tests reject the null hypothesis that there was no structural break on 04.01.2021. Therefore, it can be said that the results of the Chow break test seem to be robust.

While this paper has followed the methodology carefully, there are still some limitations that need to be considered. Firstly, the missing data points for the EUA series on 26.12.2019, 13.04.2020, and 05.04.2021 should be considered when evaluating the analysis. While the impact of this on the econometric models is likely negligible due to the removal of all data points on these days, it still needs to be kept in mind. One other limitation was the relatively small sample size for trading phase IV (353 observations). Although that sample size is still large enough to capture the dynamics of the relationship between market fundamentals and EUA futures, the market continues to evolve, and a conclusion on trading phase IV can not be made yet. Therefore, I would recommend repeating the analysis in a few years when more data on trading phase IV becomes available.

With the target of reaching net-zero emissions by 2050, the topic of European emissions trading will remain relevant over the next few decades. Thus, further research is needed to capture the market dynamics of the EU ETS market. As this paper relied on daily returns to capture the dynamics between energy and carbon commodities, the focus was mostly on the short and medium-term relationships. To gain a deeper understanding of the medium to long-term dynamics, the models discussed in this paper should be repeated on a weekly and monthly time scale. While this paper examined the impact of energy commodities on EUA futures, there are other factors affecting demand for EUA futures. Research on earlier trading periods shows that both macroeconomic conditions and electricity prices influenced EUA futures. Therefore, it would be interesting to estimate a model for trading phase IV controlling for both macroeconomic conditions and electricity prices.

Another aspect that could improve the understanding of the EUA futures market is the impact of freely allocated certificates. By investigating the impact of freely allocated certificates, the future policy could take the potential loss of market efficiency into account. Moreover, investigating the impact of the increase in renewable energy sources could also provide further insight into the EUA futures market.

This paper investigated the impact of energy commodities on EUA futures. All in all, it can be said that energy commodities remain an important driver of EUA futures. For trading phase IV, this paper found evidence that coal is the most important driver of EUA futures in the short term, with gas and oil not having a significant influence. Coal and oil have a significant influence in the medium term, while gas remains insignificant. While the structural break analysis established that the importance of energy commodities declined from trading phase III to IV, energy commodities still have a significant impact on EUA futures in both periods. This is in line with the research of (Alberola et al., 2008), (Aatola et al., 2013), and (Certi et al., 2012), who all found a significant influence of energy commodities for earlier trading phases. The declining impact of energy commodities from trading phase III to IV could have multiple explanations. One possible explanation could be the increase of freely allocated certificates to industries at risk of relocating production to countries without a price on carbon. Another explanation could be the increasing importance of renewable energy sources. In order to identify the cause of this change, further research on both of these aspects is required

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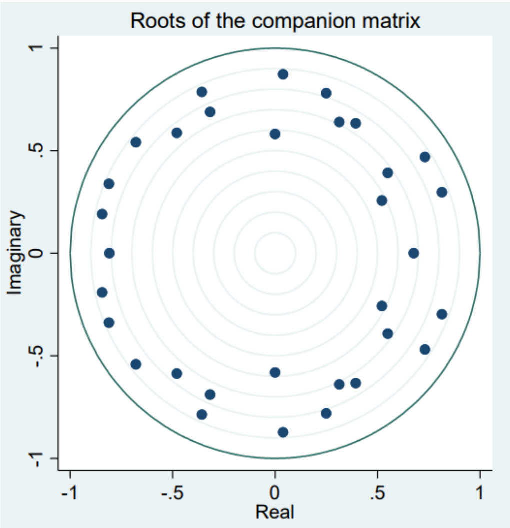
8. Appendix

Table A1: VAR Akaike information criterion (AIC)

Lags	Log likelihood	AIC
0	2526.22	-15.01
1	2552.02	-15.07
2	2567.77	-15.07
3	2590.94	-15.11
4	2614.82	-15.16
5	2647.74	-15.26
6	2662.81	-15.25
7	2679.75	-15.26
8	2703.19	-15.30*
9	2716.76	-15.29
10	2728.68	-15.27
11	2737.28	-15.22
12	2745.39	-15.17
13	2762.96	-15.18
14	2787.8	-15.24
15	2803.61	-15.24
16	2817.71	-15.22

*Notes: AIC for different VAR lag lengths * indicating the preferred lag length according to AIC*

Figure A1: VAR stability test



Notes: VAR eigenvalues graph

Table A2: Additional structural break test

Test	Test statistic	P-value
Chow-break	36.97	0***
Fisher	2.26	0***
Wald	149.28	0***
Likelihood ratio	137.73	0***
Lagrange Multiplier	127.35	0***

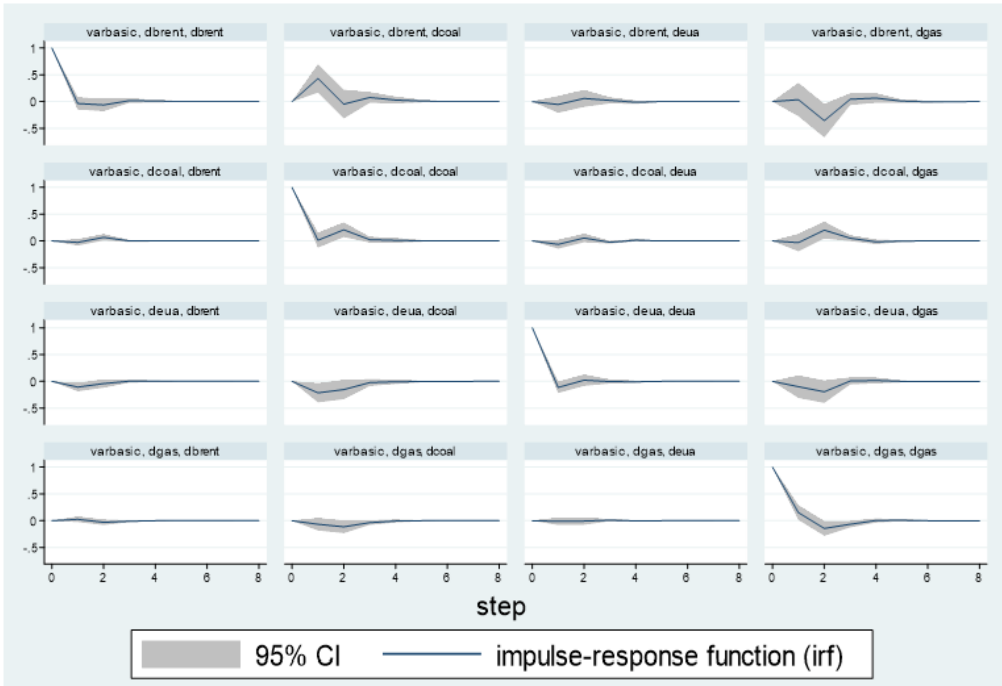
Notes: Structural break test for 04.01.2021 for the full sample from 2019 to May 2022 *** p<0.01, ** p<0.05, * p<0.1

Table A3: VAR(2) model

VARIABLES	Deua	dbrent	Dcoal	Dgas
L.deua	-0.113**	-0.108***	-0.215**	-0.101
L2.deua	-0.0127	-0.0605	-0.136	-0.194*
L.dbrent	-0.054	-0.035	0.432***	0.0364
L2.dbrent	0.0779	-0.061	-0.048	-0.354**
L.dcoal	-0.0635	-0.0267	0.0139	-0.0321
L2.dcoal	0.0467	0.0610**	0.204***	0.202**
L.dgas	-0.0112	0.0264	-0.0661	0.152**
L2.dgas	-0.00878	-0.0363	-0.117**	-0.173**

Notes: VAR (2) model on log returns for the restricted sample from 2021 to May 2022 *** p<0.01, ** p<0.05, * p<0.1

Figure A2: IRF functions VAR(2)



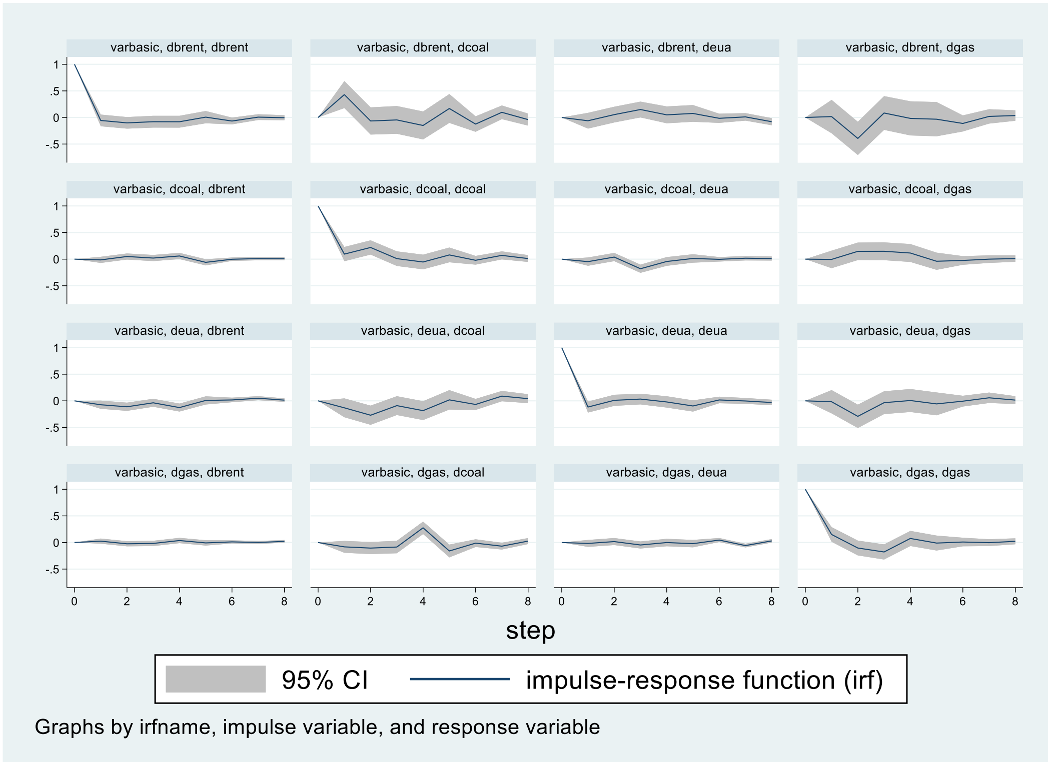
Notes: Impulse response functions based on the VAR(2) model

Table A4: VAR(5) model

VARIABLES	deua	Dbrent	Dcoal	Dgas
L.deua	-0.117**	-0.0735*	-0.132	-0.0173
L2.deua	-0.0152	-0.126***	-0.243***	-0.291***
L3.deua	0.0171	-0.056	-0.0484	-0.0358
L4.deua	-0.0133	-0.146***	-0.160*	-0.0179
L5.deua	-0.152***	-0.0287	0.0363	-0.0567
L.dbrent	-0.0612	-0.0557	0.430***	0.017
L2.dbrent	0.0635	-0.103*	-0.0891	-0.394**
L3.dbrent	0.126	-0.105*	-0.13	0.0449
L4.dbrent	0.156**	-0.103*	-0.0941	-0.128
L5.dbrent	0.0894	-0.0245	0.260*	-0.0871
L.dcoal	-0.0467	-0.0137	0.0952	-0.00471
L2.dcoal	0.0377	0.0468	0.210***	0.148*
L3.dcoal	-0.163***	0.0139	-0.0485	0.0926
L4.dcoal	-0.0556	0.0429	-0.0923	0.0966
L5.dcoal	0.0478	-0.0869***	0.0596	-0.0993
L.dgas	-0.0178	0.0253	-0.0821	0.151**
L2.dgas	0.0157	-0.029	-0.0982*	-0.128*
L3.dgas	-0.0543	-0.00802	-0.0412	-0.126*
L4.dgas	-0.0156	0.0417	0.289***	0.124*
L5.dgas	-0.0255	-0.0167	-0.272***	-0.062

Notes: VAR (5) model on log returns for the restricted sample from 2021 to May 2022 *** p<0.01, ** p<0.05, * p<0.1

Figure A3: IRF functions VAR(5)



Notes: Impulse response functions based on the VAR(5) model