Price Dynamics in the European Union Emissions Trading System: An Empirical Study of Carbon Allowances

Áron Zsolt Tenke

Dissertation written under the supervision of Professor Zoë Venter

Dissertation submitted in partial fulfilment of requirements for the MSc Finance with Specialization in Financial Markets, at the Universidade Católica Portuguesa, 2023.12.23.

Abstract (EN)

The European Union Emissions Trading System (EU ETS) has become a crucial element in regulating emissions across the EU. This study investigates the daily price fluctuations of European Union Allowances (EUAs), focusing on their price driving mechanics. The main focus of this analysis is the interplay between carbon prices, energy commodities, electricity prices, stock market performance, the profitability of coal and gas fired power plants, and weather temperature levels. The investigated sample consists of daily futures prices from 2005 to 2022. Robust methodologies such as Ordinary Least Squares and Vector Error Correction are applied to achieve significant results, which support the hypothesis of the above-mentioned variables influencing carbon prices. I find that these effects vary in each phase of the EU ETS, since these periods had different characteristics that affected these correlations. The results of this research contribute to the existing literature, offering insights for policy makers, companies that are part of the EU ETS, and market participants about the dynamics of the EUA market.

Keywords: EU ETS, EUA, CO_2 futures, Emission, Carbon pricing, Energy Markets, Vector Error Correction, Cointegration

Title: Price Dynamics in the European Union Emissions Trading System: An Empirical Study of Carbon Allowances

Author: Áron Zsolt Tenke

Resumo (PT)

O Regime Comunitário de Licenças de Emissão da União Europeia (RCLE-UE; abreviação em inglês: EU ETS) tornou-se um elemento crucial na regulação das emissões em toda a União Europeia. Este estudo investiga as flutuações diárias dos preços das Licenças de Emissão da União Europeia (LEUE; abreviação em inglês: EUA), centrando-se nos seus mecanismos de fixação de preços. O foco principal desta análise é a interação entre os preços do carbono, as matérias-primas energéticas, os preços da eletricidade, o desempenho do mercado de acções, a rentabilidade das centrais eléctricas a carvão e a gás e os níveis de temperatura meteorológica. A amostra investigada é constituída por preços diários futuros entre 2005 e 2022. São aplicadas metodologias robustas, como Mínimos Quadrados Ordinários e Correção de Erro Vetorial, para obter resultados significativos, que apoiam a hipótese de as variáveis supramencionadas que influencem os preços do carbono. Verifico que estes efeitos variam em cada fase da RCLE-UE, uma vez que estes períodos tinham características diferentes que afectavam estas correlações. Os resultados desta investigação contribuem para a literatura existente, oferecendo informações aos decisores políticos, às empresas que fazem parte do RCLE-UE e aos participantes no mercado sobre a dinâmica do mercado das LEUE.

Palavras-chave: RCLE-UE, LEUE, Futuros do dióxido de carbono , Emissões, Fixação do preço do carbono, Mercados de energia, Correção de Erro Vetorial, Cointegração

Título: Dinâmica dor preços no Regime Comunitário de Licenças de Emissão da União Europeia: Um estudo empírico das licenças de carbono

Autora: Áron Zsolt Tenke

1. Introduction:

The European Union has been combating climate change throughout history, implementing several green initiatives. One of the most influential is the European Union Emissions Trading System (EU ETS), which is a keystone in the fight against harmful carbon emissions. At the center of this system are the European Union Allowances[1] (EUAs). The main objective of my thesis is to provide an understanding behind the price drivers of these allowances. This empirical study aims to unravel the relationship between EUAs, energy commodities, electricity, stock market performance, the profitability of coal and gas power plants and weather. By utilizing robust methodologies such as Ordinary Least Squares (OLS) and Vector Error Correction Models (VECM), I provide an understanding as to what influences the prices of carbon offsets. A large body of earlier research focuses on the same subject, with Keppler and Mansanet-Bataller (2010), Lovcha, Perez-Laborda, and Sikora (2022) and Zhu, et al. (2019) all finding significant results. I find that there is a strong connection between the above mentioned series, albeit differing in each phase of the EU ETS.

The EU ETS is the result of a green initiative, which started with the Kyoto Protocol, with the aim of making EU member states carbon neutral by 2050. It was launched in 2005 and it is the world's first international emissions trading system. The system works on a cap-and-trade principle, where a limit is set on the amount of greenhouse gases a firm can produce annually. Companies need to purchase allowances when this cap is met/exceeded during the year. Fines are imposed on firms not adhering to the regulation/rules. If the company produces less than the allocated cap, it can sell its allowances. (European Comission, 2023)

The trading was split into phases. The first (2005-2007) was a so-called "learning phase", because of no pre-existing experience in the matter. Fines were lower than in the following phases and only CO_2 emissions were capped. Allowances were allocated by the EU. Supply and demand were not estimated adequately enough, hence carbon prices dropped to almost zero in 2007. The second phase (2008-2012) coincided with the Kyoto Protocol's first commitment period, in which member states had clear pre-set emission targets. In this phase caps were lowered; fines were raised and further caps for additional greenhouse gases were introduced. Aircraft operators joined the System at the beginning of 2012. The third phase (2012-2020) was the longest to date and saw

[1] Each allowance allows the emission of one tonne of CO_2.

several changes. Instead of each member state having different caps on emissions, a single EU-wide cap was introduced. The previous free allocation system was modified, and yearly auctions were introduced. The cap on emissions in the fourth phase (2021-2030) is being lowered to further reduce emissions by 2030. The goal is to decrease 2005 emissions by 62%. Maritime transport has been included in the system and the free allocation method will be slowly phased out. (European Comission, 2023).

2. Literature review

2.1 Success of the System

As mentioned above, the main aim of the EU ETS is to lower emissions across the European Union. Evidence points to a relatively successful adoption of the EU ETS. The ratio of emissions to GDP declined faster after 2007, which could be accredited to the System (Ellerman et al., 2016). However, the EU ETS could also have unwanted negative societal and macroeconomic consequences. According to Känzig (2023) the System leads to lower emissions and green innovation, however, also higher energy prices. The latter affects low-income households, which spend more on energy compared to rich households relative to their income. Therefore, they either have to lower their energy consumption or their spending on other assets, which can lead to a decrease in economic activity (Känzig, 2023).

2.2 Enterprise value

Witkowski (2022) aimed to determine the corporate financial effect the EU ETS had on polluting firms. The author analyzed 91 firms between 2008 and 2016, using separate pooled regressions with fixed, random or between-group effects. Emission allowances did not have a statistically significant effect on the return on equity (ROE) of these companies, meaning their profitability was not changed. This could be attributed to them either optimizing internal processes or passing the new costs to customers. However, allowances did affect the excess rate of return, which is ROE adjusted for the cost of equity. This can be explained as follows: by having higher emissions (i.e. number of allowances) the company is more connected to the risks associated with the price of EUAs, leading to investors to demand a premium. If a company did not reduce its verified emissions under the allocated one, its enterprise value would eventually decline. This effect could have been a motivating factor for the decrease in emissions (Witkowski, 2022).

2.3 Emission announcements

Brouwers et al. (2016) analysed whether buying or selling carbon credits had an effect on a firm's stock performance in the first two phases of the EU ETS. Allocated and verified (actual) emissions are published in so-called verification events annually on the first of May or the second of April, with the specific date varying in certain years. The authors employed an event study with different event windows to determine if any abnormal returns occurred because of the verification announcements. Their sample consisted of 368 listed companies, which accounted for 53% of the emissions in 2012. The results showed that publications had a statistically significant effect in only two years across the sample, specifically in the first year of each phase, 2006 and 2009. In both of these years having higher emissions than allocated led to a negative change in the stock price. Other verification events only had a significant impact on the stock price of firms that had high carbon emissions or were "less able to pass through the carbon-related costs in product prices" (Brouwers et al., 2016).

2.4 Tax avoidance

The EU ETS also affected the tax profile of corporations. In 2017, the EU passed a directive aiming to raise the prices of EUAs. Compagnie et al. (2023) examined whether the price shock changed the behaviour of large, polluting companies in terms of their corporate tax strategies. They found that higher allowance prices resulted in higher operating costs for these firms, leading them to turn to cost cutting methods, such as tax avoidance. The authors found that the gap between the effective tax rates of the firms with the most and least emissions was 5.13 percentage points. No effect was found on corporate taxes, meaning that the capital structure was not affected by the price shock. This phenomenon implies that the cost of pollution might be partially transferred back to society. (Compagnie et al., 2023)

2.5 Hedging

Corporations partaking in the EU ETS are exposed to numerous risks, for example, regulatory risks, as mentioned above. Chen et al. (2020) investigated the relationship between the carbon spot and futures market, using expanded GARCH models and found that the two markets are highly correlated and that there is a volatility spillover effect between the two. Their results indicated that the carbon futures market could be an efficient way to hedge the spot market (Chen et al, 2020). However, some entities would want to hedge their positions in the futures market. Jin et al. (2020)

aimed to identify the best instrument to do this, by analyzing four indices; the VIX, the commodity, the energy and the green bond. The returns of the latter was deemed to be the most correlated with the returns of carbon futures. The authors compared three dynamic hedging models (expanded GARCH) to a constant hedging model (OLS). The results showed that dynamic models are better, because of their ability to "capture the dynamic correlation and volatility spillover between the carbon futures and market index returns" (Jin et al., 2020).

2.6 Carbon and green premiums

The directive of lowering carbon emissions had an effect on both stock and bond returns. Using factor models such as CAPM, 3FF and 4FF, Oestreich and Tsiakas (2015) found that a large carbon premium was present in the first two phases of the EU ETS in Germany. Allowances in this period were allocated for free, therefore firms were able to pass through their higher marginal costs to customers, moreover, the EU ETS led to a drop in output, which in this case enabled firms to sell off their "unused" EUAs, thus generating revenue. This premium disappeared in 2013 when auctioning was introduced (Oestreich & Tsiakas, 2015). On the contrary, Ravina (2022) determined that there was a green premium present in the European bond market from 2008 to 2018. The author expanded the 2FF with an EU ETS participation factor (GMC). This new model proved to be better at asset pricing than the original, with the GMC being statistically significant. On average the GMC was positive, pointing towards the existence of a green premium in the examined period. One of the main implications of the paper is that in recent years investing in sustainable portfolios is not only ethically beneficial but also financially (Ravina, 2022).

2.7 Carbon price drivers:

Numerous papers focused on finding the drivers behind carbon prices and examining the effects that carbon prices might have on energy prices and other factors. Two important variables that the papers use that need explanation are the clean spark spread (CSS) and the clean dark spread (CDS). The formula for the former is subtracting the carbon and the gas cost from the electricity cost. The latter is calculated similarly, with coal cost instead of gas cost (Keppler & Mansanet-Bataller, 2010). These two metrics are used to determine whether coal or gas power plants operate on either loss or profit whether the measure is negative or positive respectively.

Keppler and Mansanet-Bataller (2010) utilized OLS and Granger causality to find that, through the CDS and CSS, the spot and forward prices of coal and gas impacted carbon future prices, which in turn Granger caused electricity prices in the first phase. However, this direction reversed in the second phase, where the electricity price was a cause of carbon prices (Keppler & Mansanet-Bataller, 2010). Batten et al. (2021) also used OLS as their methodology, to test the strength of the effect of electricity prices on carbon prices, however, their timeframe was set in the third phase. The authors found that building a model that is largely comprised of only the energy price explained 12% of the variation in carbon prices. Another finding of the paper was that weather in itself did not have a statistically significant effect on the carbon price, unexpected weather shocks however, had (Batten et al., 2021).

Another common modelling technique in the literature is the utilization of autoregressive models. In an early paper, Bunn and Fezzi (2009) utilized a structured VEC model to find a two-way effect between carbon price and energy prices. Their results showed that carbon prices have an influence on the price formation of electricity and gas. Impulse response analyses showed that a shock in the gas price had an almost instantaneous effect on the carbon price, while a shock in electricity took several days to take effect (Bunn & Fezzi, 2009). However, the main drivers of carbon prices have seen a slow change over the years. Lovcha et al. (2022) found that the explanatory power of gas weakened over time and instead, coal and oil came to have a larger influence on carbon prices. The authors built a structured VAR model with a moving regression window which linked carbon prices, economic activity and energy prices. They found that the independent variables together explained up to 90% of the carbon price movements. The individual contributions of independent variables fluctuated over time (Lovcha et al., 2022).

According to Zhu et al. (2019) the supply side was found to be much less influential than the demand side, because the caps and emission-lowering goals were known in advance. The authors studied different timeframes in their analysis and discovered that in the short term, coal, electricity, and stock market performance had an effect on carbon price. In the medium term, coal had a significantly negative effect. The authors argued that, theoretically, without a price put on emissions, using gas as an energy source was more costly than coal, yet also more environmentally friendly. High carbon or coal prices could make coal plants more expensive, to a point where operators were incentivized to switch to gas, which in turn would lower emissions and the demand for allowances, reducing the carbon price. This effect was expected to only occur in medium timeframes because switching takes time. This theory was somewhat invalidated by the long-term result, in which crude oil and gas have a negative influence, signaling that operators did not replace coal with either gas or oil (Zhu, et al., 2019).

3. Data

3.1 Variables

In this study, I have chosen which variables to include according to the literature mentioned above, anticipating that they will have a significant effect. The dependent variable, carbon price is represented by daily ECX EUA carbon futures. The energy prices included are Brent Crude oil futures prices, Rotterdam coal futures prices, and UK natural gas prices. In the case of electricity, the ELIX (European Electricity Index) is only available until 2020.06., however, the PHELIX base index, which is the electricity index for Germany and Austria, is accessible for the whole timespan. Germany and Austria are highly relevant markets in the EU which makes the use of the index appropriate. An OLS regression with these two indices yields an R^2 of around 80%, meaning the index efficiently captures electricity prices across Europe. Both clean spark and clean dark spread futures data are for Germany since it plays a significant role in electricity price formation in the EU. I have also chosen to include the STOXX 600 index to incorporate economic activity into the model. Several papers include the index in their studies, such as Tan et al. (2020) where the authors show that the EUA market is intrinsically linked to the stock market and less related to the bond market. Weather can also influence the output of installations, therefore affecting their carbon emissions, which in turn affects carbon prices from the demand side. However, because Europe is a large continent with several climates, there is no uniform weather data. Therefore, the daily average temperature of Munich is used in the study.

In the paper, I am using daily data from 2005.04.22, the first observation of the carbon price. One issue that arose when acquiring data was availability. The variable for coal prices is only available on Refinitiv from 2006.07.17. and the variables for the clean spark and clean dark spread from 2009.12.02., therefore they are only added to phases in which they are available in full.

3.2 Carbon price over time

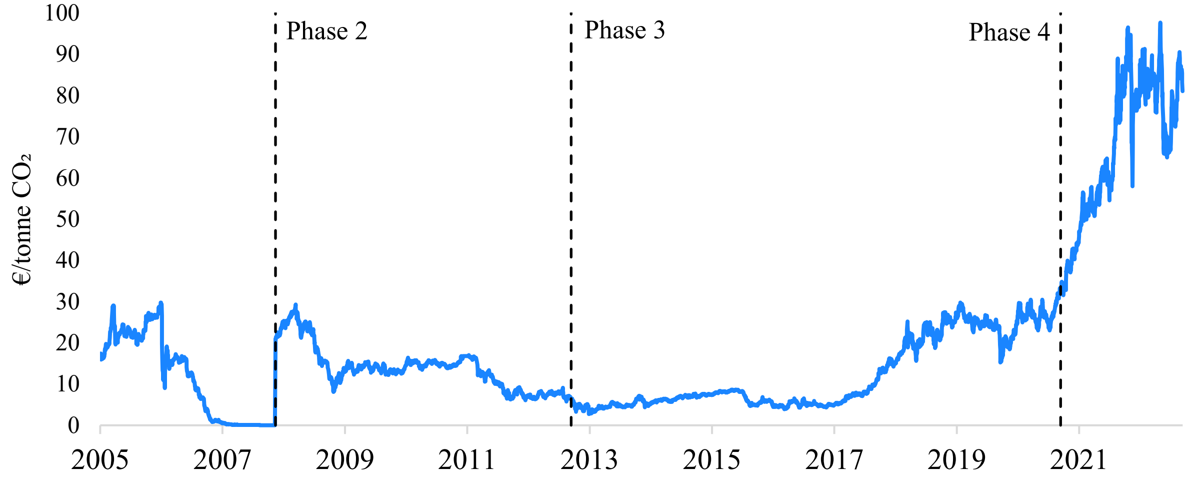


Figure 1: Daily carbon price

Figure 1 illustrates the significant fluctuations that carbon prices have seen since the creation of the EU ETS.

As mentioned above, Phase I was a learning period, with prices not being robust enough and surplus exceeding demand by a large amount. This led to prices plummeting in the first quarter of 2007. Moreover, companies were not able to bank their allowances for the next period, which is why we can observe a structural break at the beginning of Phase II. (European Comission, 2023)

The financial crisis impacted the demand side of carbon EUAs, since companies produced less, which can be seen by a large drop in price. This, combined with the still existing overallocation saw the price at a lower level at the end of Phase II compared to the beginning of the period. (European Comission, 2023)

Several regulatory actions were taken in Phase III, such as the introduction of the Market stability reserve (MSR), a directive by the European Council with the aim of reducing over allocation by adjusting supply. This led to a steady growth in prices in the second half of the Phase. Moreover, the carbon market started to mature, attracting trading activity. This in turn, raised the volatility. COVID-19 caused a dip of 36% in January of 2020, however, the recovery was quick, with the price bouncing back up to its pre-pandemic level by the beginning of February of 2020. The rebound could be accredited to several factors, such as supply adjustments with the MSR and the fact that the energy sector was not as severely affected by the outbreak of the virus. (European Comission, 2023)

As mentioned in the Introduction, emission caps were further lowered in Phase IV, leading to the price increasing once again. The increased volatility carried over from Phase III. The conflict between Ukraine and Russia had an effect on the carbon price as well. Uncertainty caused by the war caused certain parties such as funds to liquidate their positions in the market, which led to a 42% drop in prices (Watson & Burke, 2022).

Carbon price exhibits large changes over the observed period; therefore, each phase is analyzed separately in addition to examining the full timespan. Moreover, outliers can be detected across both the dependent and independent variables. Z-scores are used to determine which variables have outliers. These are calculated by subtracting the mean from the value being observed, then dividing by the standard deviation. An observation with a Z-score greater than +3 or less than -3 is generally considered an outlier. One common method to account for outliers is winsorizing. This involves replacing outliers above or below a certain percentile with the percentile itself. In this case 1% is used, meaning values below the 1^{st} and above the 99^{th} percentile are replaced. (Sullivan et al., 2021)

4.3 Descriptive characteristics

	Carbon	Oil	Gas	Electricity	STOXX	Munich	Coal	CDS	CSS
Mean	18.78	61.03	0.75	59.28	335.52	9.30	80.94	14.25	-2.74
Median	13.45	57.16	0.61	44.50	340.89	9.40	65.93	1.96	-4.73
SD	19.66	17.47	0.67	57.23	66.85	7.56	57.49	53.76	17.24
Excess kurtosis	4.01	-0.62	11.65	16.79	-0.53	-0.85	11.60	24.68	19.77
Skewness	2.10	0.42	3.34	3.94	-0.13	-0.09	3.33	4.80	3.74
Observations	4616	4616	4616	4616	4616	4616	3871	2609	2609

Table 1: Whole timespan descriptive statistics

The above table contains the descriptive statistics of each variable. Coal, CDS and CSS contain fewer observations because of their later inclusion. The variables can be clustered into three groups depending on their statistical characteristics. Oil, the STOXX index and weather (Munich) are relatively normal, with platykurtic tails and low skewness. Carbon, Gas, Electricity and Coal all have a standard deviation that is close to or bigger than the mean, which indicates high fluctuations in their values. CDS and CSS have statistical values that point to the extreme, with the presence of outliers even after winsorizing. Analyzing data like this as a whole could prove to be difficult, which further warrants the splitting of the data. As seen in Appendix 2, examining the statistics of each phase separately shows more refined results. Most notably, the kurtosis and skewness values are significantly reduced, indicating a more normal distribution of the data. Phase-specific analyses are utilized to achieve a deeper understanding of the trends behind the price movements. Phase 1 is further divided into two sub-phases to account for the significant drop in prices at the end of Q1 2007. (Groeneveld & Meeden, 1984)

4. Methodology

4.1 OLS methodology

A common statistical method for analyzing relationships between variables in finance is Ordinary Least Squares (OLS) regressions. The equation of a basic OLS is the following:

$$Y = \beta_0 + X_1\beta_1 + X_2\beta_2 + \cdots + X_k\beta_k + \varepsilon$$

Y is the dependent variable, β_0 is the intercept, betas other than the intercept are the coefficients of each independent variable, X_1, X_2, …X_k. The regression aims to optimize the residuals of the model by minimizing the squared differences between the observed and the predicted values. (Verbeek, 2008)

Several methods can be used to test the validity of an OLS regression. The Variance Inflation Factor (VIF) is used to detect multicollinearity. A high VIF indicates that a variable is correlated with one or more variables in the model. The statistical significance of the model is undermined by these variables explaining each other instead of the dependent variable. Another assumption of OLS models is the homoskedasticity of the error terms, which means the variance of the residuals is constant over time. Time series data is prone to contain largely different values, therefore heteroskedasticity is common in these datasets. If this issue is detected, it is advised to run the regression with robust standard errors, which account for the differences in the variance. The normality of the residuals is also needed in OLS regressions. This rarely applies when modelling time series data, however, the Central Limit Theorem states that if the sample size is big enough the distribution will approximate to normal distribution. (Verbeek, 2008)

Autocorrelation occurs when a variable is correlated with itself. This can lead to several difficulties when modelling. It violates the assumption in OLS models, that the residuals contain no autocorrelation. These can lead to inefficient estimators, which means that the information of the data might not be captured correctly. If high autocorrelation is present in a time series, autoregressive models like ARIMA, GARCH or, in this case, VAR and VEC can be used. (Verbeek, 2008)

4.2 VAR and VECM methodology

When talking about vector autoregressive (VAR) models and vector error correction models (VECMs), it is necessary to mention stationarity. A process is strictly stationary if the joint distribution of any segments of the time series that are shifted by a constant is the same. This condition seldom occurs in reality. Therefore, the literature uses a looser set of requirements; only the mean and the variance have to be constant over time and the autocovariance function depends only on the lag. This is called weak stationarity, further referred to as stationarity. A special form called white noise is distinguished, which is when the mean is 0 and autocorrelation is non-existent. In the case of VAR models and VECMs, it is important that the residuals are white noise. It is a method to check whether the models are accurate, reliable, and valid. (Kirchgässner et al., 2012)

Testing stationarity of a time series typically involves graphical inspection and hypothesis tests. The graphical method is a preliminary step, which can be used to inspect whether the series exhibits trends such as linear, exponential, or logarithmic. There are several hypothesis tests that can be used to identify unit processes, in this study two specific tests are used: Augmented Dickey Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS). They complement each other because the former's null hypothesis is that the process contains a unit root, while the one of the latter is that it is stationary. In this manner type I and II errors can be eliminated. (Kirchgässner et al., 2012)

The equation of the VAR model is the following:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \mu + \varepsilon_t$$

A_i is a coefficient matrix, Y_t is the vector of endogenous variables, μ_t is the vector of constants and ε_t the vector of the error terms. This means that each variable is influenced by its own lags and the lags of other variables. One important consequence of the model is that all variables are treated as endogenous, therefore it can capture two-way relationships and feedback loops (Nwafor et al., 2016). It is widely used in analyzing carbon price drivers, since the price of EUAs could have an effect on electricity and energy prices as well. The lag selection of the model is done by utilizing information criteria such as the Akaike, Schwarz, and Hannan-Quinn. Usually, they suggest different lags, therefore on some occasions manual selection is best, for example using 4 lags for monthly data or 5 lags for data with only weekdays.

Cointegration occurs when the linear combination of two or more non-stationary series is stationary. This implies a long-run equilibrium between the variables and that they share a stochastic trend. Similarly, to stationarity, a preliminary way to test cointegration is visual inspection, if two or more processes look alike, one can suspect that they are cointegrated. However, further hypothesis testing is needed. With only two time series, cointegration can be tested with the Engle-Granger test. In this instance, more than two variables exist, therefore the Johannsen test must be used. The null hypothesis of the test is that there are r=r*<k number of cointegrating vectors amongst the variables, with an alternative hypothesis that there are r=k. The test "starts" from 0 and the first number of vectors where the test fails to be rejected is the number of cointegrating vectors present in the model. It is important to correctly identify cointegration, because failing to do so can lead to biased estimates. (Johansen, 1988)

If one or more cointegrating relationship(s) are found, VECMs are preferred over VAR models. The equation of the VECM is the following:

$$\Delta Y_t = \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \cdots + \Gamma_{p-1} \Delta Y_{t-p+1} + \mu + \varepsilon_t$$

It is similar to the VAR equation, but there are some notable differences. The notation of the coefficient matrixes is Γ_i instead of A_i. It is important to note that the VECM inherently applies differencing to the variables, therefore capturing the short-term relationships. The main difference between VAR models and VECMs is the ΠY_{t-1} part of the equation, which is the error correction term. It is sometimes denoted as $\alpha\beta'$, where β' is the matrix of the cointegrating vectors. These are used to define the above-mentioned long-run equilibrium. α is a matrix of the coefficients of these vectors, each one detailing how much the variables readjust themselves in one period back to the equilibrium after a movement in the short-term. (Maysami & Koh, 2000)

VAR models and VECMs offer another point of analysis in addition to examining the regression coefficients in the form of impulse response functions (IRF). These graphs illustrate how a shock, a one unit change in the standard deviation of one variable affects other variables. It is a useful tool to understand the relationship between carbon price and its drivers. Moreover, instantaneous effects can be captured via this method, that are not shown in the regressions since only lagged variables are included in them. (Kirchgässner et al., 2012)

5. Results

5.1 OLS results

	Whole timespan	Phase 1	Phase 1.1	Phase 1.2	Phase 2	Phase 3	Phase 4
Constant	-12.71***	73.37***	40.72***	1.256***	-5.992***	10.49***	-104.1***
	(1.411)	(2.897)	(2.501)	(0.234)	(0.568)	(1.503)	(7.784)
Oil	-0.110***	-0.259***	0.683***	-0.0158***	-0.269***	0.256***	0.681***
	(0.0128)	(0.0471)	(0.0466)	(0.00310)	(0.00662)	(0.00869)	(0.0232)
Gas	22.22***	11.33***	2.773***	-0.801***	-6.100***		
	(0.412)	(1.205)	(0.915)	(0.113)	(0.631)		
Electricity		0.0226*	0.0379***	0.000843**	0.0911***	0.131***	0.0233***
		(0.0130)	(0.0135)	(0.000360)	(0.00689)	(0.0110)	(0.00486)
STOXX	0.0577***	-0.171***	-0.184***	0.000891***	0.0865***	0.00830**	0.265***
	(0.00317)	(0.00642)	(0.00518)	(0.000296)	(0.00293)	(0.00378)	(0.0178)
Munich	0.233***	0.159***	-0.263***	-0.0172***	0.125***	0.0339***	-0.366***
	(0.0214)	(0.0369)	(0.0334)	(0.00237)	(0.00793)	(0.0121)	(0.0541)
Coal					0.187***	-0.211***	
					(0.00646)	(0.00943)	
CDS						-0.895***	
						(0.0645)	
CSS						0.870***	0.0581***
						(0.0293)	(0.0204)
Observations	4,616	746	506	240	1,261	2,088	521
R-squared	67%	66%	75%	63%	85%	79%	79%

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: OLS regression results

The above table contains the results of the final OLS regressions. All residuals were heteroskedastic, therefore robust standard errors are used in every model. In the regressions for the whole timespan, the VIF for Electricity and Gas were relatively high. When removing Gas, the VIF of Electricity decreased, however Oil lost its significance and the predictive power decreased, therefore Electricity was the variable that was omitted. Gas had a high VIF in the Phase 3 and 4 models, therefore it had to be dropped. Moreover, in Phase 4, a high amount of multicollinearity was present, therefore both Coal and CDS are omitted in the final regression. The Shapiro-Wilk test for normality is rejected for all regressions, however every sample size is considered big enough for the Central Limit Theorem to apply (Verbeek, 2008). There is autocorrelation present across the regressions, which is why VECMs are utilized later, that are discussed in chapter 5.2.

The coefficient of oil is negative for the entire timespan, which could be because of the existence of a substitution effect; high oil prices lead to companies looking for other, less polluting sources of energy. However, this theory is somewhat undermined by the lack of consistency in the direction of the effect across the regressions. The variation in the scale and direction of the coefficients indicates that the relationship between the two variables is rather complicated. Oil prices themselves are influenced by a large number of factors, such as OPEC decisions, currency fluctuations, geopolitical events, global supply and demand, and many more aspects. Moreover, the role of oil in the energy mix of the EU has changed since 2005, which further contributes to the fluctuations in the coefficients.

The effect that gas price has on carbon shows a gradual shift from a positive coefficient to a negative one, which could be the result of the EU directive of relying less on fossil fuels and more on sustainable energy sources. The same trend can be seen in coal prices. With alternative sources of energy production available, coal and gas prices lose their "power" to raise carbon prices with them, instead high levels of coal and gas prices trigger a substitution effect. This finding might be slightly contested with the coefficient of oil showing a different trend.

Electricity prices reflect the output of power generation and with higher output more emissions will be created. This can be seen in the coefficients, which are all positive, however their effect is small.

The STOXX index is a method of measuring economic health and investor sentiment in the EU. The coefficient shows a positive correlation between the index and EUA prices. The confidence in a bullish market could extend to the carbon market, leading to increased spending and speculation. Another important connection is that a rising STOXX index indicates that the economy is strong, with more industrial activity, therefore higher emissions which push the demand for allowances higher.

Weather has a direct effect on energy production, influencing the demand side greatly. Emissions in countries with a dependence on fossil fuels rise during cold weather, increasing demand for EUA at the same time. Weather also influences renewable energy generation, an arid, cloudy winter can raise the demand for EUAs, since solar and wind power generation plummets. However, temperatures cannot fully capture this effect. In Phase 1, 2 and 3, higher temperatures lead to higher EUA prices. This effect reverses in Phase 4.

CSS and CDS show different coefficients across Phase 3 and 4. The positive and significant coefficient associated with CSS means that as gas power plants become more effective, their usage rises, therefore increasing the demand for EUAs. The negative sign related to CDS is difficult to interpret, since economic theory would suggest a similar effect to CSS. One explanation could be that if the switching cost to gas remains high, operators would need to increase their usage of coal plants to make up for the loss in profitability, thus driving up carbon prices. However, this theory is only speculation, the relationship between CDS and carbon price could be dependent on other outside factors.

5.2 VECM results

Coefficients are hard to interpret when analyzing the effect of a differenced variable on another differenced variable, however the direction is rather important. In every model, all variables were tested for stationarity, and it was found that in most cases one differentiation was needed to make the variables stationary. After differentiation, the optimal lag was selected, then the number of cointegrating vectors was identified. Following this, each model was run and then examined for the above-mentioned checks in chapter 4.2. Autocorrelation tests were examined up to a maximum of five lags. The full tables containing non-significant coefficients can be found in Appendix 2.

5.2.1 Whole timespan

The carbon price during the whole timespan saw large changes, therefore running a VECM for the time series raises certain complications. The model shows that autocorrelation is present in up to five lags when examined by the Lagrange Multiplier (LM) test. When graphically inspecting the correlogram of the residuals, the values "breach" the confidence interval by a large amount only twice, signalling that the autocorrelation might not be severe. Moreover, the Durbin Watson index of the model, used for testing autocorrelation in the first lag, is close to two, which implies no autocorrelation. All values, except for the eigenvalues are inside the unit circle, signalling that the model is stable. The biggest issue with the model is the residuals, as can be seen in Appendix 11. Their variance is not stable, with the main cause being the large drop in Phase 1 and the rise of the prices in the beginning of Phase 4. The ADF test is rejected at 1%, however the KPSS for stationarity can only fail to be rejected at 5%, meaning that the residuals are barely stationary. This causes several problems when analyzing the data, which is why every phase is analyzed separately. However, the coefficient and the IRF function can still be examined, albeit with care. (Kirchgässner et al., 2012)

	Whole timespan
L2D.Carbon	0.0492***
	(0.0148)
L4D.Carbon	0.0722***
	(0.0147)
L5D.Carbon	-0.0881***
	(0.0147)
LD.Oil	-0.0271**
	(0.0106)
L3D.Oil	-0.0197*
	(0.0106)
LD.Gas	-0.332*
	(0.176)
L3D.Gas	-0.947***
	(0.178)
L4D.Gas	-0.833***
	(0.175)
L5D.Gas	0.668***
	(0.173)
LD.Electricity	-0.00250***
	(0.000905)
L2D.Electricity	0.00185**
	(0.000899)
L4D.Electricity	-0.00152*
	(0.000845)
L2D.STOXX	-0.0109***
	(0.00352)
Observations	4,610

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

Table 3: Whole timespan VECM regression results

Carbon price is influenced positively by its own lags significantly at two and four days, which implies that information takes time to be fully absorbed into the price itself. The negative coefficient at the fifth lag could mean that the market readjusts itself after a rise or a fall in prices. Every significant coefficient regarding oil is negative, meaning higher energy prices lead to a drop in production or to the market expecting a drop and therefore anticipating a lower level of carbon emissions. Gas has significant negative coefficients, signalling a similar effect as oil, however, the coefficient of the fifth lag is positive, which could imply a market correction after five days. Electricity has alternating significant coefficients, going from negative to positive, then back to negative. It is hard to elaborate on which effect is more significant, the reason behind the changes could be that electricity can be generated from different sources, therefore the above-mentioned effect regarding energy prices has a complicated effect on electricity. The only significant coefficient of the STOXX index is negative. Financial investors, which entered the market in the later phases, could use carbon EUA as a hedging tool against economic slowdown. Allowances could also be bought more in a bearish stock market, with investors expecting them to outperform stocks. Weather does not have any significance, which is in line with the findings of Batten et al. (2021), that only abnormal weather influences carbon prices.

The above results are supported by the IRF graphs, with carbon having the largest effect on itself; a one-unit shock in carbon prices leads to an immediate reaction, a rise of around 0.83 units. The effect of this shock peaks at four days, then stabilizes around 0.85 units, with the effect remaining permanent. The negative effect of oil materializes after one lag. By day six the confidence interval envelops zero, suggesting that this effect is mitigated after one trading week. Gas, however, has a permanent negative effect on carbon prices, with it being the strongest after four days, then stabilizing around -0.05 units. The results related to gas are supported by the findings of Hammoudeh et al. (2014). A shock in electricity only exerts a small change in carbon prices at one lag, while STOXX has a similar effect at two lags. A shock in weather does not change carbon prices at any lags.

5.2.2 Phase 1, 1.1 and 1.2

Across all regressions related to Phase 1, a lag of one was recommended by every information criterion. No autocorrelation can be detected, except for lag two in Phase 1.1, which can be considered a small, and unharmful amount. All autocorrelation correlograms pass the visual inspection, with only occasional values being above the confidence interval. Both the Phase 1 and Phase 1.2 regressions contained one cointegrating vector. The Johansen test could not be rejected at zero for Phase 1.1, meaning that the long-term equilibrium effect most probably comes from Phase 1.2. All the eigenvalues in every regression except for the cointegrating vectors are located inside the unit circle, indicating the model's stability. The residuals related to the Phase 1 regression exhibit varying variance, with the variance being at a considerably lower level after the price drop. Despite this, ADF and KPSS tests state that the residuals are stationary and with their mean being zero, they can be considered white noise. The residuals from Phase 1.1 and Phase 1.2 do not have this issue.

	Phase 1	Phase 1.1	Phase 1.2
LD.Carbon	0.264***	0.260***	0.180***
	(0.0360)	(0.0437)	(0.0651)
Constant	-0.0182	-0.0234	-0.00276**
	(0.0208)	(0.0306)	(0.00134)
Observations	744	504	238

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

Table 4: Phase 1, 1.1, and 1.2 VAR/VECM regression results

A lack of significance can be observed across all three regressions, with only carbon being influential at one lag. The coefficient is positive, meaning carbon price movements lead to a momentum build-up in the market. The IRF graphs of Phase 1 and 1.2 are rather similar and differ only in magnitude. A shock in carbon prices leads to an instant rise in carbon prices, which reaches a maximum around three days, and stays at that level permanently. In Phase 1.1, a shock has the same instantaneous effect, however it dissipates to zero after four days. This is because VAR models do not contain long term effects, which are shown by IRF graphs converging to zero after ten to fifteen periods. (Kirchgässner et al., 2012)

In Phase 1.2 the constant is significant at one percent, with a negative value signalling that prices display downward momentum, that can be visually observed during the period. Neither of the other variables being significant could be attributed to multiple reasons. As mentioned above the first period of the EU ETS was a learning phase, with neither market participants nor the regulators having prior experience in these kinds of market conditions. The over allocation of allowances could have been a significant driver itself, weakening the effects of other factors. Another explanation could be that, in this phase, the carbon market was not linked as deeply as in the coming years to the energy and stock markets. Chen et al. (2013) found that the price mechanisms between Phase 1 and 2 greatly differed, which could have led to the different amount of significance in the corresponding regressions.

5.2.3 Phase 2

Carbon price during Phase 2 was the most stable across all phases, not having large drops or rises, except for the decline in 2008. This causes the residuals from the models to resemble a typical white noise function and the model to be stable. The LM test shows autocorrelation at lag one, however the Durbin Watson index is 1.99, which indicates no autocorrelation. The discrepancy between these two tests could be explained by the level of the autocorrelation not being high. The rank of the model is three, while four lags were included in the analysis. Three cointegrating vectors were found among the variables. (Kirchgässner et al., 2012)

	Phase 2
LD.Carbon	0.0858***
	(0.0306)
L2D.Carbon	-0.0569*
	(0.0307)
L3D.Carbon	0.0555*
	(0.0305)
L2D.Oil	-0.0181**
	(0.00813)
L3D.Gas	-1.672***
	(0.528)
LD.Coal	-0.0214***
	(0.00805)
L4D.Coal	0.0233***
	(0.00802)
LD.STOXX	-0.00737**
	(0.00296)
Observations	1,256

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

Table 5: Phase 2 regression results

Carbon prices are significant at lags one, two and three with alternating signs. After one day, EUA prices are positively influenced by their own values, a phenomenon that has persisted in the above-mentioned phases, suggesting a trend or a momentum. However, the coefficient of the second lag is negative, which suggests a correction. At three lags, the coefficient becomes positive again, which could mean information takes time to fully be absorbed into the prices. The IRF graph shows a similar picture, with a shock having an instantaneous effect, reaching a maximum on day one. This effect drops by the second day then stabilizes around day six, supporting the alternating signs of the coefficients.

The second lag of oil is significant at 5%, meaning a change in oil prices has a delayed effect on carbon prices. The related coefficient is negative, pointing to the substitution effect, which was discussed in chapter 5.2.1. The IRF graphs show that the negative effect is also significant at three lags, with it being the maximum. Gas prices have a much stronger, albeit similar effect, with the coefficient of three lags being significant and negative. One important difference between the two energy variables is that the effect of gas is permanent, with the confidence interval of the IRF graphs not containing zero in the long run, while that of oil does.

Coal is the most carbon intensive of all included energy sources, therefore it exhibits the substitution effect as well. At one lag, the assigned coefficient is negative and significant at 1%, meaning a change in coal prices takes a short amount of time to be integrated into carbon prices. An interesting point to make here is that operators do not need to react to energy price changes instead only the market would expect them to, therefore changing carbon prices. The lag at four days is positive, which could be explained by the effect of the change dissipating as time goes by, and prices rebounding. This is supported by the IRF graph, which shows that a shock in coal prices has a negative effect on carbon EUAs for three days and afterwards the effects fade into zero.

The STOXX index has a small, but negative significant coefficient at one lag. This could be explained by the hedging tool effect discussed in 5.2.1 or investor expectations that stocks and carbon prices have an inverse relationship. The IRF graph of the impulse of STOXX shows that this effect is rather small, with a reversion in the form of the IRF values going above zero after 5 days. However, the confidence interval contains zero at all lags except one, therefore this reversion is not significant.

Electricity does not have any significant coefficients and the confidence interval of the IRF graph contains zero at all lags. All three energy variables have significance in the models, which could mean that these variables have a bigger and more direct impact on carbon, leaving no significance to electricity. One other explanation could come from the findings of Johannes et al. (2013) that energy efficiency policies lead to a reduction in electricity demand, which in turn leads to a lower demand of carbon allowances, lowering their price. However, cheaper power generation meant that plants with higher emission became less expensive to operate, leading a to rise in the demand for EUAs. These complicated effects could have weakened the explanatory power electricity has on carbon prices.

5.2.4 Phase 3

Phase 3 contains the most observations, more specifically 2082 trading days. This period saw numerous changes to the EU ETS, such as the introduction of the Market Stability Reserve. The model used to examine this period was relatively stable, with a moderate amount of autocorrelation in the model. The residuals are considered to be white noise, with their variance slightly growing with time as the end of the period saw higher amounts of volatility. CDS and CSS are added to this model, which can be used to analyze more specific price driving mechanics. Two cointegrating vectors are found within the variables and five lags were included in the model. (Kirchgässner et al., 2012)

	Phase 3
LD.Carbon	-0.0484**
	(0.0222)
L2D.Carbon	0.0672***
	(0.0222)
L3D.Carbon	-0.0716***
	(0.0222)
L4D.Carbon	0.0463**
	(0.0223)
L5D.Carbon	-0.0412*
	(0.0224)
L4D.Electricity	0.00356**
	(0.00157)
L5D.Electricity	0.00310**
	(0.00146)
	-
L4D.STOXX	0.00887***
	(0.00287)
L4D.CSS	0.0246*
	(0.0138)
Observations	2,082

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

Table 6: Phase 3 regression results

All of the coefficients of carbon are significant, with the level of significance weakening from lag four. The sign of the effect of carbon alternates by lag. This could suggest volatility clustering, where periods with large volatility in carbon are followed by more volatility, which is a common phenomenon related to financial instruments. The IRF graph shows a more meaningful explanation. A one-unit shock in carbon price, which could come from news about new regulatory actions or a shift in demand has an instantaneous positive effect of around 0.43 units on carbon prices. This effect is somewhat corrected after a day, followed by alternating market reactions, up until ten lags, where the shock is completely absorbed, however its effect remains permanent at around 0.41 units. Volatility clustering could not be the only explanation. The alternating coefficients could simply signal that information takes time to be fully absorbed into the prices and during this period the market exhibits periods of momentum build-up and mean reversion.

Contrary to economic theory, neither oil, gas nor coal have any statistically significant coefficients. This lack of significance could mean that market participants adapted to mitigating the changes in fossil fuels by either hedging against shocks or efficiently forecasting prices. With more trading activity, the effect that fossil fuels have on carbon prices could have shifted over to financial market dynamics. One other explanation could be that the events in this long period, such as Europe recovering from the Sovereign Debt Crisis, the introduction of the Market Stability Reserve and the COVID-19 pandemic caused the explanatory power of fossil fuels to decrease. However, these theories do not fully explain why the variables lack significance, since in Phase 4, gas and coal are significant, which is a more mature phase with similar important events such as the energy crisis. The introduction of CDS and CSS could also mitigate the explanatory power of both coal and gas variables.

Electricity, however, does have significance in contrast to energy variables. Both coefficients of lags three and four are positive. These results are in line with Aatola et al. (2013). Electricity prices are a signal for the level of energy production. Emission is linked to production; if an installation produces more electricity, it will emit higher amounts of greenhouse gases, therefore it will have to purchase carbon credits. The increase in demand leads to the prices rising, albeit at a delay of three days. This effect remains for one more day, then dissipates. The magnitude of the coefficients is rather small, which is supported by the IRF graphs, where the confidence band contains zero at all lags. This means that while electricity does influence carbon prices, a one unit increase in its standard deviation does not have a statistically significant effect on carbon EUAs.

In Phase 3 the STOXX index has a negative and significant effect on carbon prices at four lags. In line with the other phases, this means that investors utilize carbon credits as a substitute for equities. One other explanation could be that during this period the energy mix of Europe saw certain changes. Nuclear power and renewable energy generation played a more important role in electricity generation. Since the STOXX index is a proxy for economic activity, more money could mean more investment towards green initiatives, which could be a signal for investors that the price of EUAs would decrease in the future.

As mentioned in the literature review, clean spark spread is an indicator used to measure the profitability of gas fired power plants, while clean dark spread measures the profitability of coal plants. The fourth lag of CSS is significant and positive. An increase in CSS would imply that operators could make more profits by utilizing gas fired power plants, which would signal to the market that they would be used more in the energy mix. Since natural gas is an important fossil fuel in the context of allowances, a rise in its usage would in turn later lead to a rise in demand for EUAs. Moreover, regulators could use CDS and CSS as a measure on whether to adjust or tighten policies regarding emissions. If this is the case investors would expect a reaction from the supply side as well, further supporting the relationship between CSS and carbon prices. These results are supported by the findings of Creti et al. (2012) where the authors found that the switching price between gas and coal has a deterministic role in carbon price formation.

5.2.5 Phase 4

The final and still ongoing phase of the EU ETS was prone to large price movements and many important events such as the energy crisis and the outbreak and fallout of the Russo-Ukrainian war. The model for this period contains three cointegrating vectors and five lags of each variable. The LM test shows that there is autocorrelation among the variables, however, the Durbin Watson index is 2.01 and the ACF function only breaches the confidence interval twice by a small amount, which indicates that this autocorrelation might not be severe. One method of taking autocorrelation out of the model is increasing the number of lags. At ten lags the autocorrelation dissipates fully, however, the model becomes unstable, which is shown by the inverse roots being close to the unit circle., therefore the recommended five lags are used (Kirchgässner et al., 2012)

	Phase 4
L2D.Carbon	0.113**
	(0.0476)
L4D.Carbon	-0.0822*
	(0.0489)
L5D.Carbon	-0.161***
	(0.0497)
L2D.Gas	-1.022**
	(0.489)
L5D.Gas	1.103**
	(0.473)
L2D.Coal	0.0201**
	(0.00946)
L3D.Coal	-0.0283***
	(0.00941)
L2D.Electricity	0.00612**
	(0.00280)
L2D.STOXX	-0.0733***
	(0.0239)
L2D.CDS	0.0322***
	(0.0116)
Observations	515

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

Table 7: Phase 4 regression results

As in all phases, carbon has an influence on its own price formation. Lags two, four and five are all significant, with lag two being positive and the former two negative. This signals the same phenomenon as in the above discussed phases, where prices build up momentum in the first two days then correct themselves at a four- and five-day delay. The IRF graphs show that a shock in carbon prices has an instantaneous effect, and in fact the movement at lag one is a correction, with a trend building up in the following days, then dissipating later. The delayed effects reflect that investors do not all react to news and price movements at the same time. One important distinction from the other phases is the magnitude of the reaction to the shock. In all other instances, a one-unit change in the standard deviation of carbon brought with it a change between 0 and 1 units. In Phase 4 the initial response is around 1.9 units, with the peak being above 2, and the permanent effect being around 1.9. This is caused by the larger volatility in this period. A simplistic trading strategy could be formulated around this graph, which shows that ceteris paribus carbon prices peak after three days following a shock to their own values.

The significant negative coefficient related to the second lag of gas shows that if gas prices become cheaper, carbon prices rise. Since prices are lower, more energy can be produced for the same price, which leads to a rise in demand for EUAs. At five lags, the coefficient is positive. This means that if gas is more expensive operators would switch to coal and they would produce the same unit of electricity at a higher level of emission.

Coal prices show a different effect. The second lag of coal is positive, which means coal and carbon prices move in the same direction. Coal price rising could signal an increase in demand for coal, which is the result of a higher usage rate of this energy source, leading to increased emissions. However, the IRF graph shows that the first market reaction at day one is a fall of carbon prices, the positive coefficient at the second lag is only a correction of this effect. The graph permanently stays below zero, however, the confidence band only excludes zero at lag one.

Oil does not have any significant coefficients, however its IRF graph is significant at one lag. A very similar effect can be observed to coal, where there is no instant effect in carbon prices to a shock to oil, however after one day, higher oil prices lead to lower carbon prices. As mentioned in the analysis of other phases, this phenomenon could either be caused by a substitution effect or simply by higher costs leading to lower volumes of production.

Similar to Phase 3, electricity prices have a positive correlation with carbon prices. If the PHELIX index rises, carbon price will rise two days after. Higher electricity prices generally mean higher production, therefore higher demand for EUAs. The IRF graph of electricity shows that the initial reaction in carbon to a shock in electricity is negative, followed by a large rise then a stabilization around zero. However, this effect is invalidated by the confidence band containing zero at all lags. The relationship between the STOXX index and carbon prices is similar to Phase 3. The negative correlation could come from a substitution effect as financial assets or that investors are focusing on renewables.

An important difference between the two phases is that in Phase 4 CDS is the significant variable instead of CSS. The second lag of CDS is positive and significant meaning that a rise in this index brings an increase in carbon prices two days later, or a decrease with a fall in the index. If CDS is high, coal plants are more profitable, which could lead companies to invest more in these plants and utilize them more. Similarly, to the phenomenon regarding CSS in Phase 3, regulators could use CDS as a proxy for whether rules need tightening or altering. However, one aspect that could bring in some noise to the effect of CDS is that speculations in the commodity market or hedging across a certain event could influence this index.

6. Conclusion

This empirical study investigates the dynamics behind the price movements of carbon EUAs, which are an instrumental part of the EU ETS. My main aim was to uncover the relationship between energy commodities, electricity, stock market trends, the profitability of coal and gas power plants, and meteorological variables by utilizing OLS and VECM methodologies. The results showed that the direction and significance of the effect between these variables varied over the phases of the EU ETS.

Carbon price had an overall positive effect on its own price formation, with periods of momentum building and mean reversion, where the price dropped because of market overreaction. Prices took time to fully reflect all the information, which resulted in these phenomena. The analysis showed that energy prices most often exhibit a negative relationship with carbon prices due to the existence of a substitution effect towards less carbon intensive energy sources. The coefficient related to the PHELIX index was positive across all regressions, pointing to a straightforward relationship between the electricity prices and through them electricity output and carbon prices. One result which contradicted the literature was the inverse effect of the STOXX index. Both CDS and CSS variables showed that as the profitability of coal and gas power plants grows, their usage increases which in turn makes carbon prices rise. Weather did not have any significance in the VECMs, which proved that temperature itself is already priced into the EUAs.

The analysis faced several limitations. The OLS models could include some level of spurious regression; however, this was somewhat mitigated by the inclusion of autoregressive analysis. The drivers could have been analyzed using other means. Either by more complicated models such as structured vector autoregressive models or Granger causality, however the former is beyond the methodological scope of this study. In some cases, such as in Phase 3 where volatility clustering could be suspected, Autoregressive Conditional Heteroskedasticity models could be employed to deal with the different levels of volatility. ARCH models however do not account for cointegration, therefore a combination of VECM and ARCH could have been utilized, in the form of inputting the residuals from the VECM into an ARCH model. One other avenue of investigation could be the introduction of the spot version of the variables. This method allows for the capture of immediate reactions. Spot prices have a larger volatility than futures, which leads to more interactions between the variables. The results from this analysis combined with the explanations derived from the futures could provide a broader picture about carbon price drivers.

Bibliography

Aatola, P., Ollikainen, M., & Toppinen, A. (2013). Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals. *Energy Economics*, 380-395.

Batten, J. A., Maddox, G. E., & Young, M. R. (2021). Does weather, or energy prices, affect carbon prices? *Energy economics*, 105016.

Bunn, D., & Fezzi, C. (2009). Interaction of European carbon trading and energy prices. *Fondazione Eni Enrico Mattei Working Papers*, 53-69.

Chen, H., Liu, Z., Zhang, Y., & Wu, Y. (2020). The linkages of carbon spot-futures: evidence from EU-ETS in the third phase. *Sustainability*, 2517.

Chen, X., Wang, Z., & Wu, D. D. (2013). Modeling the price mechanism of carbon emission exchange in the European Union emission trading system. *Human and Ecological Risk Assessment: An International Journal*, 1309-1323.

Compagnie, V., Stuyfs, K., & Torsin, W. (2023). Tax avoidance as an unintended consequence of environmental regulation: Evidence from the EU ETS. *Journal of Corporate Finance*, 102463.

Creti, A., Jouvet, P.-A., & Mignon, V. (2012, October). Carbon price drivers: Phase I versus Phase II equilibrium? *Energy Economics*, 327-334.

Ellerman, A. D., Marcantonini, C., & Zaklan, A. (2016). The European Union Emissions Trading System: Ten Years and Counting. *Review of Environmental Economics and Policy*, 89-107.

European Comission. (2023, December 14). *EU Emissions Trading System (EU ETS)*. Retrieved from European Comission: https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets_en

Groeneveld, R. A., & Meeden, G. (1984). Measuring skewness and kurtosis. *Journal of the Royal Statistical Society Series D: The Statistician*, 391-399.

Hammoudeh, S., Ricardo , S. M., & Nguyen, D. K. (2014). What explain the short-term dynamics of the prices of CO2 emissions? *Energy Economics*, 122-135.

Jin, J., Han, L., Wu, L., & Zeng, H. (2020). The hedging effect of green bonds on carbon market risk. *International Review of Financial Analysis*, 101509.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 231-254.

Känzig, D. R. (2023). The Unequal Economic Consequences of Carbon Pricing. *NBER Working Papers*, 31221.

Keppler, J. H., & Mansanet-Bataller, M. (2010). Causalities between CO2, electricity, and other energy variables during phase I and phase II of the EU ETS. *Energy Policy*, 329–3341.

Kirchgässner, G., Wolters, J., & Hassler, U. (2012). *Introduction to modern time series analysis.* Berlin: Springer Science & Business Media.

Lovcha, Y., Perez-Laborda, A., & Sikora, I. (2022). The determinants of CO2 prices in the EU emission trading system. *Applied Energy*, 117903.

Maysami, R. C., & Koh, T. S. (2000). A vector error correction model of the Singapore stock market. *International Review of Economics and Finance 9*, 79-96.

Nwafor, G. O., Odok, E. O., Atsu, J. U., & Esuabana, I. M. (2016). Modelling and Adequacy of Vector Autoregressive. *International Journal of Scientific Engineering and Applied Science (IJSEAS)*, 79-88.

Oestreich, A., & Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the EU Emissions Trading Scheme. *Journal of Banking & Finance*, 294-308.

Ravina, A. (2022). On Bond Returns in a Time of Climate Change. *Energy Journal*, 139-159.

Sullivan, J. H., Warkentin, M., & Wallace, L. (2021). So many ways for assessing outliers: What really works and does it matter? *Journal of Business Research*, 530-543.

Tan, X., Sirichand, K., Vivian, A., & Wang, X. (2020). How connected is the carbon market to energy and financial markets? A systematic analysis of spillovers and dynamics. *Energy Economics*, 104870.

Thema, J., Suerkemper, F., Grave, K., & Amelung, A. (2013). The impact of electricity demand reduction policies on the EU-ETS: Modelling electricity and carbon prices and the effect on industrial competitiveness. *Energy Policy*, 656-666.

Verbeek, M. (2008). *A guide to modern econometrics.* Chichester: John Wiley & Sons.

Watson, F., & Burke, K. (2022, March 02). *EU carbon prices in freefall as panic spreads*. Retrieved from S&P Global Commodity Insights: https://www.spglobal.com/commodityinsights/en/market-insights/latest-news/energy-transition/030222-eu-carbon-prices-in-freefall-as-panic-spreads

Witkowski, P. (2022). The Concept of Using the Excess Rate of Return in the Study of the Impact of EU ETS on the Value of Enterprises. *Journal of Banking & Financial Economics*, 72-93.

Zhu, B., Ye, S., Han, D., Wang, P., He, K., Wei, Y.-M., & Xie, R. (2019). A multiscale analysis for carbon price drivers. *Energy Economics*, 202-216.

Appendix

Appendix 1: Data sources

Variable	Definition	Source	Refinitiv series name (if applicable)	Earliest observation (if not from available from 2005.04.22)
Carbon	ICE ECX EUA Carbon price futures	Refinitiv	LEXCS00	
Oil	ICE Brent crude oil futures	Refinitiv	LLCC.01	
Coal	ICE Coal Rotterdam futures	Refinitiv	LMCCS00	2006.07.17
Gas	ICE Gas futures	Refinitiv	NATBGAS	
Electricity	EEX Phelix base electricity price	Refinitiv	EEXBASE	
CSS	Clean spark spread	Refinitiv	TRDEBY1	2009.12.02
CDS	Clean dark spread	Refinitiv	TRDECY1	2009.12.02
STOXX	STOXX Europe 600 Euro index	Refinitiv	DJSTOXX	
Munich	Munich daily average temperature	https://open-meteo.com/en/docs		

Appendix 2: Descriptive tables

Phase 1	Carbon	Oil	Gas	Electricity	STOXX	Munich
Mean	11.49	52.11	0.59	51.26	337.11	9.07
Median	12.45	51.64	0.56	46.95	335.74	9.75
SD	10.15	6.14	0.24	20.43	37.82	7.64
Excess kurtosis	-1.56	-0.29	2.34	4.21	-1.00	-0.87
Skewness	0.12	0.22	1.31	1.65	-0.23	-0.12
Observations	746	746	746	746	746	746

Phase 1.1	Carbon	Oil	Gas	Electricity	STOXX	Munich
Mean	16.87	49.83	0.63	52.41	321.27	8.97
Median	17.33	49.19	0.57	48.30	322.12	9.70
SD	7.88	5.08	0.26	19.86	32.71	7.84
Excess kurtosis	-0.62	-0.39	2.11	5.15	-0.91	-0.84
Skewness	-0.57	-0.02	1.46	1.85	-0.03	-0.13
Observations	506	506	506	506	506	506

Phase 1.2	Carbon	Oil	Gas	Electricity	STOXX	Munich
Mean	0.16	56.90	0.52	48.73	370.50	9.28
Median	0.09	55.68	0.48	42.34	375.70	9.80
SD	0.19	5.41	0.19	20.94	23.39	7.19
Excess kurtosis	3.51	-1.31	-1.59	1.81	0.26	-1.05
Skewness	2.07	0.19	-0.03	1.25	-1.08	-0.08
Observations	240	240	240	240	240	240

Phase 2	Carbon	Oil	Gas	Electricity	STOXX	Munich	Coal
Mean	13.84	67.67	0.60	52.05	252.50	9.04	74.90
Median	13.87	70.79	0.66	49.65	256.98	9.20	73.56
SD	5.21	17.35	0.18	14.61	32.23	7.76	19.87
Excess kurtosis	0.31	-0.98	-0.78	1.68	0.20	-0.81	0.66
Skewness	0.76	-0.40	-0.30	1.13	-0.40	-0.22	0.72
Observations	1261	1261	1261	1261	1261	1261	1261

Phase 3	Carbon	Oil	Gas	Electricity	STOXX	Munich	Coal	CDS	CSS
Mean	12.36	56.23	0.54	37.89	358.52	9.48	59.23	2.40	-7.07
Median	7.41	53.94	0.55	36.78	363.52	9.60	56.88	1.96	-6.21
SD	8.74	16.00	0.17	10.79	32.50	7.47	12.58	3.63	7.33
Excess kurtosis	-1.16	-0.84	-0.50	0.65	-0.53	-0.86	-0.71	-0.67	-1.25
Skewness	0.72	0.27	-0.24	0.40	-0.40	-0.01	0.42	-0.03	0.00
Observations	2088	2088	2088	2088	2088	2088	2088	2088	2088

Phase 4	Carbon	Oil	Gas	Electricity	STOXX	Munich	Coal	CDS	CSS
Mean	67.17	77.07	2.25	179.88	442.01	9.55	182.60	61.71	14.63
Median	69.54	73.12	2.21	152.61	441.10	9.10	148.85	3.07	3.76
SD	17.26	19.68	1.34	127.82	25.61	7.27	103.28	107.80	29.96
Excess kurtosis	-1.06	-1.22	-0.03	0.89	-0.90	-0.99	-1.08	1.61	3.30
Skewness	-0.36	0.22	0.60	1.15	-0.09	0.03	0.44	1.59	1.76
Observations	521	521	521	521	521	521	521	521	521

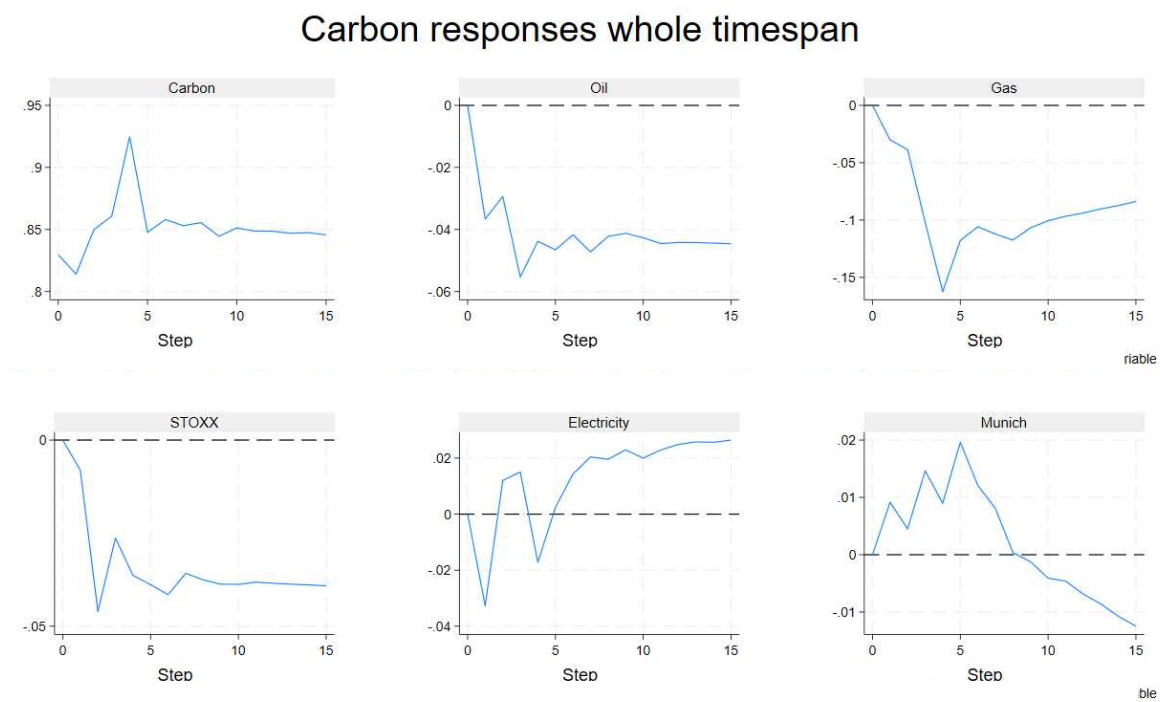
Appendix 3: VAR/VEC regression results for D.Carbon

VEC/VAR	Whole timespan	Phase 1	Phase 1.1	Phase 1.2	Phase 2	Phase 3	Phase 4
L._ce1	-0.00046	8.74E-08		-0.00344	-0.00429	-0.00066	0.00368
L._ce2	-4.2E-06				-0.00149	0.000126	-0.00652
L._ce3	-0.0198				-0.152		-0.0728
LD.Carbon	-0.0175	0.264***	0.260***	0.180***	0.0858***	-0.0484**	-0.0646
L2D.Carbon	0.0492***				-0.0569*	0.0672***	0.113**
L3D.Carbon	0.0157				0.0555*	-0.0716***	0.0285
L4D.Carbon	0.0722***				-0.00887	0.0463**	-0.0822*
L5D.Carbon	-0.0881***					-0.0412*	-0.161***
LD.Oil	-0.0271**	0.0358	0.0533	0.00137	0.00953	-0.0141	-0.0659
L2D.Oil	0.0156				-0.0181**	-0.00097	0.0458
L3D.Oil	-0.0197*				0.00156	-0.00275	-0.0391
L4D.Oil	0.011				-0.00538	0.00744	-0.011
L5D.Oil	0.00256					-0.00841	-0.00718
LD.Gas	-0.332*	-0.502	-0.491	-0.0425	-0.0205	-0.618	-0.308
L2D.Gas	-0.171				0.153	-0.177	-1.022**
L3D.Gas	-0.947***				-1.672***	0.327	0.239
L4D.Gas	-0.833***				0.0427	1.063	-0.454
L5D.Gas	0.668***					0.181	1.103**
LD.Coal					-0.0214***	0.0107	-0.0147
L2D.Coal					-0.00375	0.0127	0.0201**
L3D.Coal					-0.00486	-0.017	-0.0283***

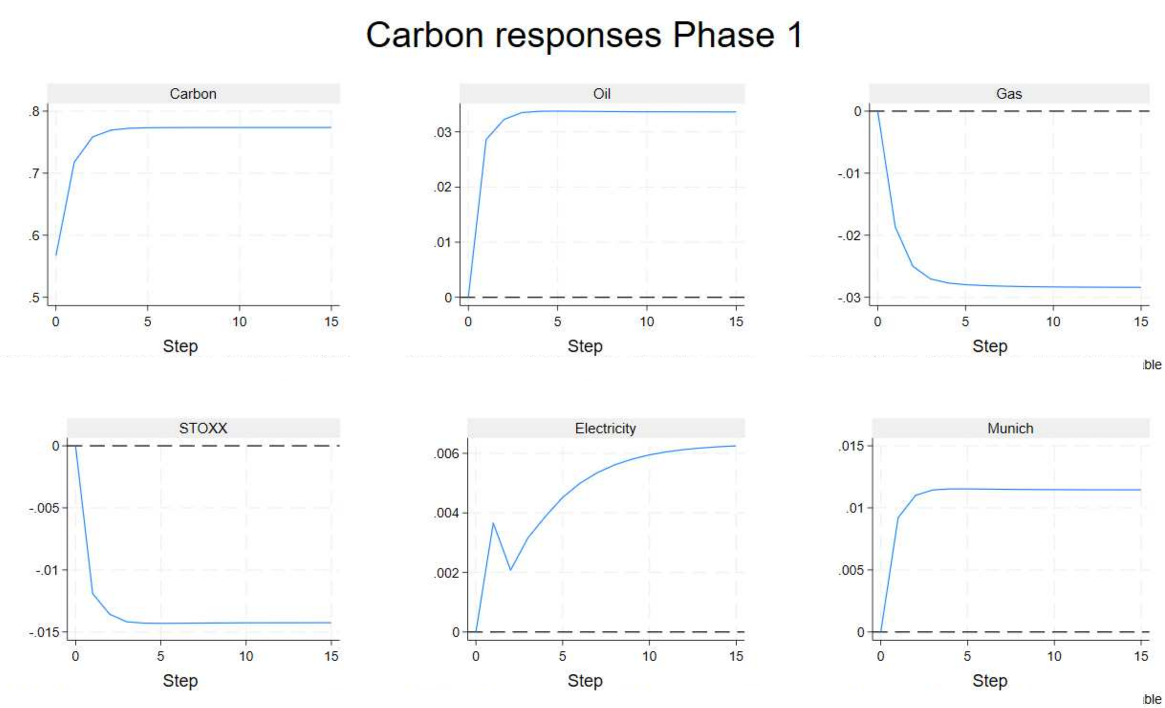
L4D.Coal					0.0233***	-0.00649	-0.0113
L5D.Coal						-0.0141	0.00799
LD.Electricity	-0.00250***	0.000342	0.000601	0.000014	0.000369	0.000219	-0.00028
L2D.Electricity	0.00185**				0.00168	0.00083	0.00612**
L3D.Electricity	0.000422				-0.00133	0.00132	0.00311
L4D.Electricity	-0.00152*				0.000806	0.00356**	-0.00353
L5D.Electricity	0.00101					0.00310**	-0.00213
LD.STOXX	-0.00238	-0.00383	-0.00787	-0.00011	-0.00737**	-0.00018	0.00274
L2D.STOXX	-0.0109***				-0.00083	0.00172	-0.0733***
L3D.STOXX	0.0055				-0.00285	0.00408	0.0285
L4D.STOXX	-0.00141				0.0037	-0.00887***	0.0254
L5D.STOXX	-0.00114					0.00328	-0.00353
LD.CDS						0.00578	0.012
L2D.CDS						0.00699	0.0322***
L3D.CDS						0.0174	0.0158
L4D.CDS						-0.00105	-0.00453
L5D.CDS						-0.00546	0.00695
LD.CSS						-0.00649	-0.00192
L2D.CSS						0.00321	-0.014
L3D.CSS						0.0131	-0.0217
L4D.CSS						0.0246*	0.000324
L5D.CSS						0.0202	-0.0111
LD.Munich	0.00556	0.0039	0.00618	0.000104	0.00147	-0.00568	0.067
L2D.Munich	-0.00106				0.00447	-0.00287	-0.0164
L3D.Munich	0.00628				-0.00291	0.00148	0.0739
L4D.Munich	-0.0008				-0.00629	0.00171	0.0253
L5D.Munich	0.00517					-0.00592	0.0568
Constant	0.0106	-0.0182	-0.0234	-0.00276**	-0.00788	0.0129	0.106
Observations	4610	744	504	238	1,256	2,082	515

*** p<0.01, ** p<0.05, * p<0.1

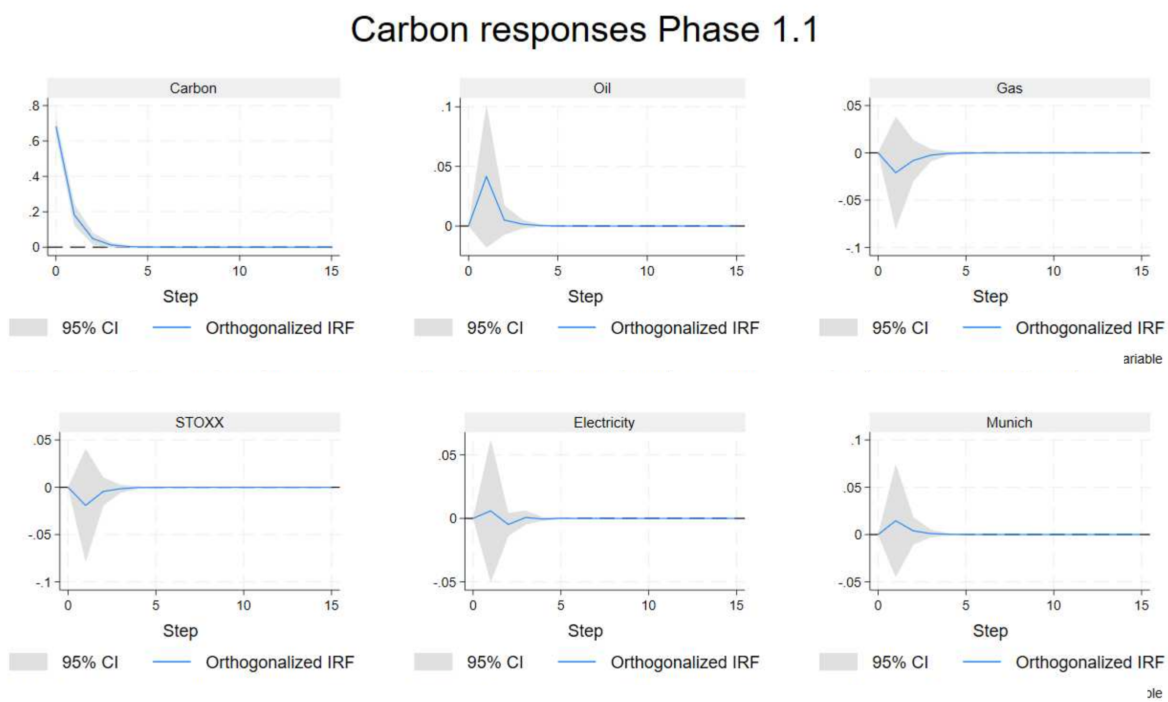
Appendix 4: Whole timespan IRF graphs



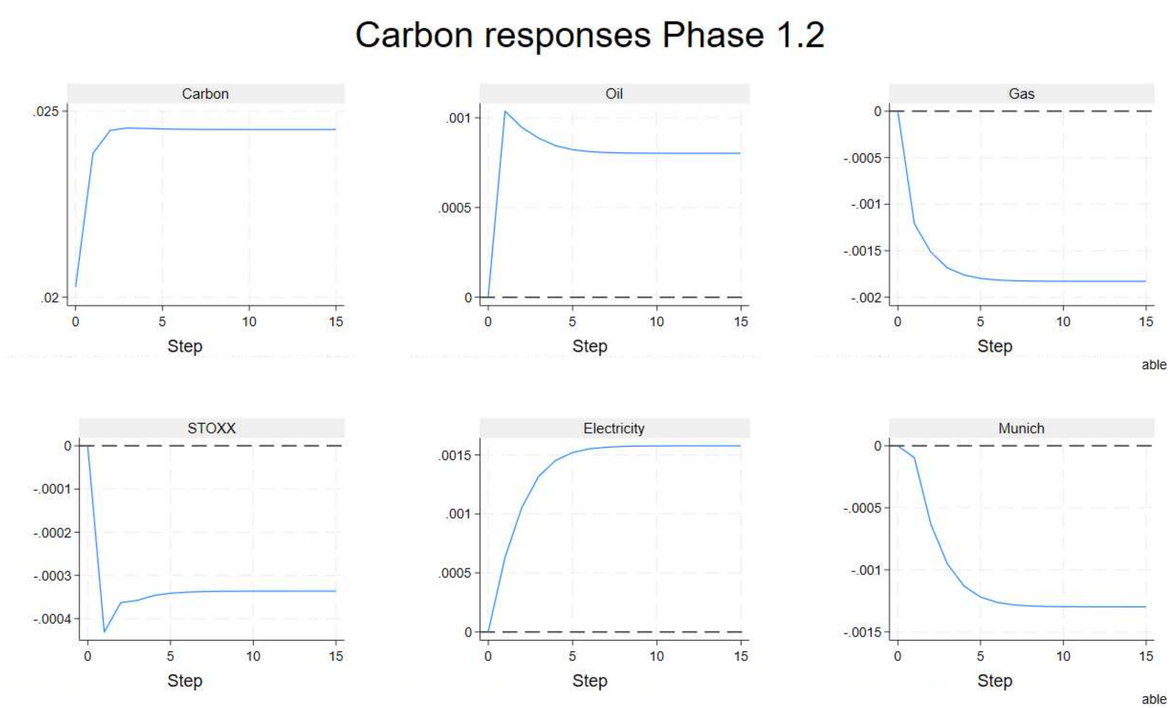
Appendix 5: Phase 1 IRF graphs



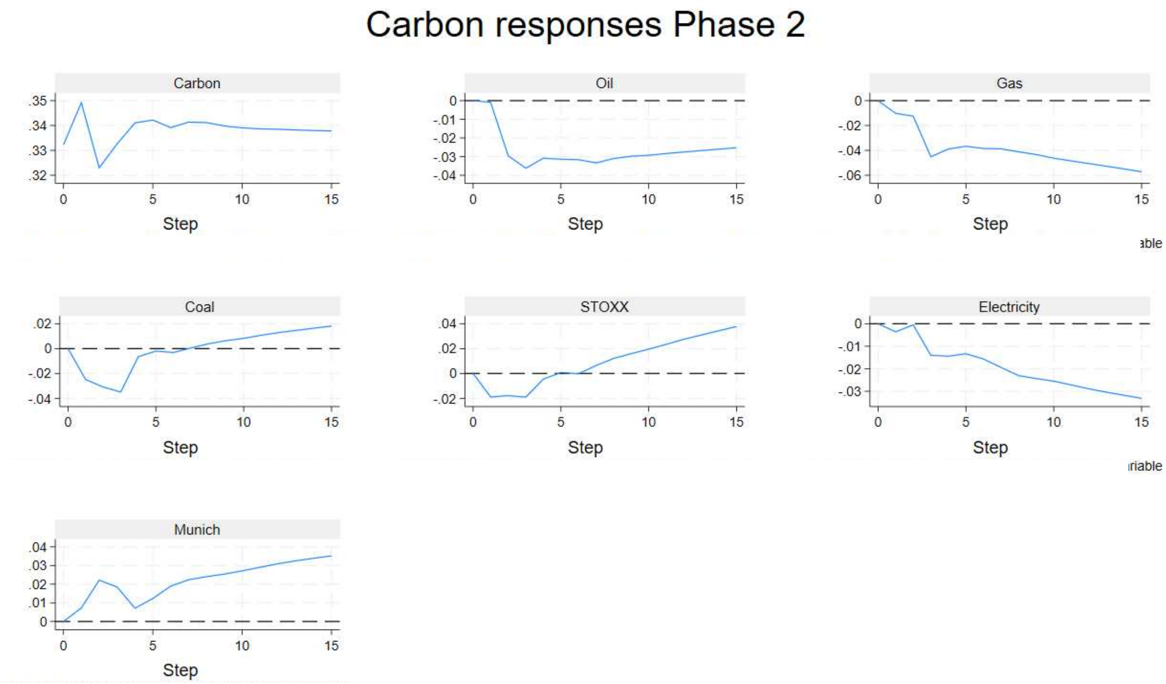
Appendix 6: Phase 1.1 IRF graphs



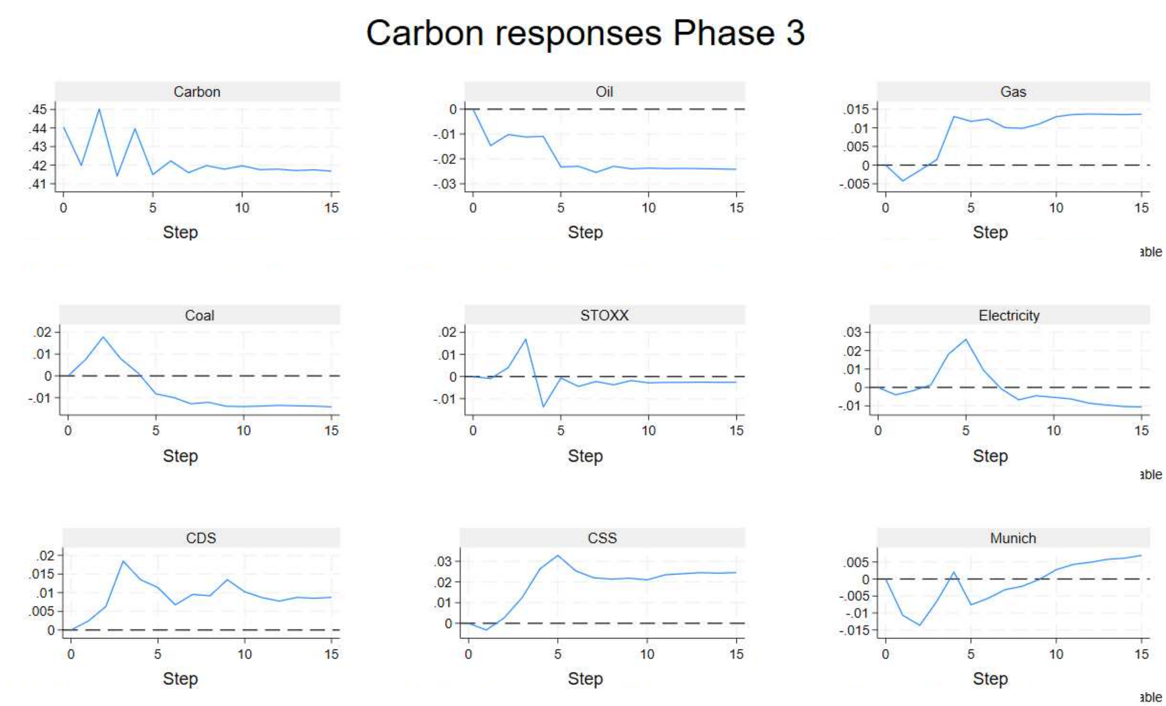
Appendix 7: Phase 1.2 IRF graphs



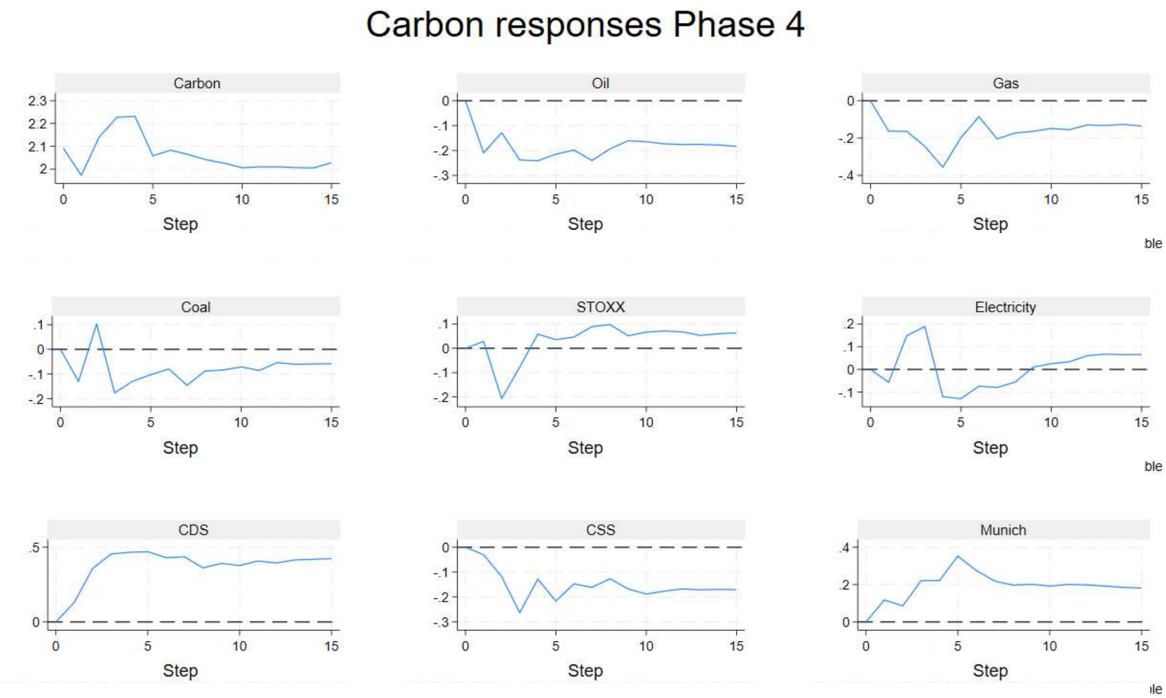
Appendix 8: Phase 2 IRF graphs



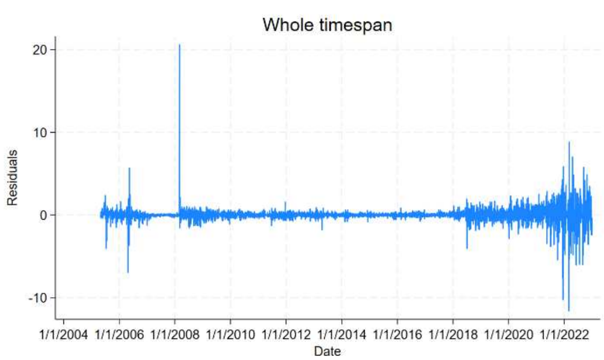
Appendix 9: Phase 3 IRF graphs

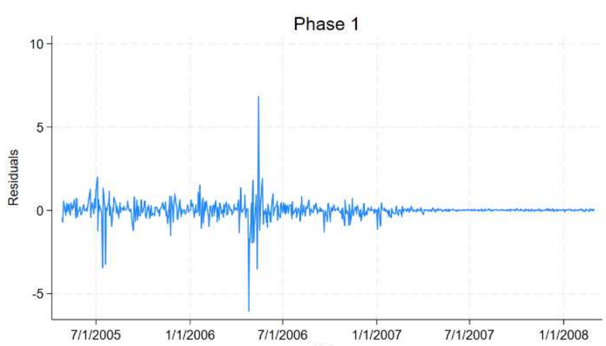


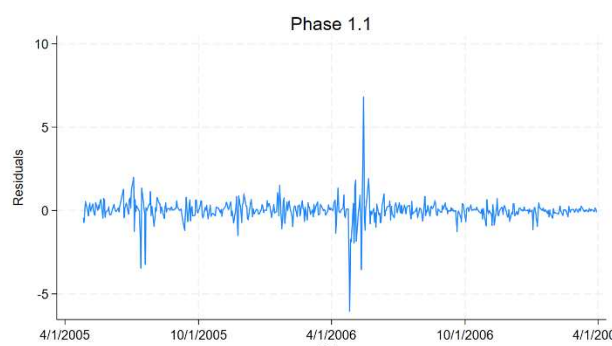
Appendix 10: Phase 4 IRF graphs

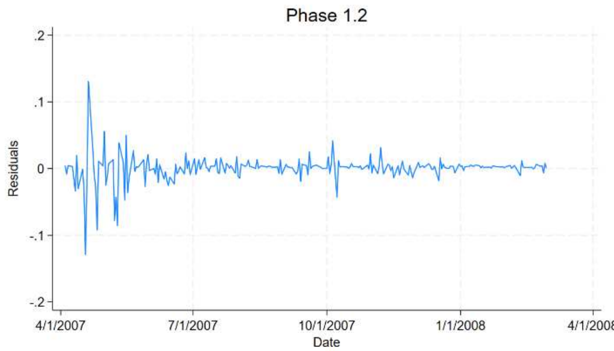


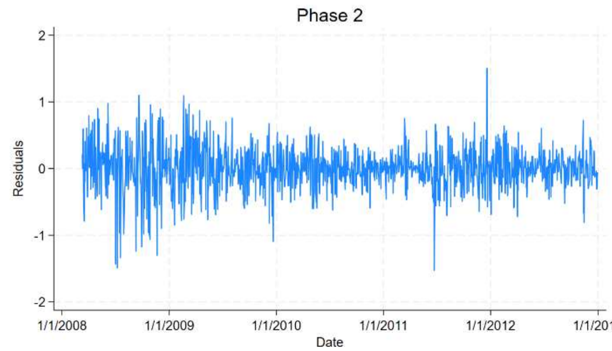
Appendix 11: Residuals:

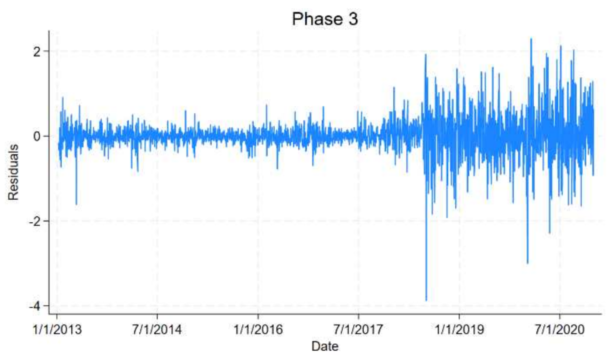


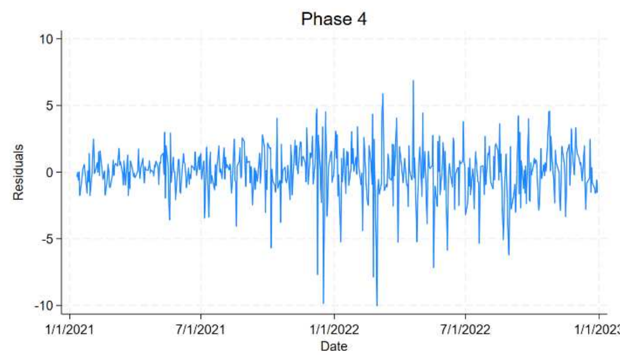




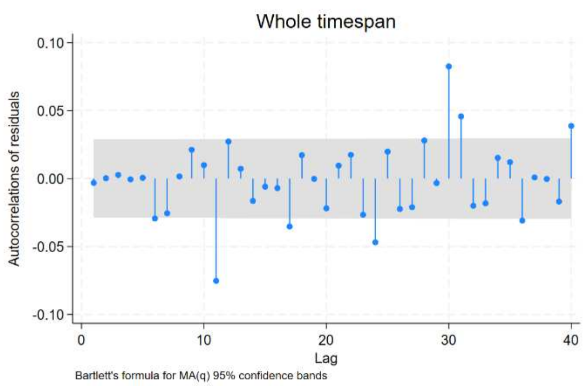


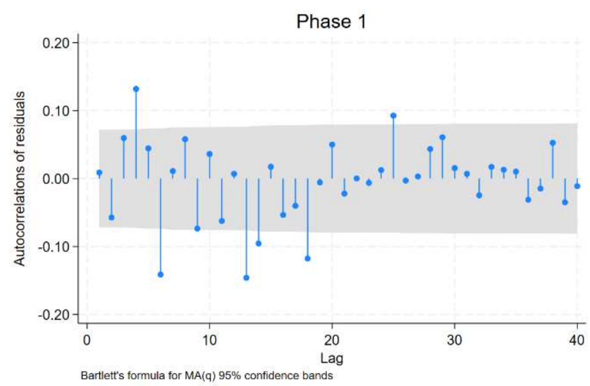


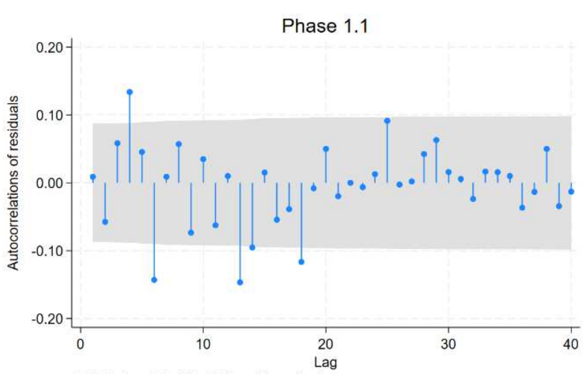


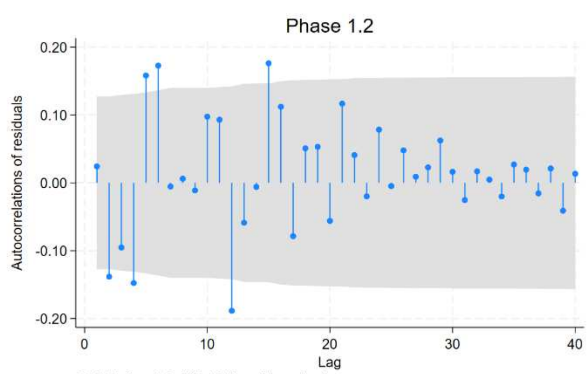


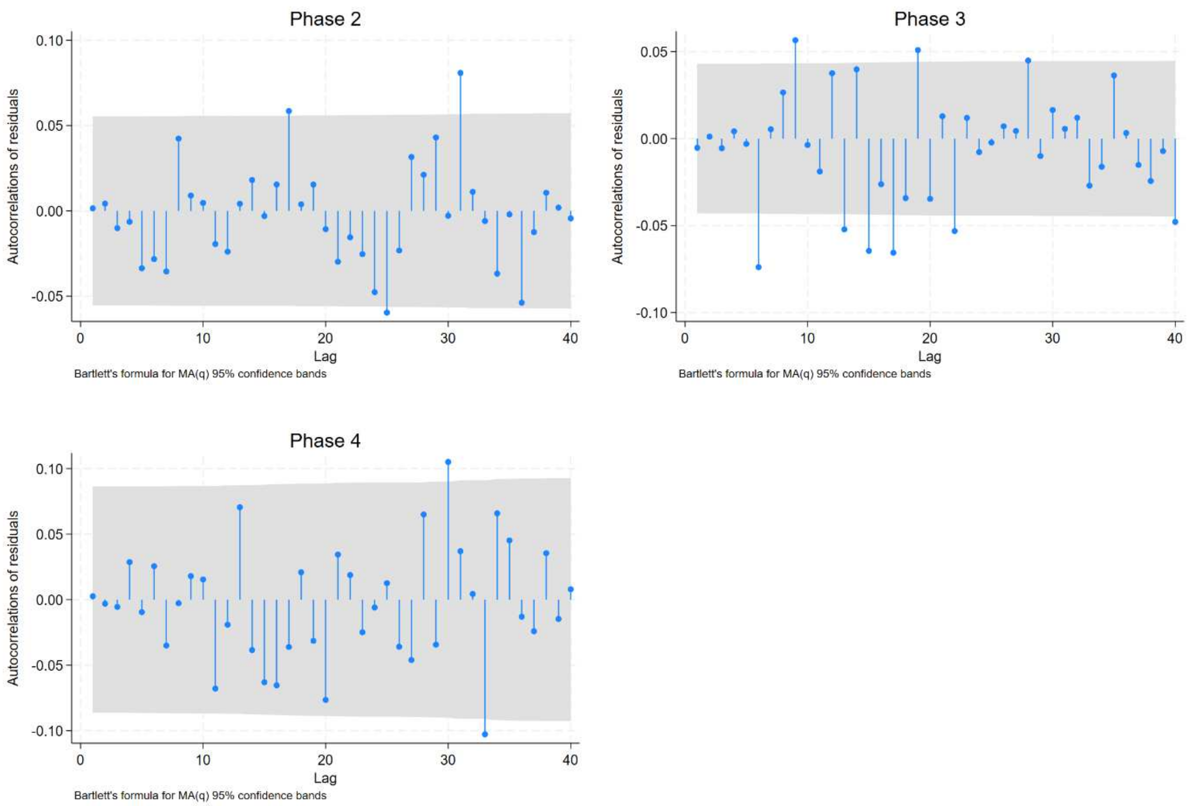
Appendix 12: Residual correlograms:










Phase 2
Autocorrelations of residuals
0.10
0.05
0.00
-0.05
0
10
20
30
40
Lag
Bartlett's formula for MA(q) 95% confidence bands
Phase 3
Autocorrelations of residuals
0.05
0.00
-0.05
-0.10
0
10
20
30
40
Lag
Bartlett's formula for MA(q) 95% confidence bands
Phase 4
Autocorrelations of residuals
0.10
0.05
0.00
-0.05
-0.10
0
10
20
30
40
Lag
Bartlett's formula for MA(q) 95% confidence bands