What Determines the Price of Carbon? New Evidence From Phase III and IV of the EU ETS*

Bente Dittmann[†], Tobias Lauter[†], Marcel Prokopczuk[†], Philipp Sibbertsen[†]

November 14, 2024

Abstract

In this paper, we provide new evidence on the determinants of EU emission allowance prices by analyzing the most recent time period, i.e. phases III and IV. We consider energy (oil, natural gas, coal) and electricity prices as well as profit spreads of marginal power generation (clean dark spread, clean spark spread) using various modeling approaches. We find that none of the approaches that have been proposed in the early literature on carbon pricing is suitable to explain the allowance price in more recent samples. Among the variables, crude oil appears to be the most important market fundamental, as it explains the largest share of variance on its own. However, the explanatory power of all variables diminishes compared to what has been documented before. Previous literature shows that the market fundamentals are able to explain about 30% of the variation of EU emission allowances in phase I, while we show that the explanatory power drops to below 5% in the more recent trading phases III and IV. We conjecture that as more and more industries fall under the regulation, the economic mechanics have fundamentally changed.

JEL classification: C22, C32, G13, Q49

Keywords: EU ETS, EUA price fundamentals, Carbon price

*Contact: dittmann@fcm.uni-hannover.de

†School of Economics and Management, Gottfried Wilhelm Leibniz University Hannover, Koenigsworther Platz 1, 30167 Hannover, Germany.

1 Introduction

Global climate change is one of the most important problems of modern society. It is an obstacle to economic development and human health. One widely accepted way of tackling climate change is to reduce greenhouse gas (GHG) emissions. On the basis of the targets of the Kyoto Protocol from 1997, the EU Emissions Trading Scheme (EU ETS) was developed and came into force in 2005. It was the first emission trading system and continues to be the largest in existence today.

The EU ETS is based on a *cap-and-trade* idea. Within this concept, upper limits (caps) are set for the total amount of GHGs that may be emitted by certain sectors of the economy in a given period. Within these caps, companies receive or purchase emission allowances (EUAs) that entitle them to emit one tonne of CO_2-equivalent per allowance. Once a year, the installations must report their emissions and surrender sufficient allowances to cover them.[1] If a company is unable to submit enough allowances, it must pay a penalty.[2] The cap is lowered each year to reduce the total amount of emissions and induce a scarcity, which will ensure that the allowances have a positive value and the emissions are cut back.

The price of the permits is determined by the market as they can be traded freely, including also futures and options markets. This creates the necessity to understand the pricing mechanism. Christiansen et al. (2005) suggest three factors that are likely to influence the allowance price. These are policy and regulatory issues; market fundamentals, including weather and production levels; and non-fundamentals, such as technical indicators. The influence of market fundamentals on the allowance price in the first two phases of the EU ETS has been extensively researched (Mansanet-Bataller et al., 2007; Alberola et al., 2008a; Alberola et al., 2008b; Hintermann, 2010; Aatola et al., 2013; Lutz et al., 2013; and

[1] Data for a given year must be verified by an accredited verifier by 31 March of the following year. After the verification, an equivalent number of emission allowances must be surrendered by 30 April of that year.

[2] The penalty amounts to €100 per uncovered tonne of emissions, which increases annually since 2012 in line with the European consumer price index. The penalty has to be paid additional to the cost of submitting allowances due in the next compliance period, which reduces the available permits in the next period. Further, the name of the penalized company is published.

others). But some argue that the relationship between the allowance price and its price determinants changes over time (Aatola et al., 2013; Koop and Tole, 2013; Lutz et al., 2013; Koch et al., 2014; Batten et al., 2021).

In this paper, we test this hypothesis. We contribute to the literature by being the first to analyze the price drivers of emission allowances during phase III and the first part of phase IV. We consider linear regressions (Alberola et al., 2008a) and augment it with higher-order polynomials (Hintermann, 2010), structural vector autoregressive (SVAR) models (Hammoudeh et al., 2014), and a cointegration analysis (Creti et al., 2012). Further, we focus on abatement-related fundamentals that have been documented as price drivers in the literature, which are crude oil, natural gas, coal, and electricity prices, as well as the clean dark spread and the clean spark spread. We find that crude oil is the most important price determinant among the abatement-related variables. Although it explains the largest share of variation, this share is extremely small, especially compared to previous results from phase I and II, and the significance of oil is not robust to other modeling approaches. Considering higher polynomials of the determinants improves the overall performance slightly, which hints at allowance prices exhibiting non-linear relationships with fundamentals. Nevertheless, the explanatory power is still low. Through the estimated SVARs, we find some significant impulse-responses of the allowance price, but these are small in magnitude. We find evidence of a long-term equilibrium in phase III of the EU ETS based on a cointegration analysis, but the corresponding vector error correction model (VECM) explains very little of the allowance price variation. Overall, we conclude that the abatement-related fundamentals alone are not sufficient for explaining emission allowance prices in phases III and IV. The results give rise to the assumption that the allowance return can be better explained using proxies for economic activity.

The remainder of this study is organized as follows. Section 2 explains the mechanics of the EU ETS, while Section 3 gives an overview of the related literature. Section 4 discusses the data and methods. Section 5 shows the empirical results, and Section 6 concludes.

2 EU Emission Trading Scheme

The EU ETS operates in phases. The first phase was a *learning-by-doing* phase. In this period, almost all allowances were allocated free of charge and the caps were set at the national level in national allocation plans, which were added up to the overall cap. The amount of available permits exceeded actual emissions in the first phase, which led to a sharp drop in allowance prices in April 2006, when the first verified emissions were disclosed and the surplus became apparent. Phase I is isolated as banking of allowances was prohibited, which caused the price to fall to zero at the end of the phase. The spot price development can be seen in Figure 1.

The second phase was the first commitment period to the Kyoto Protocol. From this phase onward it has been allowed to bank permits from one trading phase into the next. The national caps were lowered because they are now based on verified emissions. Several countries began conducting auctions to distribute allowances, reducing the share of free allocations to 90%. New countries joined the scheme and aviation was included at the beginning of 2012, although only flights within the European Economic Area were considered until the end of 2023. The economic crisis in 2008 had a strong impact on the allowance price throughout phase II, as it led to an unexpected sharp drop in emissions and thus producing a large surplus of allowances.

Phase III introduced an EU-wide cap instead of national ones. Auctioning became the standard method for allocating allowances and new gases and industry were included. Thus, the emissions prior to phase III are not comparable to the ones in the latest two trading periods. It can also be argued that, due to the fact that almost all installations now have to buy the allowances required, their prices are not comparable. Thus a change in the pricing process can be expected, which is underlined through the increased open interest in EUA futures after 2013. In 2019, the Market Stability Reserve (MSR) was introduced to address the surplus of allowances in the market, which resulted in higher and more stable carbon prices.

Phase IV began in 2021, and will run until 2030. Free allocation has been extended for another decade for the sectors with the highest risk of carbon leakage. The reduction target was increased through a preliminary political agreement on an emissions trading reform from December 2022, “Fit for 55”. The new target is to reduce GHG emissions by at least 55% by 2030 compared to 2005 emission levels. Furthermore, maritime transport is also to be included in the ETS through an annual phase-in between 2024 and 2026. Additionally, a new, separate ETS is to be created for buildings, road transport, and fuels.

3 Related literature

EU emission allowance prices are determined by a standard supply and demand balance. The supply side is fixed as it is the EU wide cap set out by the EU ETS Directive. The demand side is a function of expected GHG emissions. The level of GHG emissions is determined by various factors such as energy demand, energy prices (e.g. coal, gas, oil), weather conditions (e.g. temperature fluctuations) or economic activity. The demand can also be influenced by speculation, as around 35% of long positions in EUA on the European Energy Exchange (EEX) are held by institutions that are not obliged to surrender allowances under the EU ETS. Mansanet-Bataller and Pardo (2008) and Afonin et al. (2018) analyze EUAs as stand-alone investments or their potential benefit when included in portfolios. Further, considerable effort has been made to analyze the price dynamics of emission allowances (Benz and Trück, 2009; Daskalakis et al., 2009; Isenegger and von Wyss, 2009; Carmona and Hinz, 2011; Hitzemann and Uhrig-Homburg, 2018).

Previous literature (Mansanet-Bataller et al., 2007; Alberola et al., 2008a; Hintermann, 2010; Bredin and Muckley, 2011; Creti et al., 2012; Batten et al., 2021) has shown the importance of energy prices in explaining carbon prices. Alberola et al. (2008a) highlight the influence of energy prices (natural gas, oil, coal, electricity) and temperature variation on carbon prices in the first trading phase and thereby identify the effect of the disclosure of the first verified emissions. The results are further investigated in later trading periods by Aatola et al. (2013), Lutz et al.

(2013), Koch et al. (2014), and Batten et al. (2021), showing a gradual decrease in the explanatory power of energy prices, a loss of significance for the weather variables, and rather sharp changes in the significant factors, their magnitude and sign. Alberola et al. (2008b) and Chevallier (2011) highlight the importance of economic activity, either sector specific or overall European economic activity, for the permit price. We summarize existing research in Table 1.

The majority of the studies focus on the first two trading phases, and their results have to be considered with caution when transferring to more recent trading periods. This is on the one hand the case due to the extreme price drop in phase I highlighted by Alberola et al. (2008a), but also due to the fact that there was a large surplus of allowances which peaked in 2013 (European Commission and Directorate-General for Climate Action, 2021). Moreover, the dynamics investigated with the transition from phase I and II are not applicable to later phase shifts, as the banking prohibition was removed. Other major changes, such as the inclusion of more sectors and gases, took place in phase III. It therefore is necessary to take up prior approaches and test the validity of their results in more recent periods with newer market regulations.

4 Data & Methods

4.1 Data

We employ daily data that covers the period from January 1, 2013, to March 31, 2023, thus encompassing phases III and part of phase IV of the EU ETS. The data is obtained from Refinitiv Eikon's financial database and Datastream. We use EUA daily closing spot prices (€) from the EEX for our main analysis. For robustness, we also use the EUA daily closing futures prices of a futures chain (€) from the Intercontinental Exchange (ICE).

The market determinants considered are crude oil, coal, natural gas, and electricity prices, as well as the clean spark spread and the clean dark spread.[3] Oil prices are ICE Brent crude oil futures ($/barrel) and the corresponding index ($/barrel). Natural gas prices are ICE UK NBP Natural Gas monthly futures (UK pence/therm) and the London Natural Gas Index (UK pence/therm). Coal prices are ICE Rotterdam Coal monthly futures ($/ton). All price series are converted to Euros. Since there is no single electricity price series that represents all electricity prices in the EU, we follow Aatola et al. (2013) and use the German baseload electricity price index (€/MWh) from Marex Spectron, as Germany is the largest country in the EU and produces the highest share of electricity.[4]

The clean dark spread (€/MWh) is the difference between the peak electricity price and the price of coal used to generate the electricity, adjusted for the cost of emission allowances. It therefore represents the marginal profit that a coal-fired power plant can make from the sale of an additional unit of electricity, adjusted for fuel purchase costs and the carbon price. The clean spark spread (€/MWh) is the equivalent for natural gas-fired plants and is defined as the difference between the peak hour electricity price and the natural gas price, adjusted for input and allowance costs (Alberola et al., 2008a).

We test each time series using the ADF (Said and Dickey, 1984), PP (Phillips and Perron, 1988), and KPSS (Kwiatkowski et al., 1992) test, showing that all time series are integrated of order 1. Therefore, we transform each time series to its natural logarithm and take first differences, except for the spreads which will only be differenced due to the possibility of a non-positive spread. For the cointegration analysis in Section 5.2.2, the variables stay in log-levels. Descriptive statistics of the transformed variables are given in Table 2, while Table 3 displays the correlations.

[3] We omit weather variables that were included by Alberola et al. (2008a), as more recent studies have shown that only extreme weather events had an impact and that these have lost their relevance for the allowance price over time (Lutz et al., 2013; Batten et al., 2021).

[4] Days with negative electricity prices are excluded from the analysis.

4.2 Methodology

4.2.1 Contemporaneous regression

First, we estimate contemporaneous regressions as in Alberola et al. (2008a) and Batten et al. (2021). We include oil, coal, natural gas, and electricity prices as well as the clean dark spread, and the clean spark spread as explanatory variables. The model for the return of carbon (EUA_t) is:

$$\begin{aligned} EUA_t = \alpha + \beta_1\ EUA_{t-1} + \beta_2\ brent_t + \beta_3\ coal_t + \beta_4\ ngas_t \\ + \beta_5\ elec_t + \beta_6\ clean\ dark_t + \beta_7\ clean\ spark_t + \epsilon_t, \end{aligned} \quad (1)$$

where t indicates the calendar day. EUA_{t-1} is the EUA return lagged by one day, $brent_t$ is the brent crude oil return, $coal_t$ is the coal return, $ngas_t$ corresponds to the natural gas return, $elec_t$ is the electricity return, $clean\ dark_t$ is the clean dark spread change, $clean\ spark_t$ is the clean spark spread change, and ϵ_t is the error term. All variables are contemporaneous, except for the lagged EUA return. The regression is estimated using an OLS estimator with a Newey–West covariance matrix to make the standard errors robust to autocorrelation in the residuals and heteroskedasticity.

4.2.2 Structural vector autoregressive model

Due to endogeneity problems of electricity, clean dark spread, and clean spark spread with the EUA price, the coefficients of the contemporaneous regression may be biased. To address this fact, Aatola et al. (2013) suggest using a reduced-form VAR. However, the contemporaneous relationships between the variables may be important. To take this into account, we estimate a structural VAR as in Hammoudeh et al. (2014). A decision must be made on the identifying restrictions, i.e. as to which current value should influence another current value, but not vice versa. To determine these restrictions, we follow Hammoudeh et al. (2014) and assume the following chain of causality:

$$\begin{aligned} &elec_t \;\rightarrow\; coal_t \;\rightarrow\; ngas_t \;\rightarrow \\ &\qquad brent_t \;\rightarrow\; clean\,dark_t \;\rightarrow\; clean\,spark_t \;\rightarrow\; EUA_t. \end{aligned} \tag{2}$$

We assume that the electricity price influences the other prices, but not vice versa, as per assumption the energy demand has a greater impact on the pricing mechanism of the other variables. The coal price is assumed to be influenced by the electricity price, whereas it also has an impact on the gas and oil prices, as it remains the primary fuel in energy production. Crude oil is not that often used for energy generation, hence it is assumed to be influenced not only by electricity and coal prices but also by natural gas prices. The spreads are determined by the factors prior in our chain of causality, and therefore should be influenced contemporaneously by all of these factors. The clean dark spread is before the clean spark spread, as the share of energy generated using coal is larger. We do not place any restrictions on the carbon price, since we assume that it can be contemporaneously influenced by all the other variables. Consequently, the allowance price is ordered last. The lag length p is determined using the Akaike (1974) information criterion (AIC).

4.2.3 Cointegration

So far only short-term relationships are considered, but there is also the possibility of long-term equilibrium relationships. Bredin and Muckley (2011) and Creti et al. (2012) consider long-term equilibria using cointegration methods. Thus, we consider a standard VECM and use the Johansen (1988) method to determine the cointegration relationship. For this analysis, the variables are expressed in log-levels, except the spreads. We determine the optimal lag length using the AIC and test for bivariate cointegration of the individual variables with the price of allowances to avoid spurious cointegration results, considering that energy prices are cointegrated with each other but not necessarily with the price of allowances.

5 Empirical results

5.1 Univariate Analysis

5.1.1 Full phases

Panel (a) of Table 4 shows the results of Regression (1) for phase III, while Panel (b) shows the results for phase IV. It becomes apparent that the discussed factors together are only able to explain 4.7% of the variation of the allowance spot return in phase III and 0.6% in phase IV, whereas they explained 34.17% in phase I (Alberola et al., 2008a) and 6.6% in the time span from 2013 to 2017 (Batten et al., 2021). Thus, taking the entire phase III, the explanatory power of energy prices is further reduced, while their power diminishes in the analyzed time frame of phase IV, where none of the determinants exhibits a significant coefficient. The following analysis therefore focuses on the results of the third trading phase.

Oil is the factor that explains the largest share of variation alone and has a rather high and positive coefficient. It was also a significant factor in phase I and II with varying coefficient sizes. Alberola et al. (2008a) find small coefficients in their sub-periods while Creti et al. (2012) show higher coefficients in the entire time span of phase I and also in phase II. Lutz et al. (2013) again find smaller coefficients in phase II, while Koch et al. (2014) are not able to identify a significant effect of oil in that trading period. Thus, there is a large variation in the documented effect of oil on the allowance return. The only consistency is that the coefficient of oil is positive, suggesting that oil influences the return on allowances not through its carbon intensity as an energy source, but rather as an indicator of aggregate economic activity.

In our analysis the coefficient of coal is significant and positive. In the first trading period of the system, coal was found to be insignificant on the one hand (Mansanet-Bataller et al., 2007; Hintermann, 2010) and on the other hand it is found to be significant with either a negative (Alberola et al., 2008a) or a positive coefficient (Chevallier, 2011; Aatola et al., 2013). In phase II the same variety as in phase I can be found, covering an insignificant (Koch et al., 2014), a significant positive (Chevallier, 2011; Lutz et al., 2013), and significant negative coefficient (Aatola et al., 2013). For the period from 2013 to 2017, Batten et al. (2021) find that coal is a significant factor with a negative coefficient. Thus, coal is the factor with largest variety of effects on the allowance returns. This could be due to two potentially opposing effects that determine the relationship between coal and the return on allowances. The first is the widely held view that economic activity drives commodity demand and prices. Lutz et al. (2013) argue that a change in aggregate demand may affect commodity and allowance prices in the same way, leading to a positive relationship for returns as well. The second effect is the substitution effect, where installations can switch from coal to another input factor. This effect implies that a company would switch from coal to one of its substitutes when the price of coal is increasing. In the case of oil and natural gas as substitutes this would cause fewer emissions, which in turn results in a negative relation between coal and EUA returns. Our results suggest that the economic activity effect outweighs the substitution effect.

Natural gas is a significant factor with a positive coefficient, but explains less than 1% of the allowance return. It was also a significant factor with nearly the same size for the coefficient in phase I and II (Alberola et al., 2008a; Chevallier, 2011; Aatola et al., 2013; Koch et al., 2014), but Lutz et al. (2013) document a greater magnitude of the coefficient. In the time frame from 2013 to 2017, Batten et al. (2021) find that natural gas is not significant. The only consistency of this factor is again a positive sign. This supports on the one hand the assumption of fuel switching, where electricity producers switch from coal to natural gas as input for their energy generation, as gas produces about 50% fewer emissions than coal (Benz and Trück, 2009). On the other hand, natural gas could also be viewed as a proxy for economic activity.

The coefficient of electricity is insignificant, has a negative sign, and a small size. However, in the time frames from 2005 to 2010 and 2013 to 2017 it was a significant price determinant, with a positive coefficient and varying sizes (Alberola et al., 2008a; Aatola et al., 2013; Batten et al., 2021). Thus, there is a change in the sign, which might be due to the fact that the mix of the baseload electricity production switches to greener methods to produce energy, which causes electricity to have a negative and less strong relationship with the EUA return.

The clean dark spread is significant at the 10% level with a positive sign if it is not controlled for any other factors. The sign turns negative in phase IV. The magnitude of the coefficients found here is smaller than the ones found in prior literature. Alberola et al. (2008a) find a significant effect of the clean dark spread with a negative sign in phase I and Batten et al. (2021) confirm the sign in the period from 2013 to 2017, however the coefficient is not significant. The positive sign found here can be explained by the fact that the clean dark spread is above the clean spark spread but close to zero in phase III, thus the electricity production using coal is slightly more profitable and increases the allowance demand. In order to have a measurable influence on the allowance price, the spreads need to be stable so it is beneficial for companies to switch their input fuel. In phase IV, however, the spreads are highly volatile, so that no clear effect can be identified.

The coefficient of the clean spark spread is insignificant and has different signs depending on whether it is controlled for the other factors and which phase is examined. Again, the magnitude of the coefficients is smaller than the ones found in prior literature. In phase I and from 2013 to 2017, the clean spark spread had a positive coefficient and was significant (Alberola et al., 2008a; Batten et al., 2021). The change in sign, low magnitude, and insignificance of the coefficients, as well as the spread being near to zero, makes it not possible to identify an interpretable pattern.

We calculate the Ljung–Box (Ljung and Box, 1978) test for each regression in Table 4 to investigate whether the residuals are truly independent. In phase III, it can be seen that the null hypothesis of this test is rejected. However, in phase IV the test cannot be rejected as easily, but we consider this phase for the same robustness analysis as in phase III.

5.1.2 Structural breaks within periods

The results above highlight that it is necessary to examine both phases separately as substantial changes can be observed. Alberola et al. (2008a) show that such differences exist within phases, and they have revealed that the publication of the first verified emissions in phase I had a significant impact on the pricing dynamics of the spot market. Thus, we use the minimum Lagrange Multiplier unit root test of Lee and Strazicich (2013) to check whether there is a break in the intercept or the trend slope of the data generating process of the logarithm of the price series of the allowance spot price in phase III and IV, respectively. This test allows us to estimate the potential breakpoints endogenously. Figure 2 shows the natural logarithm of the allowance price together with the estimated breakpoints. We assume that these breakpoints reflect a shift in the pricing mechanism of the allowance price, meaning that the effect should be reflected when modeling the EUA return. The breakpoints in each phase are shown by the dashed lines, while the solid line shows the shift from one trading period to the next.

The potential breakpoint in phase III occurs on March 20, 2018. This break is consistent with the publication of new EU ETS regulations on March 19, 2018 and with a general increase in the price level caused, among other things, by the introduction of the MSR (European Commission and Directorate-General for Climate Action, 2021). The breakpoint in phase IV is estimated to be on February 24, 2022, which coincides with the date on which Russia's aggression against Ukraine began. It seems reasonable that such an event has had an influence on the whole economy in Europe and also on the EU ETS market. These two dates are used to divide each phase into two parts and analyze the determinants of the allowance return series and the change in their explanatory power over the period. The results of Regression (1) for the sub-periods of phases III and IV are shown in Table 5 and 6, respectively.

In Table 5 it becomes visible that roughly the same factors remain significant in the two sub-periods. However, natural gas is not significant in the first sub-period, while it is again in the second, and coal is significant in first sub-period but not in the second. The share of explained variance increases to a new high in the second sub-period, hinting during the later part of phase III, the allowance price is more strongly driven by the energy variables. But when we control for the breakpoint using dummy variables, no coefficient is significantly different from each other across the sub-periods, showing that there is no evidence supporting the hypothesis of sub-periods in phase III. The Ljung–Box test can again be rejected giving rise for further robustness checks.

In the first sub-period of phase IV, the lagged allowance return, oil, and coal as well as the clean spark spread are significant factors; however the spread is only significant if it is not controlled by the lagged allowance price. In the second sub-period the clean dark spread is the single significant factor, but it is only significant when it is controlled for all other factors and the *F-Statistic* is still insignificant. The share of explained variance is increased compared to the complete phase and it is also higher in the first sub-period. Furthermore, the coefficients of EUA_{t-1}, oil, coal and clean spark spread show a significant difference when we control for the breakpoint using dummy variables. However, given the relatively short periods, these results should be interpreted with caution. The null hypothesis of the Ljung–Box test can be rejected in the first sub-period, but not in the second. For the sake of completeness, we include both sub-periods of phase IV in the further robustness checks.

To sum up, most explanatory variables are not significant, the share of explained variance is low, and there are only some variables which exhibit a significant change at the 10% level over the sub-periods. Thus, different pricing regimes within trading phases can be ruled out as a possible reason for the small explanatory power.

5.1.3 Non-linear relationships

Hintermann (2010) shows that the relationships between the allowance price and its market fundamentals might be non-linear. To test this, we employ the $RESET$ test of Ramsey (1969) and apply it to Regression (1) for all periods discussed previously. The corresponding *p-values* are reported in Table 7, where we test the inclusion of second- and third-order polynomials in Panels (a) and (b), respectively. Under the null hypothesis, the coefficients of all higher polynomials are jointly zero. Rejection implies adding higher-order polynomials to the model. The last column of Table 7 shows the *p-value* of Regression (1), including all variables for each time period. In each of the other columns, only one variable is included to determine which factor might have a non-linear relationship with the allowance return.

The results show that in each period the linear regression is misspecified and non-linear relationships exist. At some point, each factor has a non-linear relationship with the allowance return, with the exception of electricity. We include each factor with its polynomials tested with the $RESET$ test and employ the General to Specific method to determine which are the relevant factors in each period. The results of these regressions are shown in Table 8.

First, it has to be noted that the electricity return gets excluded from all regressions. Thus, this factor does not have any explanatory power in the third and fourth phase of the EU ETS. Furthermore, natural gas gets excluded for phase IV, but is a significant factor with linear and non-linear relationships with the carbon return in the sub-periods of this phase.

The allowance return has a non-linear relationship with itself in both trading periods, while the coefficients are positive in phase III and negative in phase IV. The overall effect of EUA_{t-1} on the carbon return is an increase in each period, no matter the actual sign of the lagged allowance return. The extreme price changes that would cause a decrease, as suggested by the negative non-linear coefficients, happen rarely. Oil remains significant as a linear factor and starts to show non-linear relationships with the allowance return at the later part of phase III, where the signs of the coefficients are negative. Thus, the impact of more extreme returns of oil on the allowance return would go against the economic activity effect, but the size of these coefficients are caused by less than 10% of the data. Thus, the prior explanation of the effect of the oil return remains valid. The coal return starts to have non-linear relationships with the carbon return in phase IV, where the non-linear factors now exhibit a negative coefficient. Through the non-linearity, the interplay of the economic activity and substitution effect can be seen. The allowance return decreases when the coal return decreases as economic activity is reduced, while the allowance return also decreases when the coal return increases, as coal gets substituted by other inputs which produce fewer emissions. However, the substitution effect only realizes by extreme values of coal returns. It is revealed that natural gas is not a relevant factor for phase IV and the first sub-period of phase III. While there is evidence for non-linear relationships, the overall the effect of natural gas on the allowance return stays the same as in Section 5.1.1. Both spreads have significant non-linear relationships with the allowance return in all periods under investigation and increase the allowance return nearly always as the changes in the spreads are rather small.

The share of explained variance increases for each period, but the effect is most noticeable in phase IV. This is not surprising considering that mostly non-linear factors remain from the General to Specific approach. Nevertheless, the explanatory power falls short in comparison to the results of earlier phases (34.17% in phase I Alberola et al., 2008a), which shows that simply adding higher polynomials is not sufficient to explain the carbon price.

The performance of the linear and non-linear regressions for the entire phases and their sub-periods worsens when EUA futures returns instead of spot returns are considered. The explanatory power decreases further and the *F-statistics* are insignificant. Only in the first sub-period of phase IV are the energy variables able to explain about 13% of the EUA futures return variation. Considering non-linear factors with the General to Specific approach, shows that the EUA futures return can be explained significantly in each of the time periods discussed, reaching a high of 19% in the first sub-period of phase IV.

5.2 Multivariate modeling

The different variables discussed in this paper influence each other in many ways, e.g. the different fuel prices are expected to be cointegrated as they can be substituted for each other in energy production. To tackle the endogeneity problem, we consider a standard SVAR to estimate any interdependencies. Furthermore, long-term equilibria have been discussed in the literature (Bredin and Muckley, 2011; Creti et al., 2012; Koch et al., 2014), which may be of greater importance than the short-term dynamics of the allowance price, as the permits are only needed once per year. Thus, we also consider the possibility of cointegration.

5.2.1 SVAR

Using a SVAR enables us not only to tackle the problems of endogeneity but also to consider possible lead–lag relationships, since prices are not recorded simultaneously and agents might react with a delay. As the interpretation of the coefficients of a SVAR is not as straightforward, we focus on the adjusted R^2 and accumulated impulse response functions. Note that the comparability with Hammoudeh et al. (2014) is limited as they considered data from US American markets. However, we expect similar results because the economic mechanisms should be comparable even if the sample is different.

Based on AIC, we pick a SVAR(3) with 23 parameters per equation for phase III and an SVAR(2) with 16 parameters per equation for phase IV. However, none of these models improves the explanatory power for the allowance return. In phase III, 1.17% can be explained by the SVAR, while in phase IV 0.38% can be explained.

Figure 3 displays the accumulated impulse response functions. The left column shows the responses of the EUA return in percent to the different shocks in phase III while the reactions in phase IV are shown in the right column.

We can see that a positive shock to the oil return causes a permanent same-direction price effect of the EU emission allowances in phase III. Hammoudeh et al. (2014) find a first positive and later negative effect of an oil shock, which aligns with our results. Here, the argument of the economic activity effect takes hold, where an increase in the return of a commodity represents an increase of economic activity, causing more emissions and higher permit returns. The positive shock to the change in clean dark spread also causes a permanent reaction, but this is only narrowly significant at the 5% level. This shock increases the allowance return but the increase is below 0.5%. The direction of the response aligns with economic expectation as an increased profit margin of energy generation using coal should increase emissions and thus allowance prices. The reactions on a shock to the natural gas or coal return are transitory and vanish after 2 days. Here, the shock to natural gas causes an increase while Hammoudeh et al. (2014) find a decrease. Overall, an increase seems more likely as power producers would switch to coal as an input factor in energy production and therefore increase emissions. Further, the effect of natural gas could also be explained with the economic activity effect. The only variables that do not cause a significant response in phase III are electricity and the clean spark spread.

In phase IV, shocks to all of the variables do not cause a significant response in the allowance return. Based on the adjusted R^2s, the performance of the two SVARs for the allowance return is worse than the performance of an OLS regression. Thus, this model also does not seem to be able to explain more recent permit prices, even though Hammoudeh et al. (2014) found very high adjusted R^2s of about 90% in their sample from 2006 to 2013. Using EUA future returns instead of spot returns does not change the results of this model significantly.

5.2.2 Cointegration

We employ cointegration analysis to determine the existence of potential long-term equilibrium relationships between the price of allowances and its fundamentals. Our approach broadly follows Creti et al. (2012), as we first consider bivariate cointegration in order to identify which variables are truly cointegrated with the allowance price. A bivariate analysis avoids spurious cointegration results, since energy prices are cointegrated among themselves but not necessarily with the EUA price. Table 9 shows the critical values and test statistics for the Johansen (1988) test. For the sake of brevity, we only report results for which we find a significant cointegrating relationship.

We can see that the allowance price in phase III is cointegrated with the electricity price and the clean dark spread. To measure the significance of the long-term equilibrium we estimate a VECM(3). The estimation results are provided in Table 10. Cointegration vector 1 is significant, documenting the long-term equilibrium in the trivariate system. However, the share of explained variance is only around 0.6%, which again falls short of the explanatory power of the OLS regression. Thus, the long-term equilibrium in phase III of the EU ETS is not sufficient to characterize the allowance price.

In phase IV, there is evidence for cointegration between the allowance price and the clean spark spread. To model this relationship, we estimate a VECM(5) visible in Table 10. The cointegrating vector is not significant, thus providing no support for a long-term equilibrium in phase IV. The share of explained variance of this VECM is 0.3%. That no cointegration can be found in phase IV is not surprising due to the relatively short time span and the major economic disruptions during this period, e.g. the lasting effects of the pandemic and the war in Ukraine.

To sum up, we find evidence for a long-term equilibrium in phase III even though it does not explain a sizable share of the variation in the permit price. In phase IV, we are not able to identify a significant long-term equilibrium. When considering EUA futures instead of spot prices, there is no long-term equilibrium in either trading phase.

6 Conclusion

In this paper, we investigate the price determinants of carbon allowance prices in the most recent trading periods. We employ different econometric approaches that have been suggested in the literature. We perform OLS regressions for phases III and IV together, separately, and for endogenously defined sub-periods. Furthermore, we estimate SVARs to address endogeneity concerns and employ Johansen cointegration tests to identify long-term equilibria.

Our empirical results exhibit much lower explanatory power compared to what has been documented in the literature for phases I and II. The reduced explanatory power could be driven by the changing regulations, such as the composition of industries that fall under the regulation. As the EUA market has matured, its integration with energy and electricity prices might have changed.

Bibliography

Aatola, P., Ollikainen, M., and Toppinen, A. (2013). Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals. *Energy Economics*, 36:380–395.

Afonin, A., Bredin, D., Cuthbertson, K., Muckley, C., and Nitzsche, D. (2018). Carbon portfolio management. *International Journal of Finance & Economics*, 23(4):349–361.

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6):716–723.

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

Alberola, E., Chevallier, J., and Chèze 1, B. (2008b). The EU emissions trading scheme: The effects of industrial production and CO2 emissions on carbon price. *Economie Internationale*, (4):93–125.

Batten, J. A., Maddox, G. E., and Young, M. R. (2021). Does weather, or energy prices, affect carbon prices? *Energy Economics*, 96:105016.

Benz, E. and Trück, S. (2009). Modeling the price dynamics of CO2 emission allowances. *Energy Economics*, 31(1):4–15.

Bredin, D. and Muckley, C. (2011). An emerging equilibrium in the EU emissions trading scheme. *Energy Economics*, 33(2):353–362.

Carmona, R. and Hinz, J. (2011). Risk-neutral models for emission allowance prices and option valuation. *Management Science*, 57(8):1453–1468.

Chevallier, J. (2011). A model of carbon price interactions with macroeconomic and energy dynamics. *Energy Economics*, 33(6):1295–1312.

Christiansen, A. C., Arvanitakis, A., Tangen, K., and Hasselknippe, H. (2005). Price determinants in the EU emissions trading scheme. *Climate Policy*, 5(1):15–30.

Creti, A., Jouvet, P.-A., and Mignon, V. (2012). Carbon price drivers: Phase I versus Phase II equilibrium? *Energy Economics*, 34(1):327–334.

Daskalakis, G., Psychoyios, D., and Markellos, R. N. (2009). Modeling CO2 emission allowance prices and derivatives: Evidence from the European trading scheme. *Journal of Banking & Finance*, 33(7):1230–1241.

European Commission and Directorate-General for Climate Action (2021). *Review of the EU ETS market stability reserve: final report*. Publications Office of the European Union.

Hammoudeh, S., Nguyen, D. K., and Sousa, R. M. (2014). What explain the short-term dynamics of the prices of CO2 emissions? *Energy Economics*, 46:122–135.

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

Hitzemann, S. and Uhrig-Homburg, M. (2018). Equilibrium price dynamics of emission permits. *Journal of Financial and Quantitative Analysis*, 53(4):1653–1678.

Isenegger, P. and von Wyss, R. (2009). The Valuation of Derivatives on Carbon Emission Certificates – a GARCH Approach. *Available at SSRN 1343835.*

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12(2-3):231–254.

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

Koop, G. and Tole, L. (2013). Forecasting the European Carbon Market. *Journal of the Royal Statistical Society: Series A*, 176(3):723–741.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, 54(1-3):159–178.

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

Ljung, G. M. and Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika*, 65(2):297–303.

Lutz, B. J., Pigorsch, U., and Rotfuß, W. (2013). Nonlinearity in cap-and-trade systems: The EUA price and its fundamentals. *Energy Economics*, 40:222–232.

Mansanet-Bataller, M. and Pardo, A. (2008). CO2 Prices and portfolio management. *Politics & Energy eJournal*.

Mansanet-Bataller, M., Pardo, A., and Valor, E. (2007). CO2 prices, energy and weather. *The Energy Journal*, 28(3).

Phillips, P. C. and Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2):335–346.

Ramsey, J. B. (1969). Tests for specification errors in classical linear least-squares regression analysis. *Journal of the Royal Statistical Society: Series B*, 31(2):350–371.

Said, S. E. and Dickey, D. A. (1984). Testing for unit roots in autoregressive-moving average models of unknown order. *Biometrika*, 71(3):599–607.

Figure 1: Development of the price of EU ETS allowances.
This figure shows the development of the spot price of European emission allowances (EUA) in Euros since the start of the EU ETS. The different trading phases are indicated by the vertical dashed lines.

Figure 2: EUA price series with breakpoints.

The figure shows the natural logarithm of the EUA spot price series over phases III and IV. Breakpoints are estimated on this time series in each phase, respectively, with the minimum Lagrange Multiplier unit root test of Lee and Strazicich (2013) to test for a break in the intercept or slope of the time series. The end of phase III is marked by the solid gray line while the dashed gray lines show the estimated breakpoints in each phase.

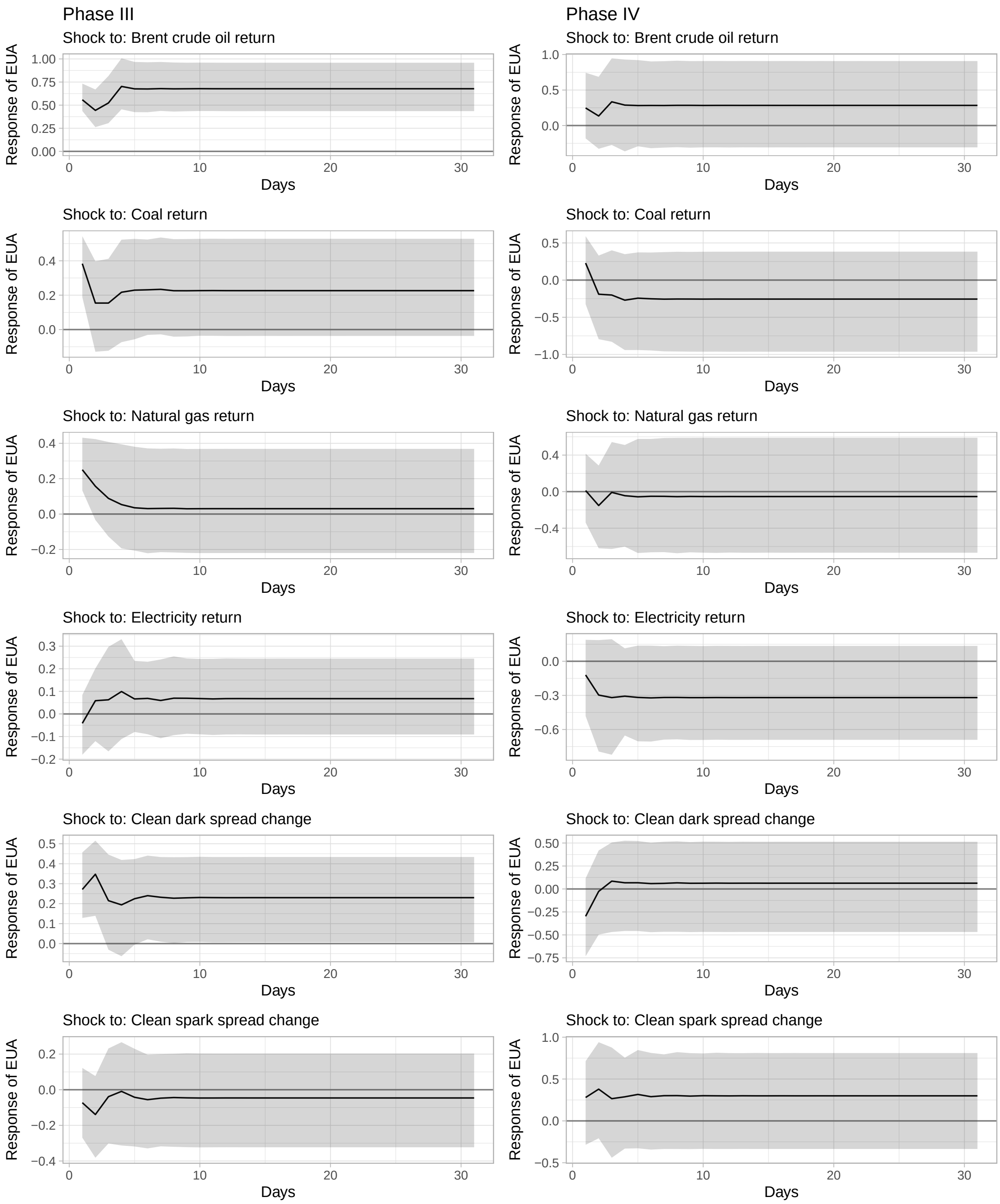

Figure 3: Accumulated impulse response function of SVAR.
The figure shows the accumulated impulse response functions for phase III in the left column and for phase IV in the right column. The gray bands visualize the 5% confidence intervals.

Table 1: Literature overview.

The table lists a brief overview of the relevant literature on the EU ETS. The Table lists the time period, the method, and a brief summary of the 5% significant coefficients or an important result, as well as the adjusted R^2 in parentheses.

Paper	Phase Time span	Method	Results
Mansanet-Bataller et al. (2007)	Phase I 2005	Linear Regression	Changes in Brent and natural gas prices, extreme temperature events (40.9% – 47.81%)
Alberola et al. (2008a)	Phase I 2005 – 2007	Linear Regression (with dummy variable for structural break)	Electricity, coal, oil, gas, clean dark, and clean spark spread, and extreme cold temperatures and lagged EUA spot price (10.47% – 35.58%)
Hintermann (2010)	Phase I 2005 – 2007	Structural model under assumption of efficient markets	Fuel prices, summer temperatures, and precipitation (5.74% – 61.12%)
Bredin and Muckley (2011)	Phase I & II 2005 – 2009	Cointegration analysis	New Pricing regime in Phase II along with increasing efficiency
Creti et al. (2012)	Phase I & II 2005 – 2010	Cointegration analysis (with dummy variable for structural break)	Equilibrium relationship in both phases with increasing importance of fundamentals in the second phase
Aatola et al. (2013)	Phase I & II 2005 – 2010	Linear Regression Instrumental Variables Vector Auto Regression (with dummy variables for influential observations)	German electricity, gas, and coal prices, mineral and paper (22% – 40.9%)
Lutz et al. (2013)	Phase II 2008 – 2012	Markov regime-switching model Non–switching GARCH model	Gas and stock index for both volatility regimes Oil, coal, gas, stock index and commodity index
Hammoudeh et al. (2014)	Phase I, II & III 2006 – 2013	Bayesion structural VAR	Oil has a positive effect, gas and electricity have a negative effect, coal has a positive effect if electricity is excluded
Koch et al. (2014)	Phase II & III 2008 – 2013	Linear Regression Cointegration analysis	Economic sentiment index, wind/solar production, and stock index are significant while there is no equilibrium relationship (9.7% – 44%)
Batten et al. (2021)	Phase III 2013 – 2017	Linear Regression	Oil, coal, electricity, and clean spark spread (1.8% – 12.27%)

Table 2: Descriptive statistics.

This table shows the descriptive statistics of all variables for phases III and IV, respectively. It reports mean, standard deviation, minima, and maxima, as well as the skewness and kurtosis of each time series return, except for spreads in first differences only. We test means against zero using a t-test and report the significance by stars, where ***, **, and * correspond to a significance level of 1%, 5%, and 10%, respectively. Phase III spans from 01.01.2013 to 31.12.2020 ($N = 1,939$), while phase IV spans from 01.01.2021 to 31.03.2023 ($N = 412$).

(a) Phase III

	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
EUA spot price	0.001	0.034	−0.447	0.211	−1.312	19.227
Brent crude oil	−0.001	0.025	−0.315	0.196	−1.336	27.003
Coal	−0.0001	0.015	−0.180	0.177	0.149	35.212
Natural gas	−0.0002	0.023	−0.294	0.297	1.383	64.316
Electricity	−0.0003	0.256	−3.091	3.045	0.068	37.619
Clean dark spread	−0.008	1.296	−18.580	25.110	2.546	103.415
Clean spark spread	0.008	0.992	−9.140	7.080	−0.588	16.582
EUA futures price	0.001	0.035	−0.431	0.245	−1.156	17.224

(b) Phase IV

	Mean	Std.Dev.	Min.	Max.	Skewness	Kurtosis
EUA spot price	0.002	0.036	−0.177	0.162	−0.450	3.087
Brent crude oil	0.002*	0.029	−0.156	0.100	−0.655	3.620
Coal	0.002	0.057	−0.541	0.327	−1.749	24.986
Natural gas	0.002	0.066	−0.580	0.452	−1.787	34.589
Electricity	0.001	0.259	−1.652	1.525	−0.139	7.666
Clean dark spread	−0.061	22.635	−150.620	113.230	−0.346	11.042
Clean spark spread	−0.044	20.210	−168.370	165.700	0.263	29.943
EUA futures price	0.002	0.036	−0.177	0.162	−0.451	3.112

Table 3: Pearson–correlations.

This table presents Pearson–correlations of returns of all variables, except the spreads which are only differenced. Phase III, which spans from 01.01.2013 – 31.12.2020 ($N = 1,939$), in panel (a) and phase IV, which spans 01.01.2021 – 31.03.2023 ($N = 412$), in panel (b). The significance of each value is indicated by stars, where ***, **, and * correspond to a significance level of 1%, 5%, and 10%, respectively.

(a) Phase III

	EUA spot price	Brent crude oil	Coal	Natural gas	Electricity	Clean dark spread	Clean spark spread	EUA futures price
EUA spot price	1	0.185***	0.107***	0.081***	−0.025	0.072***	0.012	0.334***
Brent crude oil		1	0.122***	0.054**	−0.044*	−0.032	−0.02	−0.057**
Coal			1	0.147***	−0.009	0.111***	0.029	0.016
Natural gas				1	0.134***	0.076***	−0.047**	0.02
Electricity					1	0.074***	0.018	0.009
Clean dark spread						1	0.411***	0.015
Clean spark spread							1	0.012
EUA futures price								1

(b) Phase IV

	EUA spot price	Brent crude oil	Coal	Natural gas	Electricity	Clean dark spread	Clean spark spread	EUA futures price
EUA spot price	1	0.087*	0.048	0.036	−0.024	−0.069	−0.028	0.999***
Brent crude oil		1	0.226***	0.074	0.096*	0.132***	−0.106**	0.085*
Coal			1	0.228***	0.12**	0.262***	−0.015	0.048
Natural gas				1	−0.021	0.13***	−0.083*	0.032
Electricity					1	0.066	0.057	−0.021
Clean dark spread						1	0.4***	−0.068
Clean spark spread							1	−0.027
EUA futures price								1

Table 4: Time series regression in phases III and IV.

This table presents the coefficients of time series regressions of phase III (January 1, 2013 – December 31, 2020) in Panel (a) and phase IV (January 1, 2021 – March 31, 2023) in Panel (b). All variables are expressed in log-differences, except for spreads, which are only differenced. The Ljung–Box (Ljung and Box, 1978) test, R^2, adjusted R^2, and *F-statistic* are calculated for each regression and are specified in the last four rows in each Panel. The regressions are estimated with the OLS estimator. Newey–West standard errors are in parentheses. ***, **, and * correspond to a significance level of 1%, 5%, and 10%, respectively.

(a) Phase III

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EUA_{t-1}	0.005							0.013
	(0.026)							(0.026)
Brent crude oil		0.252***						0.238***
		(0.041)						(0.043)
Coal			0.238***					0.154**
			(0.061)					(0.062)
Natural gas				0.118***				0.086***
				(0.031)				(0.033)
Electricity					−0.003			−0.004
					(0.003)			(0.004)
Clean dark spread						0.002*		0.002
						(0.001)		(0.001)
Clean spark spread							0.0004	−0.0005
							(0.001)	(0.001)
Observations	1,938	1,939	1,939	1,939	1,939	1,939	1,939	1,938
Ljung–Box	20.109***	24.836***	20.623***	20.753***	20.262***	19.680***	20.648***	22.831***
R^2	0.00002	0.034	0.011	0.007	0.001	0.005	0.0001	0.051
Adjusted R^2	-0.0005	0.034	0.011	0.006	0.0001	0.005	-0.0004	0.047
F-Statistic	0.044	68.419***	22.530***	12.838***	1.216	10.141***	0.265	14.709***

continued on the next page

Table 4: Time series regression in phases III and IV. *continued*

(b) Phase IV

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
EUA_{t-1}	−0.082							−0.071
	(0.052)							(0.047)
Brent crude oil		0.108						0.097
		(0.108)						(0.083)
Coal			0.030					0.028
			(0.062)					(0.049)
Natural gas				0.020				0.021
				(0.035)				(0.032)
Electricity					−0.003			−0.004
					(0.008)			(0.006)
Clean dark spread						−0.0001		−0.0002
						(0.0001)		(0.0001)
Clean spark spread							−0.00005	0.0001
							(0.0002)	(0.0001)
Observations	411	412	412	412	412	412	412	411
Ljung–Box	8.266	9.359*	9.885*	10.472*	10.648*	11.302**	10.934*	8.785
R^2	0.007	0.008	0.002	0.001	0.001	0.005	0.001	0.023
Adjusted R^2	0.004	0.005	-0.0001	-0.001	-0.002	0.002	-0.002	0.006
F-Statistic	2.786*	3.127*	0.956	0.547	0.231	1.957	0.321	1.379

Table 5: Time series regression in sub-periods of phase III.

This table presents the coefficients of time series regression in the two sub-periods of phase III. All variables are expressed in log-differences, except for spreads, which are only differenced. The total sample of Phase III was divided into two parts with the first part corresponding to the interval from January 1, 2013 to March 20, 2018 in Panel (a) and the second part corresponding to the interval from March 21, 2018 to December 31, 2020 in Panel (b). The Ljung–Box (Ljung and Box, 1978) test, R^2, adjusted R^2, and *F-statistic* are calculated for each regression and are specified in the last four rows of each Panel. The regressions are estimated with the OLS estimator. Newey–West standard errors are in parentheses. ***, **, and * correspond to significance levels of 1%, 5%, and 10%, respectively.

(a) January 1, 2013 to March 20, 2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.0005	0.001	0.0004	0.0005	0.0004	0.0005	0.0004	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EUA_{t-1}	0.004							0.012
	(0.033)							(0.032)
Brent crude oil		0.232^{***}						0.204^{***}
		(0.047)						(0.048)
Coal			0.287^{***}					0.222^{**}
			(0.092)					(0.093)
Natural gas				0.110^{*}				0.055
				(0.060)				(0.056)
Electricity					−0.004			−0.004
					(0.005)			(0.005)
Clean dark spread						0.002		0.004^{*}
						(0.002)		(0.002)
Clean spark spread							−0.0005	−0.002
							(0.002)	(0.002)
Observations	1,322	1,323	1,323	1,323	1,323	1,323	1,323	1,322
Ljung–Box	40.208^{***}	44.090^{***}	40.811^{***}	42.147^{***}	40.696^{***}	41.644^{***}	40.971^{***}	42.936^{***}
R^2	0.00002	0.018	0.011	0.003	0.0004	0.004	0.0001	0.033
Adjusted R^2	-0.001	0.017	0.010	0.002	-0.0003	0.004	-0.001	0.028
F-Statistic	0.025	24.329^{***}	14.870^{***}	3.541^{*}	0.569	5.735^{**}	0.167	6.495^{***}

continued on the next page

Table 5: Time series regression in sub-periods of phase III. *continued*

(b) March 21, 2018 to December 31, 2020

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.002	0.002	0.002	0.002	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EUA_{t-1}	0.003							0.020
	(0.040)							(0.050)
Brent crude oil		0.265^{***}						0.254^{***}
		(0.069)						(0.073)
Coal			0.197^{**}					0.104
			(0.079)					(0.074)
Natural gas				0.122^{***}				0.101^{**}
				(0.037)				(0.042)
Electricity					−0.003			−0.004
					(0.003)			(0.004)
Clean dark spread						0.002		0.001
						(0.001)		(0.001)
Clean spark spread							0.001	0.0003
							(0.001)	(0.001)
Observations	614	615	615	615	615	615	615	614
Ljung–Box	11.658^{*}	16.209^{***}	12.819^{**}	11.487^{*}	11.606^{*}	13.106^{**}	11.624^{*}	16.001^{***}
R^2	0.00001	0.074	0.015	0.017	0.001	0.008	0.002	0.102
Adjusted R^2	-0.002	0.073	0.013	0.015	-0.001	0.007	0.001	0.092
F-Statistic	0.005	49.030^{***}	9.198^{***}	10.298^{***}	0.604	5.203^{**}	1.483	9.856^{***}

Table 6: Time series regression in sub-periods of phase IV.

This table presents the coefficients of time series regression in the two sub-periods of phase IV. All variables are expressed in log-differences, except for spreads, which are only differenced. The total sample of phase IV was divided into two parts with the first part corresponding to the interval from January 1, 2021 to February 24, 2022 in Panel (a) and the second part corresponding to the interval from February 25, 2022 to March 31, 2023 in Panel (b). The Ljung–Box (Ljung and Box, 1978) test, R^2, adjusted R^2, and *F-statistic* are calculated for each regression and are specified in the last four rows of each Panel. The regressions are estimated with the OLS estimator. Newey–West standard errors are in parentheses. ***, **, and * correspond to significance levels of 1%, 5%, and 10%, respectively.

(a) January 1, 2021 to February 24, 2022

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.006***	0.003*	0.004**	0.004***	0.004***	0.004***	0.005***	0.004	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
EUA_{t-1}	−0.255***							−0.224***	
	(0.048)							(0.055)	
Brent crude oil		0.347***						0.289**	0.345***
		(0.105)						(0.131)	(0.092)
Coal			0.122**					0.100**	0.101**
			(0.048)					(0.040)	(0.042)
Natural gas				0.034				0.047	0.040
				(0.026)				(0.093)	(0.034)
Electricity					0.003			0.004	0.001
					(0.011)			(0.015)	(0.008)
Clean dark spread						0.0001		−0.0001	−0.0001
						(0.0002)		(0.001)	(0.0002)
Clean spark spread							0.001*	0.001	0.001***
							(0.0004)	(0.002)	(0.0004)
Observations	215	216	216	216	216	216	216	215	216
Ljung–Box	3.157	14.318***	17.414***	19.041***	18.265***	18.778***	16.516***	2.305	11.619**
R^2	0.063	0.061	0.037	0.004	0.001	0.004	0.021	0.162	0.123
Adjusted R^2	0.059	0.057	0.033	-0.0003	-0.004	-0.0004	0.016	0.134	0.098
F-Statistic	14.434***	14.008***	8.314***	0.930	0.113	0.910	4.542**	5.734***	4.886***

continued on the next page

Table 6: Time series regression in sub-periods of phase IV. *continued*

(b) February 25, 2022 to March 31, 2023

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.0004	0.0001	0.00003	0.0001	0.0001	−0.0001	0.00003	0.0005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)
EUA_{t-1}	0.038							0.051
	(0.056)							(0.048)
Brent crude oil		−0.018						0.045
		(0.104)						(0.082)
Coal			−0.039					0.033
			(0.058)					(0.054)
Natural gas				0.003				0.028
				(0.060)				(0.032)
Electricity					−0.010			−0.010
					(0.011)			(0.006)
Clean dark spread						−0.0002		-0.0003^{**}
						(0.0002)		(0.0001)
Clean spark spread							−0.0001	−0.0001
							(0.0001)	(0.0001)
Observations	194	195	195	195	195	195	195	194
Ljung–Box	6.808	5.302	4.984	5.283	5.530	5.881	5.170	8.206^{*}
R^2	0.002	0.0002	0.004	0.00002	0.004	0.023	0.006	0.048
Adjusted R^2	-0.004	-0.005	-0.001	-0.005	-0.001	0.018	0.001	0.012
F-Statistic	0.290	0.046	0.776	0.004	0.845	4.577^{**}	1.232	1.338

Table 7: *RESET* test.

This table shows the results of the *RESET* test from Ramsey (1969) for the regressions in Tables 4, 5, and 6, respectively. Shown are the *p–values* of the test for misspecification of the functional form, thus testing whether the addition of the factors to the power of two or three is beneficial. Panel (a) shows the *p–values* if only squared factors are considered, while Panel (b) shows the results if factors to the power of two and three are considered.

(a) Second–order polynomial

	EUA_{t-1}	Brent crude oil	Coal	Natural gas	Electricity	Clean dark spread	Clean spark spread	All
Phase III	0.044	0.604	0.529	0.314	0.902	0.868	0.597	0.473
01.01.13 – 20.03.18	0.010	0.582	0.741	0.435	0.463	0.595	0.896	0.344
21.03.18 – 31.12.20	0.048	0.408	0.427	0.387	0.976	0.924	0.448	0.499
Phase IV	0.393	0.349	0.064	0.193	0.584	0.098	0.012	0.002
01.01.21 – 24.02.22	0.954	0.409	0.107	0.859	0.614	0.589	0.276	0.332
25.02.22 – 31.03.23	0.227	0.601	0.020	0.114	0.488	0.364	0.012	0.013

(b) Second– and third–order polynomial

	EUA_{t-1}	Brent crude oil	Coal	Natural gas	Electricity	Clean dark spread	Clean spark spread	All
Phase III	0.001	0.142	0.240	0.020	0.807	0.002	0.100	0.0001
01.01.13 – 20.03.18	0.001	0.496	0.487	0.094	0.715	0.079	0.661	0.011
21.03.18 – 31.12.20	0.119	0.023	0.062	0.021	0.808	0.003	0.181	0.002
Phase IV	0.487	0.001	0.013	0.414	0.829	0.056	0.010	0.0001
01.01.21 – 24.02.22	0.906	0.083	0.270	0.115	0.873	0.019	0.441	0.035
25.02.22 – 31.03.23	0.417	0.040	0.063	0.044	0.771	0.444	0.027	0.026

Table 8: Time series regression in phases III and IV.

This table presents the coefficients of a time series regression of phase III and phase IV, as well as the two sub-periods identified for each phase separately. Equation (1) has been augmented with all factors to the power of two and three. All variables are expressed in natural logarithms and first differences, except for spreads, which are only differenced. The R^2, adjusted R^2, and *F-statistic* are calculated for each regression and are specified in the last three rows. The regressions are estimated with the OLS estimator. The significance of each coefficient is indicated, where ***, **, and * correspond to a significance level of 1%, 5%, and 10%, respectively.

	Phase III			Phase IV		
		sub-periods:			sub-periods:	
	Entire	01.01.2013 – 20.03.2018	21.03.2018 – 31.12.2020	Entire	01.01.2021 – 24.02.2022	25.02.2022 – 31.03.2023
Intercept	0.001*	0.001	0.002*	0.004**	0.007***	−0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
EUA_{t-1}					−0.233***	0.171*
					(0.065)	(0.096)
EUA^3_{t-1}	1.214***	1.260***		−15.037***		−23.684**
	(0.361)	(0.377)		(5.116)		(9.219)
Brent crude oil	0.226***	0.205***	0.321***	0.289***	0.501***	
	(0.030)	(0.047)	(0.049)	(0.081)	(0.120)	
Brent crude oil^2				−2.701**	−7.791***	
				(1.217)	(2.703)	
Brent crude oil^3			−2.250**	−38.094***	−79.251***	
			(0.978)	(13.376)	(26.532)	
Coal	0.156***	0.233***			0.109***	0.156**
	(0.050)	(0.074)			(0.040)	(0.075)
Coal^2				−0.181*		
				(0.105)		
Coal^3						−4.599**
						(1.806)
Natural gas	0.155***		0.243***		0.185***	−0.105*
	(0.052)		(0.068)		(0.061)	(0.063)
Natural gas^2					−0.151*	
					(0.088)	
Natural gas^3	−2.038*		−2.948**		−0.878***	0.753***
	(1.085)		(1.204)		(0.319)	(0.287)
Clean dark spread	0.004***	0.006***	0.004***			−0.0002*
	(0.001)	(0.002)	(0.001)			(0.0001)
Clean dark spread^2	0.0002***		0.0002***	−0.00000***		
	(0.0001)		(0.0001)	(0.00000)		
Clean dark spread^3	−0.00002***	−0.0001***	−0.00001***	−0.00000***	−0.00000***	
	(0.00000)	(0.00002)	(0.00000)	(0.000)	(0.00000)	
Clean spark spread	−0.002**	−0.003**	−0.002*		0.001***	
	(0.001)	(0.001)	(0.001)		(0.0003)	
Clean spark spread^2	−0.0005**		−0.001**	0.00000***	−0.00003**	0.00000***
	(0.0002)		(0.0002)	(0.00000)	(0.00002)	(0.00000)
Observations	1,938	1,322	615	411	215	194
R^2	0.067	0.046	0.136	0.101	0.241	0.137
Adjusted R^2	0.062	0.042	0.123	0.083	0.199	0.100
F-Statistic	13.820***	10.591***	10.589***	5.631***	5.847***	3.686***

Table 9: Results of Johansen's (1988) cointegration eigenvalues test.

This table shows the null hypothesis, critical values and test statistics of bivariate Johansen (1988) eigenvalue tests. The critical values correspond to the 95% significance level. The lag length is determined using the AIC.

Null hypothesis	Critical value	Phase III		Phase IV
		with Electricity	with Clean dark spread	with Clean spark spread
None	15.67	28.276	22.695	21.403
At most 1	9.24	2.159	1.809	9.091
Lags		13	4	6

Table 10: VECM for phases III and IV.

This table presents the results of a VECM estimation for phases III and IV. All variables are expressed in natural logarithms, except for spreads. A VECM(3) was estimated for phase III and a VECM(5) for phase IV. Here, *dl*1 stand for log-difference with one lag. The *F-statistic* and the adjusted R^2 were calculated and are reported in the last two rows. ***, **, and * correspond to significance levels of 1%, 5%, and 10%, respectively.

		Phase III	Phase IV
		Coefficient	Coefficient
Cointegration vector 1		-0.003^{**}	-0.0003
Cointegration vector 2		0.004	
*dl*1	EUA spot price	0.001	-0.076
	Electricity	0.006^{*}	
	Clean dark spread	0.0003	
	Clean spark spread		0.0001
*dl*2	EUA spot price	-0.069^{***}	0.047
	Electricity	0.005	
	Clean dark spread	-0.001	
	Clean spark spread		-0.0001
*dl*3	EUA spot price	-0.044^{*}	-0.060
	Electricity	0.006	
	Clean dark spread	-0.001	
	Clean spark spread		-0.0002
*dl*4	EUA spot price		
	Electricity		-0.031
	Clean dark spread		
	Clean spark spread		-0.0002
*dl*5	EUA spot price		-0.009
	Electricity		
	Clean dark spread		
	Clean spark spread		0.0001
R^2		0.012	0.029
Adjusted R^2		0.006	0.003
F-Statistic		2.059^{**}	1.093