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Working Paper

European Electricity and interrelated Futures Markets: A cointegrated Vector Autoregressive Analysis

EWL Working Paper, No. 05/12

Provided in Cooperation with:

University of Duisburg-Essen, Chair for Management Science and Energy Economics

Suggested Citation: Fritz, Andreas (2012) : European Electricity and interrelated Futures Markets: A cointegrated Vector Autoregressive Analysis, EWL Working Paper, No. 05/12, University of Duisburg-Essen, Chair for Management Science and Energy Economics, Essen

This Version is available at:

<https://hdl.handle.net/10419/103288>

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and Energy Economics

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EWL Working Paper No. [05/12]

**EUROPEAN ELECTRICITY AND
INTERRELATED FUTURES MARKETS:
A COINTEGRATED VECTOR AUTOREGRESSIVE ANALYSIS**

by

Andreas Fritz

August 2012

European Electricity and interrelated Futures Markets: A cointegrated Vector Autoregressive Analysis

by Andreas Fritz

Abstract

This study investigates the price formation of electricity futures at the European Energy Exchange (EEX) and aims at understanding the price formation in connection with interrelated futures markets such as ARA coal at the Intercontinental Exchange (ICE), natural gas at the Title Transfer Exchange (TTF) and CO₂ allowances. Results obtained from using a vector error correction model suggest that price formation in the futures markets for electricity can be explained to some extent fundamentally. Electricity futures price dynamics show dependency on marginal generation costs. A stable long-term equilibrium between electricity futures prices and marginal costs, namely prices of hard coal, natural gas and CO₂ allowances could be found. An impulse response analysis reveals that in the longer run the electricity futures price converge to marginal costs of a hard coal power plant. This is useful information for electric utilities and regulatory bodies since futures markets serve several purposes for energy utilities, including price discovery, hedging, valuation and trading.

Keywords: Energy, Cointegration, Electricity Market, Futures Market

JEL-Classification: Q40

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The author is solely responsible for the contents which do not necessarily represent the opinion of the Chair for Management Science and Energy Economics.

1 Introduction

Since liberalization of the energy industry in Europe began, electricity is traded at Energy Exchanges both on spot and futures markets like raw materials or commodities such as crude oil, barley or grain. An important difference of electricity compared to other commodities is the lack of economically sensible storage possibilities. Supply and demand need to be in balance at any moment in time. This implies that the conventional theory of storage – linking spot and futures prices – breaks down. Futures markets should still reflect anticipated supply and demand during the period of delivery of the futures contract but this means they behave more according to the expectation theory. Assuming rational expectations, an electricity futures price equals the expectation of a future spot price plus a risk premium. The ongoing discussion on price formation in electricity futures markets is frequently focusing on the sign of these market risk premia rather than on fundamental influencing factors (see among others Bessembinder, Lemmon 2002, Benth et al. 2008; Redl et al. 2009). In this paper we question to what extent energy futures prices are fundamentally driven, which comprises a price formation based on fuel prices, mainly natural gas and hard coal for continental Europe.¹ To answer this question, we focus on expectation building of market participants for a given future period using electricity futures prices and prices from interrelated futures markets. In doing so the cointegration behavior of futures prices, such as electricity, hard coal, natural gas and CO₂ emission allowances is also investigated. The reasoning behind is the assumption pointed out above that the futures price equals the spot price at delivery corrected possibly by a risk premium. The spot price itself is a function of fuel prices and CO₂ allowances. Thus a stable relationship i. e. cointegration (cf. section 3)², should also exist between electricity and fuel prices in futures markets. This paper tries to shed some light on this issue. For electric utilities and regulatory bodies, understanding the price formation in futures markets is necessary, given that these markets serve several purposes for energy utilities, including price discovery, hedging, valuation and trading.

In modeling the interactions of prices in European futures markets many relationships have to be considered. In markets with a huge amount of fossil-fueled power generation like continental Europe, basic power system economics clearly suggest a strong relationship between the electricity price and its related input factors natural gas and hard coal along with CO₂ allowances. A reasonable assumption is that either natural gas or hard coal is at the margin. From this fundamental view point, crude oil is not expected to influence power prices directly, given that only a small proportion of European power stations is running on oil. Yet indirectly, fuel oil is expected to influence the power price via the gas and partly also the coal price. Given these a priori economic relationships a systems based modeling approach seems to be useful. One way of dealing with this issue could be to set up a highly parameterized model of simultaneous equations with numerous assumptions about price formation and market structure. These a priori restrictions are however difficult to specify and justify

¹ This is also interesting because of the financialization of energy futures markets. Financialization stems from a greater presence of financial investors. Financial investors treat electricity as an asset class which causes (physical) commodity markets to behave more like financial markets. Finally, prices could drive away from price levels that would be determined by physical supply and demand relationships only.

² One important point has to be made here. Cointegration means by definition that price differences of energy prices (namely spreads) are stationary and cannot diverge to far from each other. This is useful information especially for realistic power plant valuation purposes because its implication is that (clean) dark and (clean) spark spreads are stationary as well.

in detail and wrong specifications may induce misleading estimation results. Moreover, the simultaneous equations model (SEM) could not capture the dynamic relations between the fossil fuels and CO₂ emission allowances – given that in a dynamic SEM lagged values of variables are considered to be exogenous. Hence, instead of using a SEM the focus of this article is on a data-driven cointegrated vector autoregressive (CVAR) model in order to determine relations between the variables and capture the dynamics of all variables in the system. This offers an effective formal framework for estimating long-run economic relationships and short-run dynamics from time series data.

The remainder of this paper is organized as follows. Section 2 briefly reviews price formation in electricity futures markets and related literature. Section 3 presents the data and econometric methods. Section 4 shows empirical results and section 5 provides conclusions.

2 Price formation in electricity futures markets and related literature

The electricity market in continental Europe is still highly dominated by fossil-fueled power generation. Germany obtains around 60% percent of its production from hard coal and natural gas. (see International Energy Agency 2011). In electricity spot market, the prices are directly linked to marginal generation costs of power plants, namely fuel and carbon dioxide costs weighted by the heat rate and emission factor. The difference between electricity spot prices and marginal generation costs is defined as clean spark (in case of natural gas) respectively clean dark spread (in case of hard coal) and is used for valuation purposes of power plants. These spreads or the operational margin of the power plant then also reflect the instantaneous balance between electricity supply and demand. The almost inelastic, but stochastically varying demand given electricity generation near the maximum capacity will cause the spreads to rise. These fundamental spot market developments will be incorporated in futures markets via expectation formation about the future power generation. There are at least two hypotheses on expectation formation in electricity markets. On the one hand, under the hypothesis of rational expectations and the price setting mechanism in electricity markets, only future marginal generation costs plus a risk premium should be included in electricity futures prices (see e. g. Fama, French 1987). This approach is used and tested in this article. On the other hand, a huge correlation between today's spot prices and electricity futures prices is observed as in e. g. (Redl et al. 2009). In that case the spot price may be used as an estimator for futures prices. (Redl et al. 2009) uses monthly nearby-futures prices and finds that futures prices are influenced by their own lagged values and spot prices which the authors take as an indication for adaptive expectation formation in the market. This does not necessarily mean that the rational and adaptive expectation hypotheses are contradictory. New information arrival is mostly observable in spot markets only, e. g. short-term fluctuations in supply and demand conditions. Thus it is rational for market participants to exploit the information from spot markets and incorporate it in futures market price formation. Due to the fact that this article uses year-ahead prices the information contained in spot market data for futures prices should be limited and therefore current demand or supply are not incorporated in this study.

Although there is an influence of spot markets in the short-term and futures prices may be used as estimators for future spot prices it is important to bear in mind that spot prices are not forecasted by

the term structure of futures prices³ as pointed out by (Benth et al. 2008). These curves are futures prices at time t for specific time points (delivery dates) T in the future. Prices reflect then future supply and demand conditions or rather trading needs of market participants for specific future dates. (Bessembinder, Lemmon 2002) define the expected difference between futures and spot prices as the forward premium, sometimes it is also called market risk premium. Analytically this is the difference between the futures price F_{T-t} for delivery in month T and the spot price in month T . The authors argue that due to the absence of sensible storage facilities the forward power price will be “a biased forecast of the future spot price.” (Benth et al. 2008) define a positive market risk premium as a situation where more electricity buyers hedge their positions than electricity sellers and vice versa. This is in line with the results of (Bessembinder, Lemmon 2002). They find the forward premium to be positive, if power generation will be near the maximum system capacity due to high demand or high volatility. The sign of the forward premium itself is still a focal point of research. The motivations for hedging can differ between consumers and producers depending on their specific risk-aversion. In contrast to producers, consumers might not see the need for hedging in the long term and contracts are thus traded at a high discount. The absolute value of risk premia and their signs are also dependent on the time to maturity of a specific futures contract. Even the signs of risk premia can switch from positive to negative values as time to maturity increases as shown by (Benth et al. 2008). Because they are decreasing as time to maturity increases, they are quite low in absolute terms for yearly contracts with time to maturity smaller than two years. Moreover, when using continuous year-ahead futures prices risk premia can be assumed to be constant. Thus, futures price changes are more likely to depend on other input factors or can be seen as the result of market transactions between buyers and suppliers of electricity.

Putting this together, this article focuses on price formation in futures markets only rather than focusing on the influence of spot market data on futures prices or investigating the forecasting power of futures prices for future spot prices. Additionally, the paper tests for cointegration in energy futures markets.

Various studies have been conducted in order to investigate the cointegration behavior between energy prices in general. To the best of our knowledge, the interaction between energy forward prices has been investigated for the first time in (Joëts, Mignon 2012) but the focus of their investigations is on price adjustments of oil prices rather than electricity prices. The authors are using daily forward prices of different maturities in a nonlinear panel data framework and show that the forward price series of crude oil, electricity, natural gas, hard coal and the Euro Stoxx 50 are cointegrated. Yet the authors do not investigate the electricity equilibrium or try to give fundamental explanations for price formation in electricity futures markets. This is done within this article.

(Fell 2010) also uses a cointegrated vector autoregressive (CVAR) model, but he determines the relationship between Nordic wholesale electricity prices and the EU emissions trading scheme (EU-ETS) CO₂ allowance prices. Besides he uses weekly averages of spot price data for CO₂ prices from Point Carbon, natural gas from Zeebrugge hub, coal prices for the ARA region and electricity prices from the hourly day-ahead Elspot system prices. He finds a single cointegration vector for electricity, natu-

³ Under the assumption that interest rates are deterministic, futures prices are equal to forward prices.

ral gas, hard coal and CO₂ emission allowances. In contrast to (Fell 2010) this article uses daily futures prices of the central European market. (Bunn, Fezzi 2008) make also use of spot data but the time span is ranging only from 2005 to 2006. The authors find a stable relationship between electricity, gas and carbon in United Kingdom and Germany. A study with focus on the interaction of spot and futures prices was conducted by (Redl et al. 2009). The authors use monthly spot and futures data over the time period December 2004 till April 2008 to investigate the relationship between electricity baseload spot and futures prices traded at the European Energy Exchange (EEX). Although, the authors identify one cointegration relation between spot and futures prices, they point out the sensitivity to the specification of lagged terms in the system.

A study with a long time horizon and not focusing on European spot or futures data was done by (Mohammadi 2009). He used annual data for the United States covering a period from 1960 to 2007 to investigate long-run relations between electricity, hard coal, natural gas and crude oil prices. He finds no cointegration between the four energy prices. Even in models with a smaller number of variables cointegration behavior is observed only between electricity, hard coal and natural gas, where the influence from natural gas is statistically weak. A stable long-run relations exists only between electricity and hard coal. (Mjelde, Bessler 2009) use U.S. spot prices as well showing that fuel prices (with the exception of uranium) determine electricity prices in the long-run. In the short-run electricity prices move natural gas prices. To sum up, a clear answer on cointegration behavior in energy markets cannot be given since the results from several studies differ. Results seem to depend on the time period and energy market considered but for the case of the European market at least one stable relationship between electricity, hard coal, natural gas and CO₂ allowances is to be expected in this article.

3 Data and empirical methodology

This study uses daily continuous futures⁴ settlement prices running from January 3rd, 2007 to December 30th, 2011 which sums up to 1.262 observations over a time span of five years. Despite the fact that longer time series for the case of fossil fuels and electricity could be used the analysis is restricted to the time period after 2006. That is because the European Emissions Trading Scheme (EU ETS) has been introduced in the beginning of 2005 and until the end of 2007 the first trading period in the EU ETS was considered as a test phase⁵. Thus, the analysis of this paper concentrates on the second period which has begun in 2008.

For the estimation we construct continuous front year futures from baseload year futures traded at the European Energy Exchange (EEX). The major coal importing port in Northwestern Europe is Amsterdam-Rotterdam-Antwerpen (ARA) hence we make use of ARA coal traded at the Intercontinental Exchange (ICE). For natural gas the most liquid and mature virtual trading point in Continental Eu-

⁴ Futures or futures spreads with a fixed maturity are martingales which means they are not mean reverting in the risk neutral measure. Assuming constant risk premia futures with fixed maturity are also not mean reverting in the market measure. Yet Dempster et al. 2008 show that diverging futures spreads with fixed maturity are consistent with mean reversion in spot market spreads. That is why we are using continuous year-ahead futures as a proxy for the investigation of cointegration behavior in futures markets (i. e. mean reversion of futures spreads).

⁵ This trading period was characterized by two structural breaks. The first one in April 2006 when overallocation of certificates became public and the second one due to banking restrictions between the first and the second trading period at the end of 2007.

rope, the Title Transfer Exchange (TTF) is used.⁶ In case of CO₂ allowances prices we rely on European Carbon Futures traded at EEX. Furthermore, we use the daily USD/EUR exchange rate from the European Central Bank (ECB) to convert coal prices originally quoted in US-Dollars. Finally, with the exception of CO₂ allowances, prices for each energy carrier are expressed in Euro per Megawatt-hours. Using futures prices means that short-term influences like generation failures or stochastic weather events which influence the merit order do not have to be taken into account. During that time period we do not expect any substantial changes on the supply side, i. e. we expect that in most of the times hard-coal or gas-fired power plants were at the margin. Normally, using daily prices might cause problems with autocorrelation in the residuals but in the context of vector autoregressive models the model lag order is able to account for autocorrelation. Averaging daily data to weekly data is not an option since this approach may lead to biased parameter estimates (see Geweke 1978)⁷.

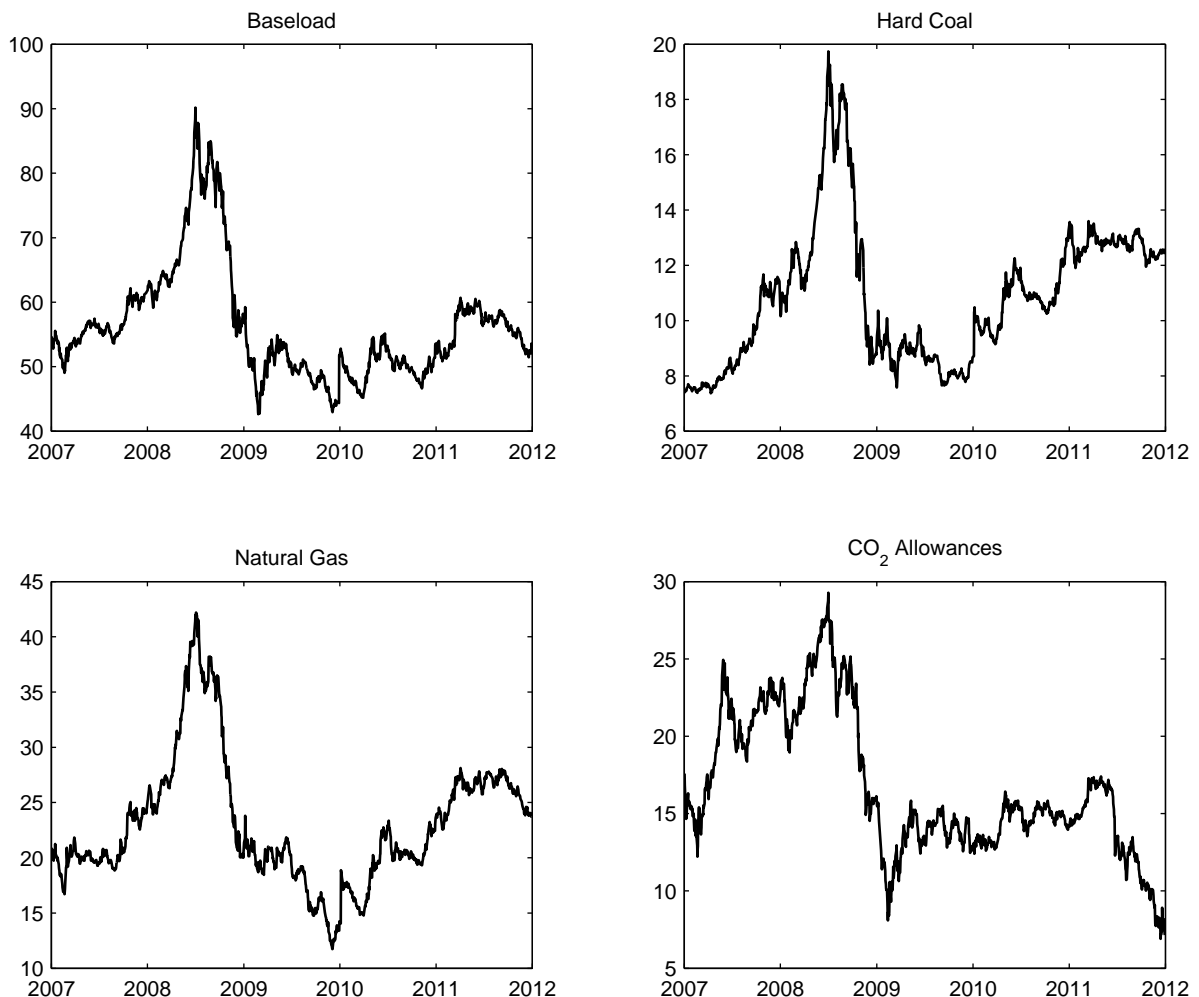


Figure 1: Daily continuous futures prices of baseload electricity, hard coal, natural gas [all in €/MWh] and CO₂ allowances [in €/t] from 2007 till the end of 2011.

⁶ We included prices from ICE and TTF since there is no liquid market and thus there are no reasonable price quotes for the sample period and traded at EEX.

⁷ In fact, using daily or weekly data (only Wednesdays) did not qualitatively change the results of the estimated cointegration relations.

From the graphical impression of Figure 1 it can be seen that all prices follow a similar pattern. They all peaked in summer 2008 and declined when the economic and financial crisis became evident in fall 2008. Summary statistics for each time series of prices are given in Table 1. The largest variation in absolute terms occur in the electricity price series followed by natural gas. Hard coal possesses the smallest price variations.

Table 1: Descriptive statistics

	Mean	Minimum	Maximum	Std. Dev.
p_t^{Elec}	56.25	42.65	90.15	8.90
p_t^{Coal}	10.90	7.37	19.74	2.53
p_t^{Gas}	23.01	11.73	42.20	5.79
p_t^{CO2}	16.61	6.90	29.27	4.54

Note: Energy Prices in € per Megawatt-Hour, EUA-prices in €/ton.

Given the main objective of the study, one severe problem is the non-stationary behavior of the time series. In order to avoid spurious regression results due to I(1) processes in the data, first differencing of futures prices might be useful. In doing so, useful information about long-run relations between the variables would be lost.

The starting point of our analysis is therefore an unrestricted VAR(p) model of order p which has the form

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + \varepsilon_t \quad (3.1)$$

where the A_i are coefficient matrices for N time series variables $y_t = (y_{1t}, \dots, y_{Nt})'$ and $\varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{Nt})'$ is an unobservable error term (see e.g. Johansen 1988). Given that we are centering on several long-run equilibria, notably cointegration relationships, the VAR model is augmented to a Cointegrated Vector Autoregressive Model (CVAR), also called Vector Error Correction Model (VECM). The VECM model is obtained from the VAR form by subtracting y_{t-1} from both sides and rearranging terms

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \dots + \Gamma_{p-1} \Delta y_{t-p+1} + \varepsilon_t \quad (3.2)$$

where $\Pi = -(I_N - A_1 - \dots - A_p)$ and $\Gamma_i = -(A_{i+1} + \dots + A_p)$ for $i = 1, \dots, p-1$. y_t is a price vector of endogenous variables, e. g. electricity, hard coal, natural gas, and emission allowances. The matrix Πy_{t-1} contains the cointegration relationships and is thus the long-run part whereas $\sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-p+1}$ is referred as the part with the short-run parameters of the model. The matrix Π can be also written as a product of $(N \times r)$ matrices α and β with rank $\text{rk}(\alpha) = \text{rk}(\beta) = r$ as $\Pi = \alpha\beta'$. The rank of the matrices α and β depends on the number of cointegration relationships r . The matrix α contains adjustment speeds of the endogenous variables to imbalances in the long-term equilibrium whereas the matrix β consists of parameters of the long-term equilibrium itself. For practical purposes it is useful to augment equation (3.2) by exogenous variables and deterministic terms. A general VECM formulation is

$$\Delta y_t = C + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \dots + \Gamma_{p-1} \Delta y_{t-p+1} + \Phi Z_{t-1} + \varepsilon_t \quad (3.3)$$

where Φ specifies influence of exogenous variables Z_{t-1} and C includes deterministic terms $C = v_0 + v_1 t$. The main feature of the model is the simultaneous estimation of price levels and differences where the latter captures short-run and the former long-run effects. For understanding the interaction between electricity, the fossil fuels and CO₂ allowances a model specification including the four variables $y_t = [p_t^{Elec} \ p_t^{Coal} \ p_t^{Gas} \ p_t^{CO_2}]'$ is investigated. Given that the model consists of four variables at most three (theoretical) steady-state cointegration relationships can be expected, which would imply that all variables follow one common stochastic trend. Without loss of generality these may be specified as: Firstly, a power market equilibrium consisting of electricity, hard coal, natural gas and CO₂ allowance prices, where electricity prices are positively influenced by positive price changes of the fossil fuels and CO₂ allowances. Formally the cointegration relationship or equilibrium correction term $ec_{t,N}$ can be written as

$$ec_{t,N} = C + \beta_1 p_t^{Elec} + \beta_2 p_t^{Coal} + \beta_3 p_t^{Gas} + \beta_4 p_t^{CO_2} + \Phi Z_t \quad (3.4)$$

where $\beta_i \neq 0$, for $i = 1 \dots 4$. Secondly, a fuel switch equilibrium between hard coal, natural gas and emission allowances ($\beta_1 = 0$) could exist, where CO₂ allowance prices should reflect the ratio of hard coal and natural gas prices. Thirdly, a fuel equilibrium between hard coal and natural gas ($\beta_{1,4} = 0$) might occur, where price changes of equal sign are expected.

4 Empirical Results

4.1 Unit root tests

In order to check for cointegration relations between the variables, the order of integration of each time series has to be determined first. Hence, we conduct unit root tests to establish that each variable has a stochastic trend and is integrated of the same order. To get a robust estimation of the order of integration traditional tests like Augmented Dickey Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) are combined with a more advanced test like Dickey Fuller-Generalized Least Squares (DF-GLS) proposed by (Elliott et al. 1996). Except for the KPSS all approaches test the null hypothesis of a unit root whereas for the KPSS tests stationarity is the null hypothesis. The results are shown in Table 2.

Relying on the ADF and DF-GLS test the null hypothesis of a unit root cannot be rejected for each of the variables. Since the null can be rejected for the first differences, each of the variables (with the exception of CO₂ allowances) is considered as integrated of order one, i. e. $I(1)$. This is also true if we delete the trend term in the test equation. The KPSS test underpins the results and additionally for the case of CO₂ allowances stationarity of first differences cannot be rejected. Hence, modeling all variables as random walk with a drift term seems to be a reasonable choice.

Table 2: Unit root tests

Variable	ADF Test		KPSS Test		DF GLS	
	const.	const. & trend	const.	const. & trend	const.	const. & trend
p_t^{Elec}	-1.45(0)	-1.62(0)	0.85[29]***	0.33[29]***	-1.44(0)	-1.45(0)
Δp_t^{Elec}	-33.05(0)***	-33.04(0)***	0.10[8]	0.09[8]	-5.85(9)***	-31.54(0)***
p_t^{Coal}	-1.80(1)	-1.75(1)	0.54[29]**	0.31[29]***	-0.62(1)	-1.50(1)
Δp_t^{Coal}	-30.65(0)***	-30.63(0)***	0.09[16]	0.08[16]	-30.51(0)***	-30.39(0)***
p_t^{Gas}	-1.43(1)	-1.43(1)	0.39[29]*	0.38[29]***	-1.28(1)	-1.37(1)
Δp_t^{Gas}	-31.79(0)***	-31.78(0)***	0.12[11]	0.11[11]	-2.05(13)**	-5.19(9)***
p_t^{CO2}	-0.78(2)	-1.98(2)	2.05[29]***	0.24[29]***	-0.64(2)	-1.45(2)
Δp_t^{CO2}	-26.35(1)***	-26.38(1)***	0.14[4]	0.07[5]	-0.95(17)	-3.43(9)**

Note: * denotes statistical significance at the 10% level, ** at the 5% level, *** at the 1% level. Δ denotes first differences. Numbers in parentheses are lag levels based on the Schwarz Information Criterion. Numbers in brackets represents the automatic Newey-West bandwidth selection using the Bartlett kernel. For the ADF test critical values are taken from (MacKinnon 1996). For the DF GLS test critical values are taken from (Elliott et al. 1996) and for the KPSS test from (Kwiatkowski et al. 1992).

4.2 Cointegration analysis

The determination of possible cointegration relations between the energy prices considered in this paper is a crucial task. In order to determine the cointegration rank r , a methodology proposed by Johansen (see Johansen 1991) is used. Following the argumentation of (Juselius, Hendry 2000) and the references therein, the cointegration rank depends on the consideration of deterministic components in the model. In applied work deterministic trend and constant terms are uncertain. One way to overcome this dilemma is to test the joint hypothesis of rank order and deterministic components using the Pantula principle. The Pantula principle starts with the most restrictive model (constant term in the cointegration space only) and ends with the least restrictive one (general linear trend term and constant). At each stage the value of the trace statistic is compared with its critical value. The procedure ends, when the null hypothesis of $r = r_0$ cointegration relationships cannot be rejected for the first time.

Since the number of cointegration relations depends also on the number of lagged variables the Johansen procedure is conducted up to 10 lags (two weeks). The lag selections k are chosen from the model selection criteria Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC) and Hannan-Quinn criterion (HQ). The AIC suggests a model including four lagged differences, whereas HQ and SIC favor a specification with one lagged difference.⁸ Therefore the cointegration tests are applied using both types of models. There is very strong evidence for a cointegration rank of one regardless of the trend assumption and number of lagged differences (cf. Table 3). The null hypothesis of $r = r_0$ cointegration relationships is not rejected for the first time at $r_0 \leq 1$ where only a constant is included. Thus, we conclude that at a 99% confidence interval a specification with constant and trend is appropriate.

⁸ Fitting the lag length of a VAR model to an appropriate order is a crucial task. Choosing a lag length in the estimation which has a lower order than the true model will induce autocorrelation in the error terms. Overfitting the model with too many lags will generate too large mean-square errors when using the model for forecasting. Both will lead to inconsistent impulse response functions. Hence it is necessary that the lag length makes sense economically. Using up to four lagged differences sounds reasonable since market participants use information up to one week back for trading in the markets considered.

Table 3: Cointegration rank test for four variable model

Deterministic terms	No. of lagged differences	$H_0: r = r_0$	Test statistic	Critical values		
				90%	95%	99%
C	1	$r_0 = 0$	55.33**	50.50	53.94	60.81
		$r_0 \leq 1$	24.52	32.25	35.07	40.78
	4	$r_0 = 0$	61.41***	50.50	53.94	60.81
		$r_0 \leq 1$	26.22	32.25	35.07	40.78
C, orth tr	1	$r_0 = 0$	54.31***	44.45	47.71	54.23
		$r_0 \leq 1$	23.55	27.16	29.80	35.21
	4	$r_0 = 0$	60.39***	44.45	47.71	54.23
		$r_0 \leq 1$	25.29	27.16	29.80	35.21
C, tr	1	$r_0 = 0$	77.74***	60.00	63.66	70.91
		$r_0 \leq 1$	41.04*	39.73	42.77	48.87
		$r_0 \leq 2$	20.29	23.32	25.73	30.67
	4	$r_0 = 0$	83.42***	60.00	63.66	70.91
		$r_0 \leq 1$	43.42**	39.73	42.77	48.87
		$r_0 \leq 2$	23.12	23.32	25.73	30.67

Note: * denotes statistical significance at the 10% level, ** at the 5% level, *** at the 1% level. The lower numbers for included lags are selected according to Hannan-Quinn and Schwarz Information Criterion while the larger number is obtained for the Akaike Information Criterion.

When estimating a VECM the trend can be modeled in both the long-run and the short-term part of the model. Using only the Pantula principle we are not sure that the trend term is of general form or orthogonal, which means the trend cancels out in the cointegration space because it is confined to some individual variables. Therefore we make use of a test proposed by (Demetrescu et al. 2009) to distinguish between the case of an orthogonal and a general trend term. The null hypothesis of an orthogonal trend which means that there is no trend in the cointegration relations can be checked by an LR test of the following form $LR = T \sum_{k=1}^r \log[(1 - \lambda_k)/(1 - \lambda_k^*)]$ where λ_k are the eigenvalues without linear trend term in the cointegration relation and λ_k^* are those with a general trend term included. The test statistic has a χ^2 distribution. Performing the test we see that the null hypothesis can be rejected at a 5% confidence level where the p -Value is 0.015. Thus we conclude, that the VECM is best modeled including a constant term and a trend in the long-run part which allows for some exogenous growth of the variables. Additionally, the paper proceeds under the defensible hypothesis⁹ that the model has one long-run relation $r = 1$.

After the determination of the cointegration rank and deterministic components the parameters from (3.3) can be estimated using maximum likelihood techniques. The estimation results for the

⁹ A model specification with two cointegration relations is only feasible if all (previous) hypotheses for $r_0 \leq 1$ would have been rejected. Since the null hypothesis could not have been rejected in the cases with constant and constant plus orthogonal term we decided to drop the second cointegration relation. Yet we have also checked a model specification allowing for two cointegration relations but we have found the economic interpretation of the estimates to be implausible.

model can be found in Table 4. The single cointegration vector β is normalized on the baseload electricity price p_{t-1}^{Elec} and consequently the cointegration equation represents the electricity equilibrium (with standard errors given in parentheses):

$$\hat{\beta}'y_{t-1} = \begin{bmatrix} 1 & -1.23 & -0.66 & -0.41 & -25.43 & 0.007 \\ & (0.456) & (0.171) & (0.151) & (2.174) & (0.002) \end{bmatrix} \begin{bmatrix} p_{t-1}^{Elec} \\ p_{t-1}^{Coal} \\ p_{t-1}^{Gas} \\ p_{t-1}^{CO2} \\ 1 \\ tr_{t-1} \end{bmatrix} \quad (4.1)$$

The identification of this stable long run relationship is relevant for the price expectation in electricity futures markets. The algebraic signs in the cointegration relation are in line with expectations, fuel prices and CO₂ allowances positively influence the power price, and all estimates are statistically significant. In absolute terms the marginal influence of hard coal is higher than the influence of natural gas which makes sense economically for the Continental Europe power system. Yet the estimated coefficients are lower than expected assuming that new hard-coal fire plants have an efficiency of around 0.45 whereas the old ones have 0.34. Thus, the expectation range of the coefficient for hard coal would have been between 2.2 and 3. A reasonable heat rate for gas-fired power plants (combined cycle gas turbines) is around 0.53 which translates into a marginal electricity price increase of 1.88. The estimated coefficient of CO₂ allowances is the lowest in absolute terms. The expectation for the CO₂ allowances coefficient, taking into consideration efficiency, would have been between 0.75 respectively 1 in the case of hard coal and 0.38 in the case of natural gas. Since the daily baseload electricity price is an average price, it is influenced not only by the variable costs of baseload plants but also by marginal costs of peakload plants. In our case these are the costs from natural gas. In economic terms this means that the impact from hard coal neglecting CO₂ costs on the electricity price is twice as high as the impact of natural gas or in relative terms hard coal (including CO₂ costs) accounts for around 65% and natural gas for 35% of baseload electricity prices.¹⁰ The constant in the equilibrium equation can be seen as a markup over marginal costs to cover fixed costs. The trend is statistically significant but negative. This could be taken as an indication that generation capacity scarcity has decreased over the sample period and that the margin above variable costs has declined.

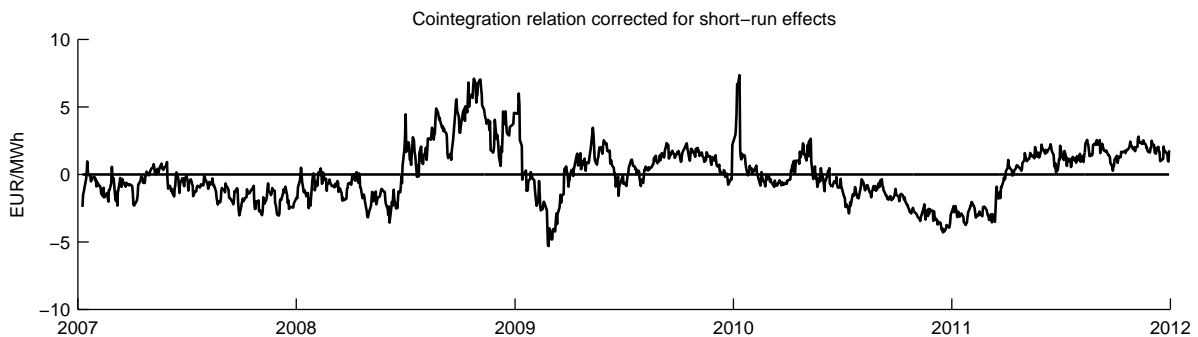


Figure 2: Cointegration relation corrected for short-run effects.

¹⁰ The estimated impact from natural gas roughly fits to expected peak hours per year. Assuming 3.000 peak hours a year (250 trading days with 12 peak hours each) leads to a share of ca. 35%.

The cointegration relation, where the short-run dynamics have been eliminated, is also depicted in Figure 2. The equilibrium error seems to be stationary since it frequently crosses the x-axis and its distance apart is never very far. From visual inspection a shifting cointegration relationship during the sample period is not likely. Three events can be seen in the figure: Firstly, the sky-rocketing prices of mid 2008 and the beginning of the global economic and financial crisis in fall 2008. Yet the adjustment towards equilibrium seems to be delayed since it takes place only in the beginning of 2009. This is not too surprising since at the beginning of each year a new delivery period (one year later) begins. Secondly, the price adjustment of the front year futures after the economic crisis between 2009 and 2010 is indicated by a spike. Thirdly, the Fukushima catastrophe and the ensuing German nuclear policy change cause a turn within a few days from negative deviation to positive deviations. Since then the equilibrium error remains positive. This could be an indication that market participants expect power prices to be higher in the future because of higher scarcity in supply.

In a next step the cointegration relation from equation (4.1) is used to perform a model reduction via imposing zero restrictions on the short-term regressors. The regressors are sequentially eliminated based on the model selection criterion AIC which is equivalent to dropping regressors with the smallest t -ratios. The resulting regression coefficients are shown in Table 4.

Overall, the adjustment speeds α show relatively low-speed reduction of imbalances in the long-term equilibrium. The negative algebraic sign of electricity indicates that if this steady state is in disequilibrium the process will be forced back towards the equilibrium. Since this has to be interpreted in error correction terms the speed of price adjustment after imbalances is highest in the electricity futures markets. The half-life computed as $\ln(2)/\ln(1 + \alpha)$ is around 12 days which means that half of a price shock has been eliminated after 12 days. In contrast, the coefficient for the hard coal equation is very small but significant. This means that hard coal can be seen as part of the system of variables but the error correction of an imbalance in the power equilibrium via coal price changes takes a while. The half-life is 58 days. In comparison to power this is a very slow reaction but economically reasonable. The price for hard coal is settled in world markets. Hence a quick feedback-loop from an Intra-European power disequilibrium to coal prices is not expected.

Table 4: Cointegrated Vector Autoregressive Model Parameter Estimates (subset model)

Long-run Relationship				
$p_t^{Elec} = 25.43^{***} + 1.23p_{t-1}^{Coal***} + 0.66p_{t-1}^{Gas***} + 0.41p_{t-1}^{CO2***} - 0.007tr_{t-1}^{***}$				
Short-run Dynamics				
	Δp_t^{Elec}	Δp_t^{Coal}	Δp_t^{Gas}	Δp_t^{CO2}
α	-0.059***	-0.012***	-0.024***	-0.024***
Δp_{t-1}^{Elec}	0	0.046***	0.095***	0
Δp_{t-2}^{Elec}	0	0	0	0
Δp_{t-3}^{Elec}	0	0.048***	0.143***	0
Δp_{t-4}^{Elec}	0	0.017**	0.052***	0.044***
Δp_{t-1}^{Coal}	0	0.039	0	-0.289***
Δp_{t-2}^{Coal}	0	0	0	0
Δp_{t-3}^{Coal}	0	-0.129***	-0.108*	0
Δp_{t-4}^{Coal}	0.205**	0	0	0
Δp_{t-1}^{Gas}	0.112***	0	0	0
Δp_{t-2}^{Gas}	0	0	0	0
Δp_{t-3}^{Gas}	-0.217***	-0.044***	-0.158***	-0.077***
Δp_{t-4}^{Gas}	0	0	-0.078***	0
Δp_{t-1}^{CO2}	0.122***	-0.035**	0	0.143***
Δp_{t-2}^{CO2}	-0.101**	-0.019**	0	-0.106***
Δp_{t-3}^{CO2}	0.18***	0	0	0.072**
Δp_{t-4}^{CO2}	0	-0.028**	0	0
Equation	R ²	Equation	R ²	
Δp_t^{Elec}	0,063	p_t^{Elec}	0,994	
Δp_t^{Coal}	0,068	p_t^{Coal}	0,843	
Δp_t^{Gas}	0,085	p_t^{Gas}	0,980	
Δp_t^{CO2}	0,067	p_t^{CO2}	0,967	

Note: * denotes statistical significance at the 10% level, ** at the 5% level, *** at the 1% level.

Concerning the short-term part of the model, we identify that the price for baseload electricity is driven by price variations in hard coal, natural gas and CO₂ allowances. Whereas the cumulative reaction is positive for hard coal and CO₂ allowances it is negative for natural gas. Intuitively this shows that in the very short-term gas price increases will lead to higher electricity prices but after a couple of days the influence is shifted from natural gas to hard coal. Electricity price variations are not driven by their own autoregressive components which is reasonable from a market efficiency point of view. Hard coal, natural gas and CO₂ allowances are driven by their own autoregressive components. The overall reaction for hard coal and natural gas is negative whereas it is positive for CO₂ allowances. The algebraic signs seem sometimes to be questionable but mostly are economically sensible.

Hard coal and natural gas price changes will lead to negative price changes after three days which indicates that interplay between supply and demand conditions can be expected. This is underlined by the fact that gas prices influence coal prices and vice versa. CO₂ allowances react to each of the other variables. The algebraic sign for the hard coal influence is economically reasonable. In the case of higher coal prices a fuel switch from coal to gas is expected and less CO₂ allowances are demanded. For natural gas the result is difficult to interpret. Usually higher gas prices have to lead to higher CO₂ prices since more hard coal is demanded and therefore more CO₂ emissions from hard coal are expected. Considering the other direction, from CO₂ to fossil fuels, higher CO₂ prices lead to lower fossil fuel prices with a significant reaction of hard coal which again indicates a fuel switch and hence less demand for hard coal. There is no significant impact of CO₂ prices on natural gas. Fossil fuel prices are found to also react to preceding electricity price changes. This is somewhat surprising since all exchanges close at 6 pm. Hence, market participants could have also exploited intraday arbitrage opportunities. Unfortunately, this information cannot be extracted from closing prices which are used in this article. Yet the contemporaneous correlation matrix of residuals reveals that pairwise correlations between electricity and the other three variables are above 0.5, which can be taken as an indication of intraday arbitrage. If there is also a delayed reaction this might be a sign of market inefficiencies.

Conducting the usual diagnostic tests for checking the model assumptions and properties like Portmanteau autocorrelation test, the null hypothesis H_0 of no serial correlation up to 16 lags could not be rejected at the 10% level. The LM-Type test for autocorrelation reveals that the model specification fails to reject H_0 no serial correlation up to 5 lags at the 10%-level as well. The residuals of the model are affected by non-normality and ARCH-effects. This does not give rise to concern since in a cointegration context the estimation is still consistent (see Gonzalo 1994). Furthermore, as argued by (Lütkepohl, Krätzig 2004), it is not recommended to rely on usual tests e. g. Chow test for model stability when using financial data where ARCH effects are likely to occur in residuals. Therefore we make use of recursive eigenvalues which are shown in Figure 3.

After estimating the model and performing a stability analysis using recursive eigenvalues and τ -statistic we conclude that the current estimation does not give rise to concern (see Figure 3). Because the cointegrating rank is $r = 1$, there is one nonzero eigenvalue. From the figure it can be seen that the recursive eigenvalue is quite stable over time and different from zero at a 95% confidence interval (upper panel). The τ -statistic compares the eigenvalue estimated from the full sample to the one obtained from the first τ -observations. Because the value of the τ -statistic does not exceed the critical value for a 5% test (dashed line in lower panel), stability of the model is not rejected.

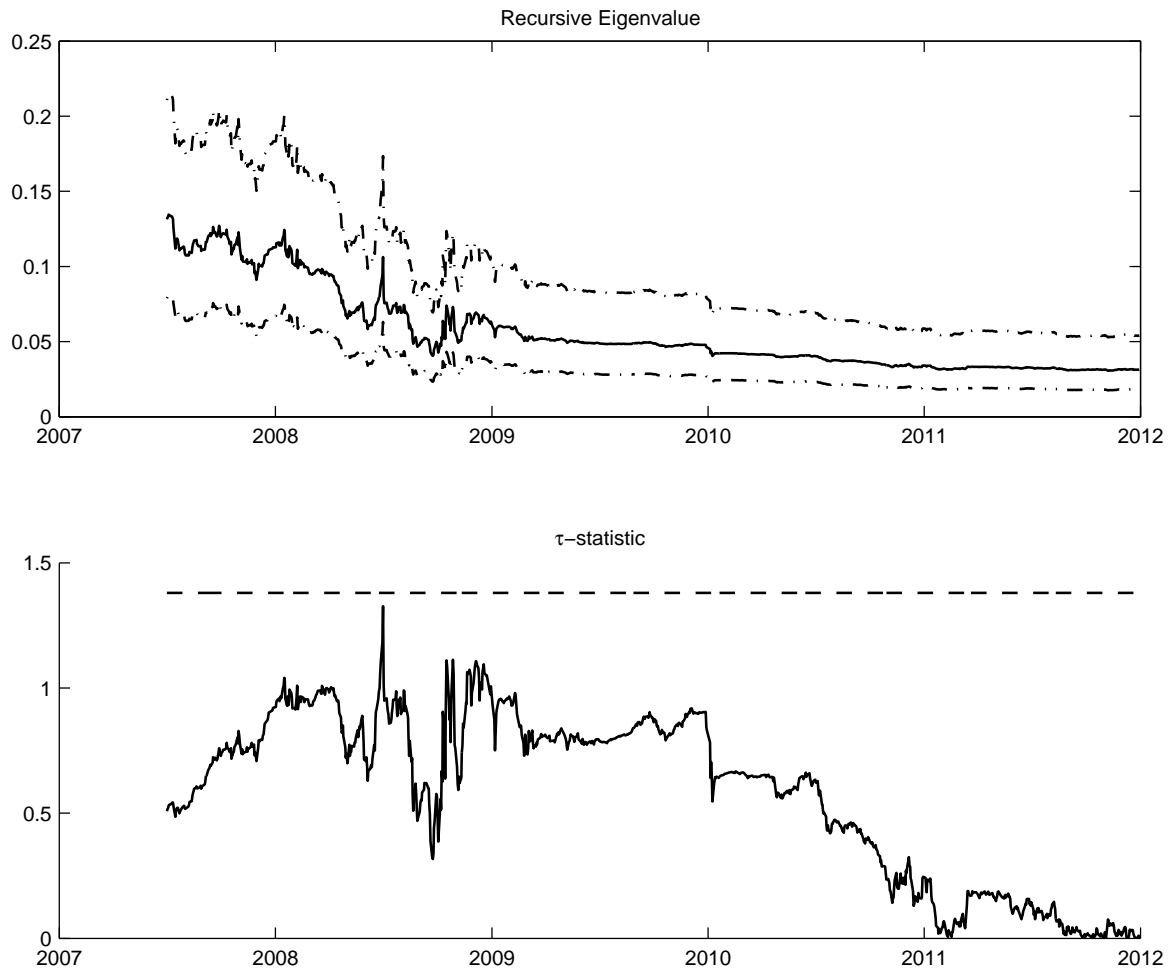


Figure 3: Recursive eigenvalues analysis for the Electricity equilibrium. Notes: Sample 2.1.2007-30.12.2011 (including $\tau = 125$ presample values).

4.3 Impulse response analysis

The analysis in the previous chapter might be useful for the identification of statistically significant parameters, yet the interaction between variables can be hardly explored. Feedback loops among the variables make it difficult to determine e. g. the impact of a 1€ increase per Megawatt-Hour of coal on the electricity price because a shock in the price of hard coal is transmitted also to all other endogenous variables. Impulse response analysis is therefore a useful tool in VECMs in tracking the impact of any variable on others in the system. Impulse response functions show whether and how the system corrects to the equilibrium after a shock. The impulse is assumed to be a one-time innovation to the whole system of variables, imposed via the error term ε_t and without new shocks. Thus, the one-time innovation in a system of $I(1)$ -variables creates a permanent increase, if there are no other interaction dynamics and no other innovations.

Since the focus of this paper is price formation in European electricity and interrelated futures markets the impulse response analysis is conducted for all endogenous variables of the analysis. Given that residuals in VECMs are usually correlated – the correlation matrix of residuals is non-diagonal – it is impossible to shock one variable with other variables being fixed. A procedure of transforming

the residuals is needed in order to get them uncorrelated. This article follows the approach of (Pesaran, Shin 1998) to account for contemporaneous correlation in the error terms and makes use of generalized impulse response functions (GIRF). In short, the GIRF-procedure follows the idea of non-linear impulse response and it is able to preserve the correlation structure so that when one variable is shocked the other variables vary as implied by the contemporaneous correlation of the residuals. The procedure can overcome the problem of ordering the endogenous variables – so it is not necessary to impose a recursive causal structure from the top to the bottom variables.

Figure 4 depicts the response traced out over 20 days (4 weeks) of all endogenous variables in the model to a price shock in electricity, hard coal, natural gas and CO₂ allowances. The generalized impulse response functions are plotted along with 90% confidence intervals based on 2000 replications of the Hall bootstrap, where responses are induced by a one-time-only 1 €/MWh respectively 1 €/t shock of innovations. It can be seen that the overall largest response occurs in electricity prices induced by a shock in hard coal. The short-term reaction of electricity prices due to a shock in hard coal increases electricity prices by around 2.5 €/MWh which fits roughly to a degree of efficiency of 40% for a hard coal power plant. Given that a huge amount of coal-fired generation in continental Europe is running and hard coal has a significant impact on base prices, the short-term response of electricity prices to a coal price increase is larger than the response to gas price increases. Even in the longer-term it seems that there is no substitution from coal- to gas-fired generation and the effect of a hard coal price shock is higher than for a gas price shock. This also fits to economic theory from peak load pricing where the baseload electricity price is determined by a baseload power plant (i. e. hard coal). Yet, it is contradictory that the influence from the peak technology (i. e. natural gas) is not diminishing after a few days. The reaction on CO₂ price shocks is also reasonable because after a few weeks the shock settles at around 0.85 €/MWh which also fits to a degree of efficiency of 40%. In the case of electricity price reaction on own price shocks it can be seen from the picture that the shock leads to higher electricity prices where after few days the effect of the shock is downward sloping and statistically significant. The shocks in the other variables on own impulses are also not fully dying out – indicating that price shocks in fuels and CO₂ allowances have permanent effects on prices.

The response of all variables to impulses in base prices is statistically significantly different from zero only a few weeks. This indicates that the short-term reaction of fuel prices to electricity prices found before is not significant in the longer run. This could also be an indication for an inefficient short term reaction respectively overreaction. In the case of coal the reaction to CO₂ price shocks is almost negligible, confirming also the results from the parameter estimation that hard coal is sluggish in the system. As pointed out in chapter 4.2 the price for hard coal is settled in world markets and therefore the reaction of world coal prices to Intra-European prices for carbon dioxide is quite low, almost zero. Overall, the effect on coal prices is quite low indicating the exogenous behavior of coal prices. The reaction of gas prices relative to coal prices induced by CO₂ price increases makes sense economically. Higher prices for carbon dioxide should switch the production from coal to gas which reduces demand for CO₂ allowances. This holds in both directions. The reaction of gas compared to hard coal price increases is larger than the other way around which indicates that gas prices are more driven by

coal price variation than vice versa. This is clear bearing in mind that gas prices of this study are European gas prices whereas hard coal prices are settled in world markets.

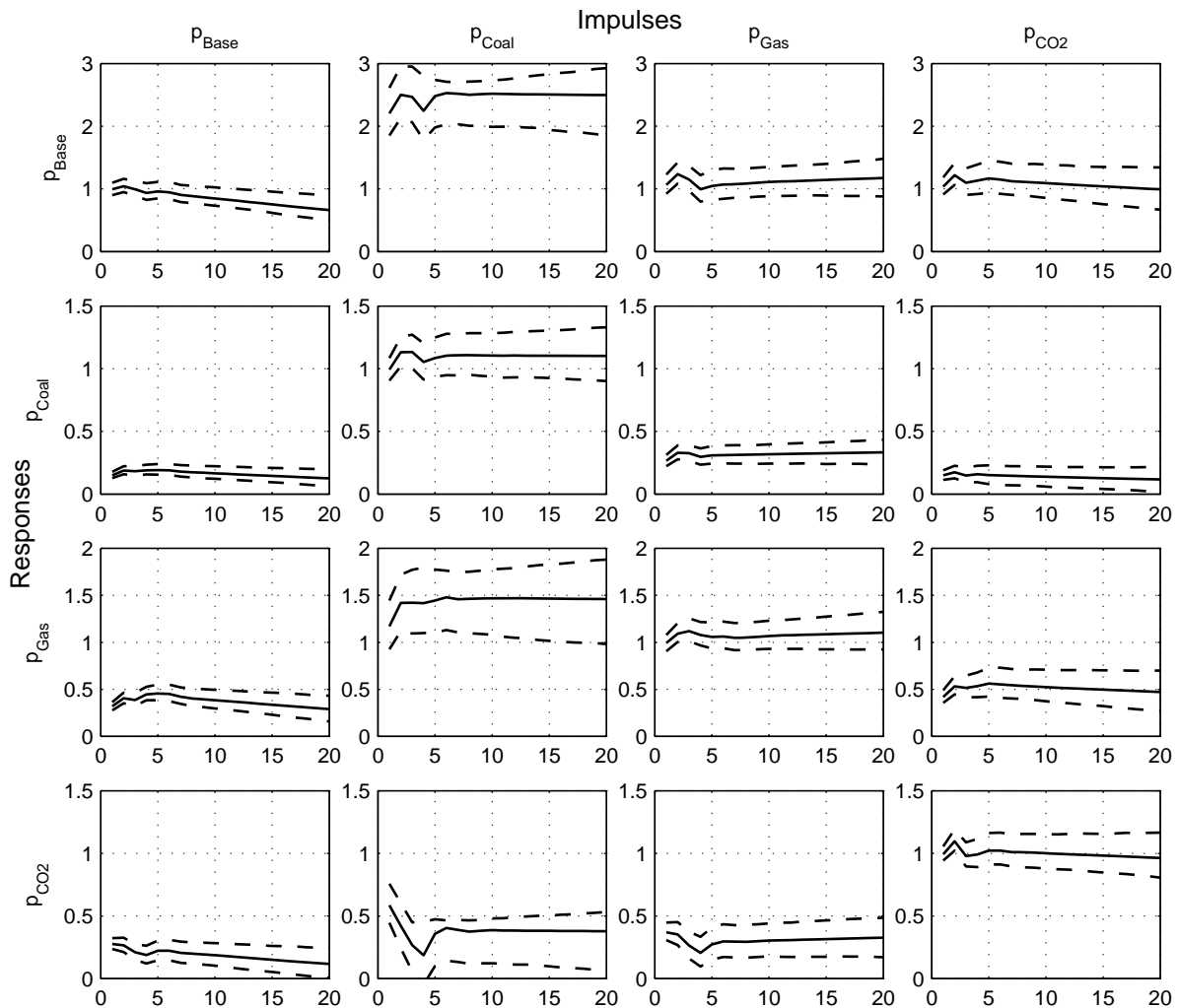


Figure 4: Generalized Impulse Response Functions. Note: Dashed lines are 90% confidence intervals based on 2000 replications of the Hall bootstrap. Number of periods is twenty. Shocks are standardized to 1 €/MWh resp. 1 €/t.

5 Conclusions and implications for energy utilities

Motivated by the financialization of commodity markets this study investigated the price formation of electricity futures prices at EEX and their interaction with interrelated futures markets for hard coal, natural gas and CO₂ allowances. From a theoretical point of view a price formation based on marginal generation costs was expected just as cointegration behavior between electricity, hard coal, natural gas and CO₂ allowances under the rational expectation hypothesis. Our results indicate a price formation of electricity in futures markets characterized by cointegration behavior. This is based on a fundamentally sound model framework. One economically reasonable long-run relation could be identified in the period between 2007 and 2011. Considering the short-term relations we find that electricity prices are driven by price variations in hard coal, natural gas and CO₂ allowances. The determination coefficient of around 6% shows that an enormous amount of volatility in daily price changes is left unexplained. An extension of the model to cope with this issue might be worth

further investigation in future research. Anyhow, considering daily prices more than 90% of the variance in prices is explained with the model. An additional impulse response analysis has shown that the electricity futures price converges to the marginal generation cost of a hard coal fired power plant. This is in line with results expected from peak-load pricing where the yearly baseload price is determined by variable costs of the baseload power plant. In continental Europe this is a hard coal power plant. To sum up, the study has shown that the electricity futures market discovers prices based on rational expectations of market participants. Year-ahead electricity futures prices can be explained at least to some extent fundamentally. The interaction of the futures markets under consideration with other European futures markets e. g. the Nordic futures market has to be left for future research.

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