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Do they still matter? – Impact of Fossil Fuels on Electricity Prices in the Light of Increased Renewable Generation *

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Abstract

During the last years, the German energy sector and especially its electricity market was affected by a major energy transition, the so called „Energiewende“. This transition led to an increase of electricity production from renewable sources and thereby affected the whole electricity market. Therefore, it provides lessons for countries, which are only beginning a similar transition away from fossil fuels to renewable energy sources. The aim of this analysis is to assess if there still exists a relationship between fossil fuel and electricity prices. Due to possible structural breaks in the time series a minimum Lagrange Multiplier (LM) stationarity test is applied, which endogenously determines possible structural breaks. Subsequently a bootstrap approach is used to estimate confidence intervals (C.I.s) for the test statistic and the possible break dates. Furthermore, the stability of the cointegration vector is assessed with the test by Hansen and Johansen (1999). The results indicate that the cointegration relationship is not stable over time. To incorporate these findings, the cointegration analysis is based on Johansen et al. (2000), which allows structural breaks in the deterministic part of the cointegration relation. These results supports the assumption that the energy transition affected the relationship between fossil fuels and electricity prices, although there still exists a relatively strong cointegration relation between fossil fuel and electricity prices in the long run.

Keywords: Structural Breaks, Bootstrap, Stationarity Test, Cointegration, Energy Economics, German Energy Transition

JEL classification: C58, G14, L94, Q41.

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1 Introduction

Over the last couple of years the German electricity market was mainly affected by the energy transition, which initially started in 2000 with the first implementation of the renewable energy act[1].

One main result of the energy transition was the increase of installed generation capacity from renewable energy sources, especially photovoltaic and wind.

As can be seen in Table 6 the share of renewable capacity nearly doubled from 26.6% in 2007 over the course of seven years to 49.6% in 2014. Partly, this increase can be attributed to the events triggered by the nuclear incident at the Fukushima Daiichi plant in Japan and the subsequent political reaction in Germany, which resulted in the immediate shutdown of around 60% of the existing nuclear generation capacity in March 2011. Nevertheless, the renewable generation capacity almost tripled in absolute terms from 36 GW in 2007 to 91 GW in 2014[2].

This increase added a lot of generation capacity to the German merit order, with no or very low marginal costs, influencing the electricity price via the merit-order effect. This merit order effect especially affects the hours of high demand during the peak hours[3], when also the production potential from photovoltaic is highest. (Tveten et al. 2013) Due to additional changes to the overall market design, the merit-order effect became much more important for the price determination on the spot market of the European Power Exchange (EPEX Spot). Beginning from January 2010, all of the electricity produced from renewables had to be sold over a public exchange. This led to a strong increase of traded volumes from 2009 to 2010 by 45% and the volume kept increasing although at a much slower pace.

This increased supply of electricity with no or very low marginal costs, in connection with the price determination algorithm of the exchange, led to a marked decrease of the yearly average price for electricity during peak hours from 55 Eur/MWh in 2010 to only 41 Eur/MWh in 2014. For a comprehensive analysis on how the renewable generation capacity affects the intra-day market and the price formation on the exchange, please see Haas et al. (2013).

The main consequence of the increased renewable generation capacity is less demand for electricity from fossil-fuel power stations with higher marginal costs during times of high demand. This is due to the fact that renewable energy sources, especially photovoltaic, are often able to satisfy a substantial part of demand during peak hours. Therefore, especially gas-fired power stations are crowded out of the market, because the residual demand can be satisfied with generation

[1]Initial implementation of the renewable energy act (‚Erneuerbare Energien Gesetz‘ (EEG)) and successive amendments in 2004, 2008, 2012 and 2014

[2]Included in this category is generation capacity from Hydro Power (2007: 5.1, 2014: 5.6), Biomass (2007: 4.7, 2017: 8.9), Wind (2007: 22.2, 2014: 38.3) and Photovoltaic (2007: 4.2, 2014: 38.2) all values in GW and taken from Burger (2016)

[3]Hours of peak demand are defined as the hours from 8:00 to 20:00

capacity having lower marginal costs. This might even result in a permanent shutdown of some, because the continued operation of these power plants becomes economically unviable.[4](Haas et al. 2013, pp. 39-41)

This becomes especially evident, when looking at the development of the full-load hours for the different energy sources over the horizon of this analysis. Full-load hours[5] are a hypothetical measurement to assess the utilization of available generation capacity. It can be interpreted as the number of hours all available generation capacity would have had to run at full utilization to generate the realized amount of electricity.

	2007	2008	2009	2010	2011	2012	2013	2014
Δ **Nuclear**	−18.0	4.1	−9.3	4.1	31.5	−8.2	−2.2	−0.4
Δ **Lignite**	−0.4	−2.6	−3.3	−1.0	16.2	0.3	1.0	−3.5
Δ **Hard Coal**	1.0	−14.4	−12.7	4.3	12.2	5.6	5.9	−8.2
Δ **Gas**	3.4	6.6	−11.1	7.1	−16.5	−12.6	−16.2	−12.7
Δ **Oil**	−8.1	−3.3	7.6	−26.8	13.6	7.1	−5.1	−27.2
Δ **Renewables**	12.0	−5.3	−14.3	−7.9	0.8	0.8	−2.3	−0.8
Δ Biomass	21.2	4.8	0.0	2.9	3.2	13.3	−6.5	−0.0
Δ Hydro	6.4	−3.6	−10.7	8.6	−21.7	23.0	4.1	−15.2
Δ Solar	−3.7	−2.1	−14.8	4.9	14.4	2.5	8.7	11.0
Δ Wind	18.2	−5.0	−12.4	−7.5	19.6	−3.3	−7.7	−1.7

Table 1: Development of full-load hours by energy source (growth rate in %) (absolute numbers are presented in Table 7 (BDEW 2016; Burger 2016).

The yearly growth rate in percent of the full-load hours is displayed in Table 1[6]. It can be seen that the German moratorium on nuclear power in 2011 had big implications for the utilization of all other fossil fuel generation capacity. The rather small changes in the utilization of renewable energy sources can be attributed by the fact, that for renewables the generation capacity and the actual production grew at nearly the same pace. In case of gas-fired power plants the utilization yields a whole different picture and although the generation capacity even grew slightly the full-load hours decreased from 3,542 in 2007 to only 2,036 in 2014. This indicates that gas-fired power plants are heavily affected by the merit-order effect and hence are often crowded out of the market. Therefore, the relationship

[4]Press release by German utility e.on stating the plan to shut down two gas-fired power stations (30/03/2015).

[5]Defined as the total electricity produced in GWh divided by the total available generation capacity in GW.

[6]Absolute values for the full-load hours and the two variables generation capacity and actual electricity generation are presented in Tables 5, 6 and 7 in the appendix.

between natural gas and electricity prices is supposed to have weakened over the sample period. The aim of this paper is to empirically analyze the relationship between fossil fuels, primarily used in generation, and the wholesale price for electricity in Germany. In particular it attempts to address various questions, whereas the fundamental question is to determine if there exists any relation between the electricity prices and the fossil fuel costs, and if so, how the major transitions in the German energy sector might have affected this relationship. A detailed analysis of these issues might shed some light on how and if the wholesale market for electricity is still driven by fundamentals or if their impact became less relevant over the recent years.

There exists a wide array of empirical literature analyzing electricity prices. Whereas one strand of literature focuses on the interdependencies of the different energy commodities and the fundamental modelling of electricity prices, there exists another strand of literature, which focuses solely on modelling the electricity market. This latter research area tries to model the stochastic properties of the electricity price by incorporating, amongst other things, volatility clustering, seasonality and extreme values. Weron (2006) offers a comprehensive overview on this strand of literature. The shortcoming of these studies, however, is that they are not suited to analyze the relationship between input fuel prices and electricity prices. The first strand of literature, which focuses on the analysis of the relationship between electricity and energy commodity prices, can be differentiated along various dimensions. Most of the studies differ regarding the markets and commodities, the time horizon and empirical methodology employed. Hence, it is not possible to find a generally valid conclusion, but most of them hint at similar concluding results.

Another broad overview of the various modelling approaches in the literature, is provided by the review of electricity price forecasting in Weron (2014). This article assesses a broad variety of modelling approaches and evaluates each approach regarding its forecasting abilities. Besides classical econometric statistical approaches the authors also include agent-based computational models and computational intelligence models, using artificial intelligence and neural networks besides others, in their assessment and thereby also provide hints at future developments in this research area.

Mjelde and Bessler (2009) focus more on the short-run dynamics and include four of the major electricity generation fuel sources, namely natural gas, uranium, hard coal and crude oil. The authors use a Vector Error Correction Model (VECM) framework to assess the dynamic interactions between the prices of these commodities and U.S. electricity spot prices between 2001 and 2008. The results of their analysis show that fossil fuels are weakly exogenous in the long run and electricity together with uranium prices react to re-establish the long-run equilibrium. Mohammadi (2009), in contrast, is more interested in the long-run relationship and uses annual price time series for electricity and the fossil fuels – natural gas, hard coal and crude oil – from 1960 to 2007. It turns out that in his application of a VECM, the impact of fossil fuels in the long run is rather mute, although in the short-run electricity prices are affected by price movements in natural gas and hard coal markets.

Apart from energy markets in the U.S., several studies also analyzed liberalized markets in Europe. Fezzi and Bunn (2009) are mainly interested in the impact the European carbon trading scheme has on electricity and natural gas prices in the UK. They also use a VECM framework and conclude that, over a relatively short sample period from April 2005 to June 2006, electricity prices are driven both by carbon and natural gas prices. In contrast, Bosco et al. (2010) focuses on the question if energy markets for electricity and natural gas are integrated across nine European countries, although the markets for the Nordic countries[7] are pooled in the Nordpool market area. The results indicate that only the electricity markets of central Europe[8] are integrated, while the Spanish and the Nordpool market area seem to not share a common trend. Additionally, the authors report strong evidence of a long-run relationship between electricity and gas prices, which cannot be observed for oil prices.

Finally, Ferkingstad et al. (2011) analyze the flow of dynamic price information for the Nordpool market area and Germany and also employ a VECM, which incorporates weekly prices for electricity, natural gas, hard coal and oil as endogenous variables. Their results indicate that natural gas has a stronger impact on electricity prices than hard coal and oil. An interesting result is the observation of Fell (2010), that the effect of input fuel prices varies with the demand level. In his VECM, the impact of carbon price is stronger in off-peak hours than in peak hours. Thoenes (2011) analyses the cointegration relationship between electricity, natural gas and carbon prices in Germany between 2008 and 2010 and the results indicate that electricity prices adapt to fossil fuel price changes in a long-term cointegration relationship.

The approach in this paper mostly relates to the fundamental modelling strand of literature presented above and also applies a VECM framework to analyze the question, if prices of fossil fuels still play a part in price determination of electricity markets. This analysis adds to the literature by using an econometric model, which incorporates many characteristics of electricity markets and especially takes fundamental structural changes into account.

The remainder of the paper is structured as follows. The next section describes the data used for the analysis in detail. In Section 3, a stationarity test, which

[7]Norway, Sweden, Finland and Denmark
[8]Austria, France, Germany and the Netherlands

allows the possibility to endogenously determine possible structural breaks, is presented and applied to the endogenous variables of the VECM framework. Then Section 4 describes this framework, which was initially developed by Johansen et al. (2000), in more detail. The application of a framework, which allows the possibility to allow structural breaks in the cointegration relation, is also indicated by the additionally applied test by Hansen and Johansen (1999). Afterwards, the results, obtained in the cointegration analysis, are presented and critically assessed. Finally the last section concludes the paper and presents possible routes for future research.

2 Data

This analysis is based on data compiled from various sources. Information regarding commodity and electricity prices are taken from Reuters Datastream. The electricity price under consideration is the Phelix Peak day-ahead price for the whole delivery area of Germany and Austria during peak times and is determined on the EPEX Spot. The Phelix Peak price covers the period of higher load from 8:00 to 20:00 and is denominated in EUR/MWh. The primary energy sources considered in this analysis are natural gas and hard coal, because those commodities are both used as input for electricity generation and they are traded on exchanges. The natural gas price used is the European Gas Index (EGIX) for both German market areas in EUR/MWh. Hard coal for delivery in Amsterdam, Rotterdam or Antwerp (ARA) is the product primarily traded on the Intercontinental Exchange (ICE) for imports into Northwestern Europe and is therefore included in the analysis. To make the results comparable, all prices are converted into EUR/MWh. The time period covered in this analysis includes all working days from September 28, 2007 to January 15, 2015, hence weekends are not considered. Since the carbon price of the second phase of the European Emission Trading Scheme (EU-ETS) only begins to become larger than zero from mid January 2009, it is excluded.

Since weather and especially temperature is one of the main exogenous factors affecting the demand for electricity and hence the price, the variables heating degree day (HDD) and cooling degree day (CDD) are included (Halvorsen 1975; Quayle and Diaz 1980). These variables are able to address the possible non-linear effect of temperature on demand by differentiating between the energy needed to heat and to cool buildings to keep the inside at a constant temperature of 18°C throughout the year. The CDD and HDD variables are calculated, based on the average daily temperature measured across Germany by Germany's National Weather Forecast Service (Deutscher Wetterdienst (DWD) 2015). A further variable possibly affecting both demand and supply and is closely related to weather and seasonality is the amount of daylight during a day. This not only affects the demand for lighting during the day, but also the potential production from photovoltaic. Therefore, the average sunshine duration across Germany, also calculated

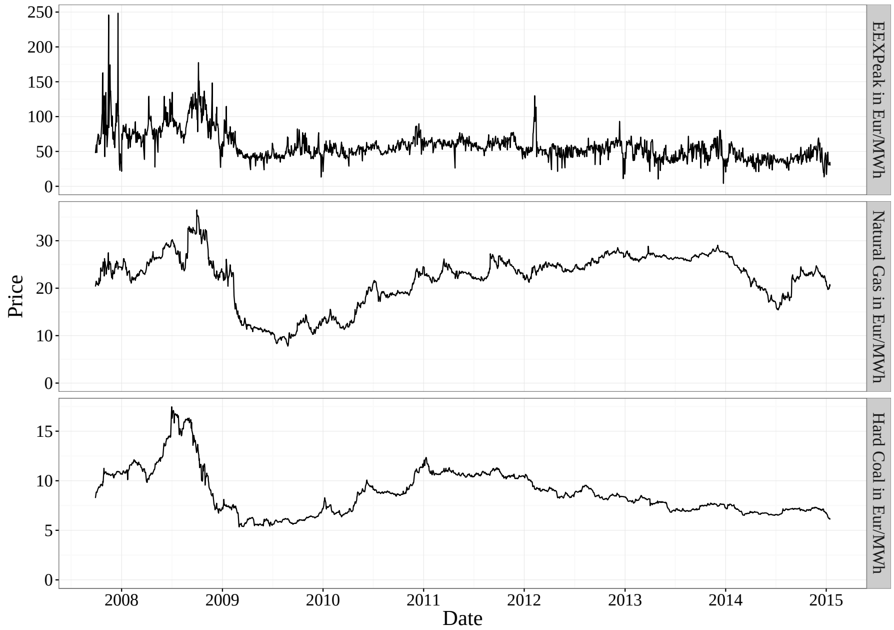

Figure 1: Graphical display endogenous variables covering the period from September 28, 2007 to January 15, 2015

from data by the Deutscher Wetterdienst (DWD) (2015), is incorporated into the model as an exogenous variable.

An additional indirect effect of weather, which might influence the supply of electricity, is the river temperature. Due to regulatory requirements, the power plants have to curtail their generation if the water temperature exceeds a threshold of 23°C. Therefore, a river temperature index is calculated, based on the daily temperatures measured at 33 stations along eight major German rivers[9]. The calculation of the river temperature index is very similar to the cooling degree day (CDD)/heating degree day (HDD) variables. If the temperature for any station used is above the threshold, the absolute difference to 23°C is calculated and weighted with the share of stations, observing temperatures above threshold on the respective day.

The seasonality of electricity prices is not only driven by weather effects, but also appears to be based on calendar effects. Therefore, dummy variables which capture the intra-week structure and all public holidays, which are observed across the whole of Germany and take place on a normal working day, are included in the analysis.

[9]included rivers are: Danube, Elbe, Ems, Main, Moselle, Neckar, Rhine and Saar

3 Preliminary tests – stationarity

3.1 Minimum Lagrange Multiplier (LM) test with structural breaks

Since the influential paper by Perron (1989), it became clear that one has to explicitly account for possible structural breaks, when testing for stationarity or a unit root – the possibility of rejecting the unit root null hypothesis decreases when the stationary alternative is true and a structural break is not considered. In the initial implementation, Perron (1989) modified the augmented Dickey-Fuller (ADF) test and included a dummy variable to account for the known or exogenous structural break. Further extensions of this procedure allowed for an unknown breakpoint to be determined endogenously in the data. One of those procedures is the test proposed by Zivot and Andrews (1992), which chooses the breakpoint according to the minimum value of the t-statistic testing the null hypothesis of a unit root. Since the power of a unit root test decreases when ignoring one break, not considering a second break also results in a loss of power. Therefore, Lumsdaine and Papell (1997) extended the initial test by Zivot and Andrews (1992) and allowed for the possibility of two structural breaks. One major issue in connection with these endogenous break tests is the assumption of no structural break under the unit root null hypothesis. Thus, the alternative hypothesis is that there are structural breaks in the series, which also includes the possibility of a unit root with structural break. Therefore a rejection of the null in such tests does not necessarily imply a rejection of the unit root hypothesis per se.

The minimum LM stationarity test used here was first proposed by Lee and Strazicich (2003). It has some advantages over the more commonly used tests for stationarity or a unit root. Most notably is the possibility to allow the a unit root with breaks, which considerably lowers the problem of „spurious rejections“. (Lee and Strazicich 2003, pp. 1-2)

The data generating process (DGP) is based on the first-order autoregressive model described in equation (1), where the variable Z_t contains exogenous variables and ϵ_t is a white noise process.

$$y_t = \delta^T Z_t + X_t, \text{with } X_t = \beta X_{t-1} + \epsilon_t, \tag{1}$$

The exogenous variables included in Z_t depend on both, the assumed model for the DGP and the structural break. For the case of breaks in the intercept, the model for the DGP corresponds to model A defined in Perron (1989, pp. 4-6) and is often referred to as the „crash“ model. To appropriately incorporate such changes of the intercept into the model, Z_t can be described as $Z_t = [1, t, D_{1t}, D_{2t}]^T$, where $D_{it} = 1$ for $t \geq T_{Bj} + 1$, $\{j = 1, 2\}$, and $D_{it} = 0$ otherwise. The date of the break is denoted by T_{Bj}. The second model considered in this analysis is model C from Perron (1989), which not only allows for breaks in the intercept but also in the trend of the DGP and is often referred to as the „break“ model.[10] In order to account for possible changes in the trend, an additional variable DT_{it} is included in Z_t, with $DT_{it} = t - T_{Bj}$ for $t \geq T_{Bj} + 1$, $\{j = 1, 2\}$, and $DT_{it} = 0$ otherwise. Note that the unit root null hypothesis in these models is represented by the coefficient β in equation (1) being equal to one. The advantage of this formulation is that structural breaks are not only included under the null, but also under the alternative hypothesis $\beta < 1$. The regression, which determines the LM stationarity test statistic can be estimated with the following equation:

$$\Delta y_t = \delta^T \Delta Z_t + \phi \tilde{S}_{t-1} + u_t, \tag{2}$$

where $\tilde{S}_t = y_t - \tilde{\psi}_x - Z_t\tilde{\delta}$, $t = 2, ..., T$; $\tilde{\delta}$ are the coefficients of the regression of Δy_t on ΔZ_t and $\tilde{\psi}_x$ is given by $y_1 - Z_1\tilde{\delta}$, which is the restricted maximum likelihood estimator (MLE) of $\psi_x (\equiv \psi + X_0)$.

According to equation (2), the unit root null hypothesis is expressed by $\phi = 0$ and the corresponding LM test statistics are then defined as

$$\begin{aligned} &\tilde{\rho} = T\tilde{\phi}, \\ &\tilde{\tau} = t\text{-statistic testing the null hypothesis } \phi = 0. \end{aligned} \tag{3}$$

To account for possible autocorrelation in the residuals, augmented terms $\Delta\tilde{S}_{t-j}$, $\{j = 1, ..., k\}$, can be included in the test equation (2) (Lee and Strazicich 2013, p. 4). In accordance with Ng and Perron (1995, pp. 271-272), a general to specific approach is used to determine the optimal number of k augmented terms. In this approach, the model initially is defined in the most general form with k_{max} lags of the augmented terms. In each step of an iterative procedure, the significance of the augmented term with the highest lag-order is checked. If significant then $k = k_{max}$; otherwise the non-significant augmented term is removed and the procedure is repeated for $k_{max} - 1$ until the coefficient of the lagged augmented term becomes significant.

The location of possible break points $\lambda_j = \frac{T_{Bj}}{T}$, $\{j = 1, 2\}$ is determined by employing a grid search algorithm, minimising the unit root test t-statistic across all possible break locations and combinations in case of more than one break.

$$LM_\tau = \operatorname*{Inf}_{\lambda} \tilde{\tau}(\lambda) \tag{4}$$

Due to possible endpoint problems, which are common in endogenous structural break tests, the grid search algorithm is only applied to a subsample of the total

[10] The third case described by Perron (1989), Model B allows a break in trend and is called the „changing growth“ model by Perron (1989, p. 5), but following the reasoning of Lee and Strazicich (2013, p. 3) it is not considered here.

observations κ, and per default 10% of the observations are left out at each end of the time series. An additional requirement is that the second break point can only occur at least two periods after the first break in the „crash“ model and for the „break“ model that gap needs to be at least three periods.

The critical values for the unit root null hypothesis are derived by Lee and Strazicich (2003) and depend, for the case of a break in intercept and trend, also on the location of the break λ_j. The relevant critical values of the LM_τ test statistic for testing for a unit root hypothesis are provided in Appendix 8.

3.2 Bootstrap procedure and results of minimum Lagrange Multiplier (LM) test with structural breaks

In addition to the standard implementation of the minimum LM test, the bootstrap approach by Chou (2007) is employed to obtain critical values for the test statistic. Additionally, it also allows a detailed analysis of the distributional properties of the test statistic and the possible break points. The first step of the bootstrap procedure is to apply the minimum LM test on the time series, based on equation (2), to determine the minimal test statistic and the two possible break dates. Based on these results, the test regression's coefficients are used to calculate restricted residuals, which do incorporate the possible structural breaks under the null hypothesis. These restricted residuals are then resampled and used, together with the test regression's coefficients, to construct a pseudo sample y_t^*. This resampling procedure is then repeated 1.000 times and the minimum LM test is applied to each of the new pseudo samples. For each run, the results are stored and it is then possible to analyze the distributional characteristics and calculate the 95-% percentile bootstrap C.I.s for the two possible break occurrences. These results, shown in Table 2, indicate, that the break dates don't seem to be statistically significantly different and therefore it is possible to assume that the two structural breaks do occur on the same dates for all time series. In appendix C histograms with the relative frequency of breaks are provided, which also indicate that it's not possible to assume different break dates for all three time series. Therefore, it is assumed that the two structural breaks occur for all time series on 19th Dec 2008 and 07th Dec 2010 respectively. This decision is rather ad-hoc and the first break is set to occur on the found break for the electricity price. The second break is assumed to happen on the 07th December 2010, since this break is found independently in the time series of the natural gas and hard coal prices.

In case of the test statistic, one-sided 99% C.I.s are calculated and shown in Table 2. Based on these results it is not possible to reject the unit root hypothesis for all three time series, because the lower confidence limits are not exceeded by any of the test statistic.

	test stat.[a]	T_{B1}[b]	T_{B2}[b]
EEXPeak	-11.28 [-23.70]	19/12/2008 [11/07/2008, 07/02/2012]	08/10/2010 [24/11/2008, 26/02/2014]
Natural Gas	-3.49 [-20.06]	13/02/2009 [04/08/2008, 16/03/2010]	07/12/2010 [10/03/2010, 16/11/2012]
Hard Coal	-3.61 [-20.20]	30/10/2008 [14/07/2008, 04/04/2011]	07/12/2010 [14/04/2010, 02/10/2013]

Table 2: Results of bootstrap procedure of minimum LM test with the possibility of two structural breaks in trend and intercept.

[a] 99% bootstrapped one-sided lower confidence limits in squared brackets

[b] 95% bootstrapped two-sided C.I.s in squared brackets

Figure 2: Graphical display endogenous variables with the break dates identified by the minimum LM test

(dashed vertical lines indicate the break dates on 19/12/2008 and 07/12/2010)

4 Cointegration analysis

4.1 Methodology

In this part of the analysis, a possible cointegration relationship between the variables is investigated and especially the possible structural breaks indicated by the minimum LM stationarity test are explicitly considered in more detail. Due to the fundamental changes the market for electricity in Germany underwent during the sample period, the possible cointegration relationship might have changed as well. Therefore, before conducting the cointegration analysis in detail, the test by Hansen and Johansen (1999) is employed to analyze, in a VECM framework, if the assumed cointegration relationship is stable over time. This LM type of test makes it possible to identify structural breaks in a multivariate framework, which were already indicated by the univariate minimum LM stationarity test. The basic idea of this test is the recursive estimation of a basic VECM, which assesses the constancy of the long-run parameter β, given that the short-run dynamics are held constant over time. (Hansen and Johansen 1999) It is important to note that with this test it is only possible to reject the null hypothesis of a stable cointegration parameter, because it does not formulate a specific alternative hypothesis (Hansen and Johansen 1999, p. 307). Figure 3 shows the recursively estimated test statistic for the cointegration vector β. Additionally, the vertical lines depict the dates of structural breaks indicated by the minimum LM stationarity test. It is striking that those relatively closely match the period of high values for the test statistic between the end of 2008 and 2010. Since the maximum value of the test statistic 4.797 for the cointegration vector β, is far greater than the 5% critical value of 2.44, the null hypothesis of a constant β can be safely rejected. Based on the results of the minimum LM stationarity and the stability test of Hansen and Johansen (1999), the detailed analysis of the possible cointegration relationship is conducted using the method initially developed by Johansen et al. (2000). Furthermore, it is also used to estimate the whole VECM to determine the nature of the cointegration vector. This method is a generalization of their maximum likelihood cointegration test developed earlier in Johansen (1988, 1991) and allows to consider structural breaks at known points in time. In the following part, the main building blocks of the model are introduced briefly. In order to consider the structural breaks when testing for the cointegration rank, it is necessary to define $q-1$ intervention and indicator dummies, which indicate each structural break between each subsample q. The definition of intervention and indicator dummies follows the notation used by Joyeux (2007). The intervention dummies are defined as follows:

$$D_{j,t} = \begin{cases} 1 & \text{for } T_{B,j-1} \leq t \leq T_{B,j}, \\ 0 & \text{otherwise,} \end{cases} \qquad \text{for } j = 2, ..., q,$$

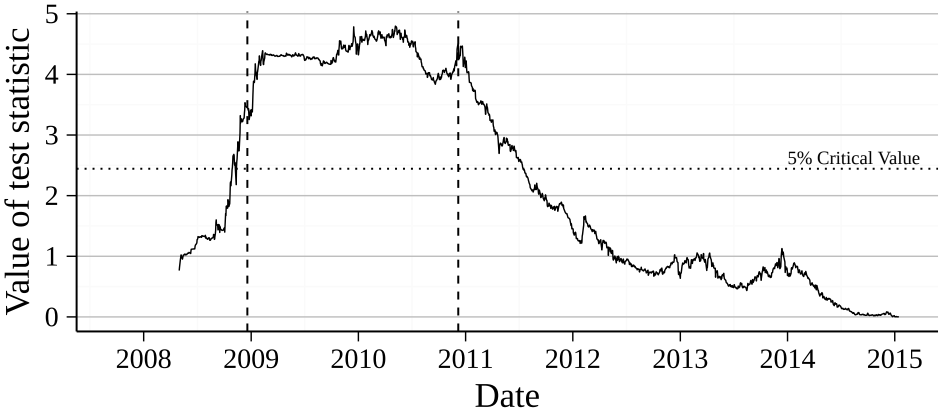

Figure 3: Recursively estimated test statistic for β constancy (Hansen and Johansen 1999)
(dotted horizontal line indicates 5% critical value at 2.44; dashed vertical lines indicate the break dates on 19th Dec 2008 and 07th Dec 2010; first 150 observations not used in the recursive calculation)

and

$$D_{j,t-k} = \begin{cases} 1 & \text{for } T_{B,j-1} + k + 1 \leq t \leq T_{B,j} + k, \\ 0 & \text{otherwise,} \end{cases} \qquad \text{for } j = 2, ..., q.$$

The indicator dummies need to be defined according to the following definition:

$$I_{j,t} = \begin{cases} 1 & \text{for } t = T_{B,j-1} + 1, \\ 0 & \text{otherwise,} \end{cases} \qquad \text{for } j = 2, ..., q.$$

Johansen et al. (2000, pp. 218-219) allows to distinguish between three different cointegration hypotheses, whereas in this case only the most general is considered. In this model, all time series follow a trending pattern, but it allows breaks not only in the trend of each individual time series, but also in the cointegrating relations and is originally denoted as $H_l(r)$, where r denotes the cointegration rank.

If the following vectors are defined: $D_t = (1, ..., D_{q,t})^T, \mu = (\mu_1, ..., \mu_q), \gamma = (\gamma_1^T, ..., \gamma_q^T)^T$ it is possible to express the model for all q subsamples in a condensed form similar to equation (5). The lagged intervention dummy D_{t-k} multiplied with a time trend t is part of the cointegration relationship and has the coefficient γ.

$$\Delta Y_t = \alpha \begin{pmatrix} \beta \\ \gamma \end{pmatrix}^T \begin{pmatrix} Y_{t-1} \\ tD_{t-k} \end{pmatrix} + \mu D_{t-k} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \sum_{i=0}^{k-1} \sum_{j=2}^{q} \kappa_{j,i} I_{j,t-i} + \delta X_t + \epsilon_t \quad (5)$$

Due to the generalization, new asymptotic critical values are needed, since the asymptotic distribution of the test statistic now also depends on the locations of the structural breaks in the sample[11] and the difference between the number of time series p and the cointegration rank r. To calculate the new critical values and the respective p-values, the procedures implemented by Giles and Godwin (2012) are used.

4.2 Empirical results

Empirical results for the whole sample with structural breaks

Besides the endogenous price series of electricity, natural gas and hard coal, all the additional variables discussed in section 2 are included in the model as exogenous variables to account for possible effects of weather and seasonality. The VECM is implemented as presented in the previous section, with no constant or trend in the cointegration relation and the lag order for the endogenous variables is set to five, according to the Hannan-Quinn information criteria. This additionally allows to properly model the weekly structure of the data, but at the same time preserves the model's parsimony.

In a first step, the cointegration rank of the system is determined based on the trace test statistic. The results of this test can be found in Table 3, together with the calculated asymptotic critical values. Based on these results, the null hypothesis of no cointegration rank can be rejected and it is therefore safe to assume that at least one cointegration vector exists. Starting from these results,

rank	trace test statistic	10%	5%	1%
r $\leq$ 2	2.88	21.03	23.60	28.94
r $\leq$ 1	23.58	42.20	45.54	52.27
r = 0	236.20***	67.02	71.08	79.11

Table 3: Trace test statistic to determine the cointegration rank. Critical values are derived according to Giles and Godwin (2012)

the VECM is estimated with the restriction of only one cointegration rank. In Table 4 the cointegration vector β, which reports the long-run relation between

[11]Breakpoints are denoted as $\lambda_j = \frac{T_{B,j}}{T}$, where T is total number of observations and $T_{B,j}$ is the last observation of subsample j, with $j = 1, 2, ..., q$.

the variables, and the α vector, which indicates if and how the variables react to deviations from the long-run relationship, are presented.

	$\hat{\alpha}$-vector		$\hat{\beta}$- and $\hat{\gamma}$-vector	
	Parameter	t-stat	Parameter	t-stat
EEXPeak	-0.3239^{***}	-14.98	1.0000	—
Natural Gas	-0.0002	-0.18	-1.7372^{***}	-7.22
Hard Coal	0.0000	0.09	-3.3350^{***}	-6.29
$tD_{1,t-5}$	—	—	0.0235^{**}	2.52
$tD_{2,t-5}$	—	—	0.0037	0.97

Table 4: Cointegration relationship for a VECM with a cointegrating rank $r = 1$, including the loading parameters in the $\hat{\alpha}$-vector and the coefficients in the stacked vector of $\hat{\beta}$ and $\hat{\gamma}$, which incorporates the coefficients of the endogenous and the intervention variables for the two structural breaks.

The estimated cointegration vector, $(\hat{\beta},\ \hat{\gamma})^T$, in Table 4 shows that both price time series, natural gas and hard coal, are part of a long-run relationship and are important drivers of the electricity price during times of high demand. The coefficients of the two fossil fuels have the theoretically expected negative sign, which implies that an increase in one of these input factors leads to an increase in electricity prices. Given that the energy efficiency of power plants is only around 33% for hard coal and 41% for natural gas, meaning that only this share of the energy input is transformed into electricity[12]. It is interesting to see that apparently, electricity prices in the long run react over proportionally to price changes of the fossil fuels. Furthermore, when looking at the coefficients of the $tD_{j,t-5}$ intervention dummies, which take the structural breaks into account, it can be seen that only the dummy covering the second subsample from December 2008 to December 2010 is significant.

In order to analyze if the natural gas and hard coal prices are weakly exogenous for the electricity price, a Likelihood Ratio (LR) test, based on Johansen (1991), is applied on the α vector, which models the speed of adjustment to the long-run equilibrium. It is not possible to reject the simultaneous linear restriction that both coefficients are actually zero. Therefore, it is safe to assume, that both fossil fuels are weakly exogenous in the short run.

To assess the long-run relationship in more detail, a similar LR test is also applied to the cointegration vector β. For this purpose, a linear restriction is imposed, which restricts the coefficients of natural gas and hard coal prices to

[12]Calculations of energy efficiencies for various energy sources is based on average operating heat rates as published by the U.S. Energy Information Administration (EIA) (2016)

zero. As expected from the values in Table 4 it is possible to strongly reject the imposed restrictions and it can be assumed that in the long-run electricity prices are influenced by changes in natural gas and hard coal prices.

The figures 4, 5 and 6 show the impulse response functions (IRFs) of the electricity price to a shock in all three endogenous time series. IRFs for the impact on natural gas and hard coal are shown in appendix (D) for completeness. It can be seen that shocks to the electricity price are corrected within a relatively short time period. While a positive change of natural gas prices increases the electricity price in the short-run, a price increase in the hard coal market does only affect the electricity price with a delay of a couple of days and the effect is not statistically significant. These differences in the reaction of hard coal and natural gas fired power plants could possibly be attributed to different technological frictions between coal-burning and natural gas fired power plants. These technical frictions mainly consist of higher maintenance costs for switching fuels, varying load or other changes to the electricity production. These costs are considerably higher for coal-fired power plants than for power plants using natural gas. (Matisoff et al. 2014, p. 3)

The Breusch-Godfrey test, amongst others, indicates the presence of serial correlation in the residuals, hence the results need to be interpreted with caution. Additionally, a test for possible ARCH effects in the residuals also allows to reject the null hypothesis of no ARCH effects. Although, according to the results of Silvapulle and Podivinsky (2000) possible ARCH or GARCH effects might not affect the results of the cointegration analysis too much. Nevertheless, to increase the efficiency of the obtained results it might be useful to extend the VECM with a GARCH error structure, which incorporates the structure of the residuals explicitly.

Empirical results for each subsample

A implementation of the VECM framework for each of the three subsamples supports the previous results that the cointegration relationship underwent considerable changes over the course of the sample period.

The long-run coefficient of natural gas decreased from -6.662 in the first period to -2.223 in the second and is a mere -0.866 in the last period. This is a strong indication that the relationship between the electricity and the natural gas price became less important over the horizon of this analysis, although it's not a definitive proof of this hypothesis.

Another interesting result, when looking at the development of the cointegration vector β, is that over the sample horizon the impact of hard coal prices also changed. It changed, however, differently than that of natural gas prices. It is not significant in the first subsample and turns positive in the second period, which is not in line with the assumed theoretical relationship, because it means that

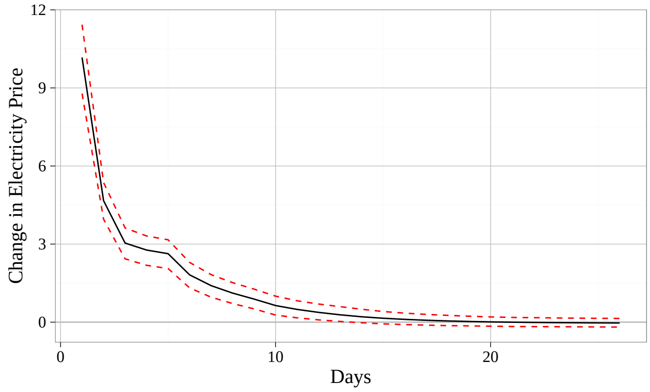

Figure 4: Response of EEXPeak electricity price to a shock in the EEXPeak electricity price

(dashed red lines indicate the 95% bootstrapped C.I.s)

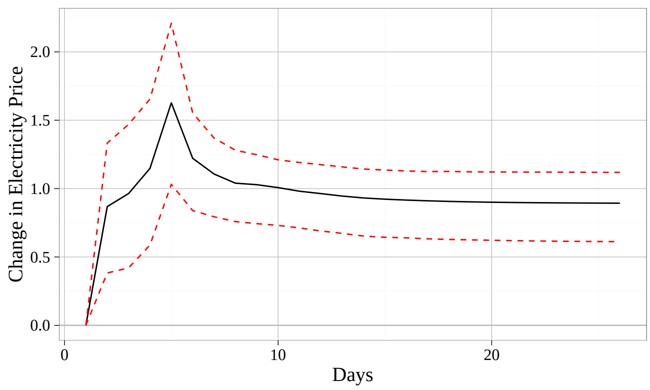

Figure 5: Response of EEXPeak electricity price to a shock in the natural gas price

(dashed red lines indicate the 95% bootstrapped C.I.s)

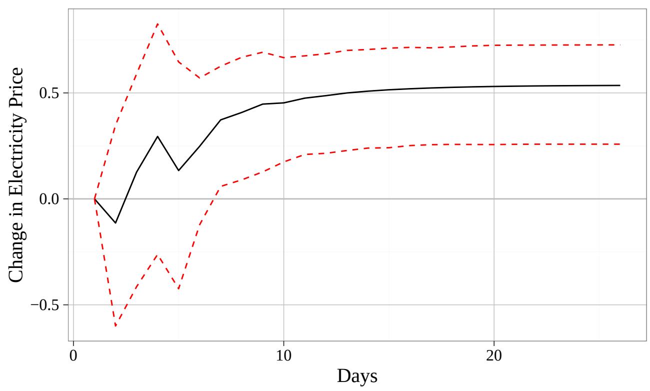

Figure 6: Response of EEXPeak electricity price to a shock in the hard coal price

(dashed red lines indicate the 95% bootstrapped C.I.s) an increase in hard coal prices leads to decreasing electricity prices. For the last period, the coefficient becomes negative and highly significant. This indicates that the impact of hard coal prices, in contrast to the natural gas price, increased over the sample horizon. One possible explanation for these two opposing developments could be the merit order effect. The increasing generation capacity of renewable energy sources shifts the merit order to the right. This then leads to the possibility to satisfy the electricity demand using generation capacity with lower marginal costs, namely the substitution of natural gas fired power plants by hard coal fired ones.

5 Conclusion and further research

This analysis examined the long-run relations and the short-run dynamics between major fossil fuels used for electricity generation and electricity prices, during a time of fundamental changes to the German electricity market. The econometric model incorporated these fundamental changes into the analysis and allowed to show that there still exists a strong cointegration relation between the prices of fossil fuels and electricity, even when taking structural breaks in the cointegration relation into account. There is strong evidence for a significant long-run impact of natural gas and hard coal prices on the price for electricity during times of high load. This, however, has strong policy implications for the aim reducing the reliance on fossil fuels, especially on hard coal or lignite, and thereby curbing carbon emissions. Since these policies might lead to increasing costs for hard coal generation capacity and hence also to higher electricity prices. The short-run dynamics are characterized by a significant and instant impact of shocks to natural gas prices on electricity prices. Whereas, an increase in hard coal prices only has a significant impact after seven days. These differences in the short-run dynamics can most probably be attributed to different characteristics of the markets, since the trading and transportation properties of coal are less flexible than the entry-exit regime of the German natural gas market.

The results of this analysis are potentially useful for other countries, which are at a different stage of replacing fossil fuels with renewable energy sources to satisfy electricity demand and reduce carbon emissions. Although most electricity markets and energy sectors differ between countries or regions, so the results are only valid for the German electricity market and can't be easily transferred to other countries.

In preparation for the cointegration analysis the non-stationarity hypothesis was examined using the test proposed by Lee and Strazicich (2003, 2013), which allows two structural breaks in the time series. In connection with the subsequently employed bootstrap approach of this test critical values for the test statistic and C.I.s for the break dates were calculated. Based on these results it was not possible to reject the unit-root null hypothesis and two structural breaks in intercept and trend were identified. Further indication for structural breaks, not only in the univariate time series, but also in the multivariate VECM framework were given by the applied stability test of Hansen and Johansen (1999).

Since the aim of this analysis mainly was to assess if fossil fuels still influence electricity prices, a couple of additional influencing factors were not included. Moreover, in some cases it was a problem of data availability, which prevented the inclusion prices for carbon emission certificates and the cross-border flows of electricity. Furthermore, it would be interesting to assess the influence of lignite, since it constitutes a sizable amount of generation capacity and also is used to generate around 30% of all electricity in Germany (BDEW 2016). However, since there is no liquid market for lignite and most of it is directly burned close to the mining site, no market price for lignite exists. A probably more important effect might be the actual production from renewable sources. If sufficient data on actual production from renewables would be available, it could directly be incorporated in the econometric model. In this case it would be possible to get a better understanding of suspected non-linearities in the relationship, depending on the amount of electricity generated from renewable energy sources.

Econometric methods to modelling these non-linearities, include for example the threshold cointegration methods by Balke and Fomby (1997). If these non-linearities are themselves functions of exogenous variables, as it might be the case here, the application of a open-loop threshold autoregressive system (TARSO) model might be beneficial (Tong 1990).

Another area for future research might be to explicitly model the time-varying nature of the cointegration relationship. This would be possible by using the time-varying VECM framework, by Bierens and Martins (2010), which is an extension of the methods proposed by Johansen (1988, 1991, 1995) and allows to analyze the development of the cointegration relationship over time. Another promising approach in this research area might be using a Bayesian framework, for example Koop et al. (2011) also offer the possibility to explicitly allow the cointegration space to evolve over time.

Appendices

A Development of electricity production and installed capacity by energy source

	2007	2008	2009	2010	2011	2012	2013	2014
Nuclear	133 229	140 710	127 690	132 971	102 241	94 180	92 127	91 800
Lignite	142 328	138 090	133 653	134 169	137 888	148 147	149 163	144 328
Hard Coal	130 799	114 423	98 773	107 357	103 177	106 755	116 755	108 670
Gas	75 447	86 244	78 236	86 560	83 505	74 000	65 265	58 911
Oil	9011	8722	9058	7860	6364	6785	6446	5031
Renewables	81 779	86 433	88 303	97 789	116 650	135 997	144 124	153 684
Hydro	20 751	20 098	18 697	20 650	17 304	21 697	22 654	19 322
Biomass	18 359	21 463	24 492	27 734	31 011	37 402	38 907	41 121
Wind	39 594	40 452	38 531	37 677	48 736	50 518	51 553	57 185
Solar	3075	4420	6583	11 728	19 599	26 380	31 010	36 056

Table 5: Electricity production by energy source in GWh (BDEW 2016).

	2007	2008	2009	2010	2011	2012	2013	2014
Nuclear	21.3	21.6	21.5	21.5	12.1	12.1	12.1	12.1
Lignite	22.5	22.4	22.4	22.7	19.9	21.3	21.2	21.3
Hard Coal	29.3	29.6	29	30.2	25.7	25.1	25.9	26.2
Gas	21.3	22.8	23.1	23.8	27.1	27.2	28.2	28.9
Oil	5.4	5.4	5.2	5.9	4.2	4.1	4.1	4.2
Renewables	36.2	40.4	47.6	57.0	67.5	78.1	84.7	91.0
Hydro	5.1	5.2	5.3	5.4	5.6	5.6	5.6	5.6
Biomass	4.7	5.3	6	6.6	7.2	7.6	8.4	8.9
Wind	22.2	23.8	25.7	27.1	28.8	30.8	34.0	38.3
Solar	4.2	6.1	10.6	17.9	26.0	34.1	36.7	38.2

Table 6: Electricity generation capacity by energy source in GW (Burger 2016).

	2007	2008	2009	2010	2011	2012	2013	2014
Nuclear	6255	6514	5939	6185	8471	7803	7633	7606
Lignite	6326	6165	5967	5911	6946	6965	7033	6792
Hard Coal	4464	3866	3406	3555	4016	4246	4503	4149
Gas	3542	3783	3387	3637	3084	2720	2313	2036
Oil	1669	1615	1742	1332	1526	1639	1557	1187
Renewables	2258	2142	1856	1715	1728	1742	1702	1689
Hydro	4037	3895	3501	3817	3074	3868	4031	3463
Biomass	3890	4080	4082	4202	4337	4954	4643	4641
Wind	1785	1698	1501	1392	1694	1639	1518	1492
Solar	737	722	623	654	755	774	845	943

Table 7: Full-load hours by energy source (own calculations based on BDEW (2016) and Burger (2016)).

B Critical values for minimum LM test with structural breaks

	1%	5%	10%
LM_τ	-4.545	-3.842	-3.504

Table 8: Critical Values for the „crash“ model (Lee and Strazicich 2003, p. 1084)

LM_τ				λ_2					
	0.4			0.6			0.8		
λ_1	1%	5%	10%	1%	5%	10%	1%	5%	10%
0.2	-6.16	-5.59	-5.27	-6.41	-5.74	-5.32	-6.33	-5.71	-5.33
0.4		—		-6.45	-5.67	-5.31	-6.42	-5.65	-5.32
0.6		—			—		-6.32	-5.73	-5.32

Table 9: Critical Values for the „break“ model (Lee and Strazicich 2003, p. 1084)

C Histograms for break dates

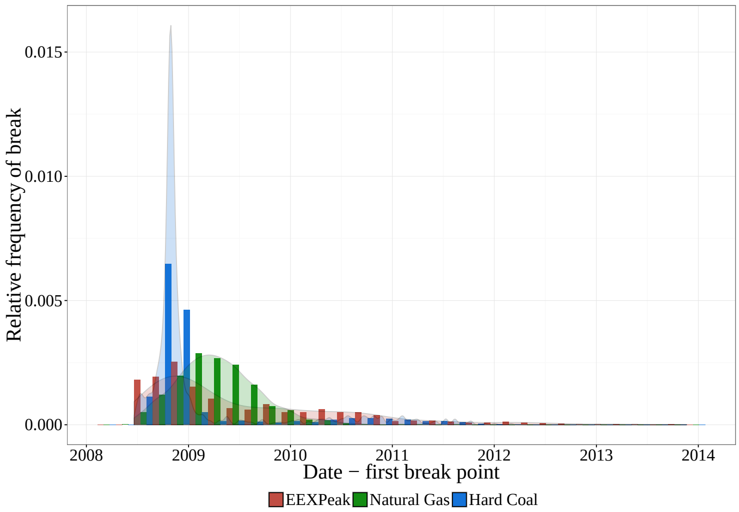

Figure 7: Histogram for the location of the first break

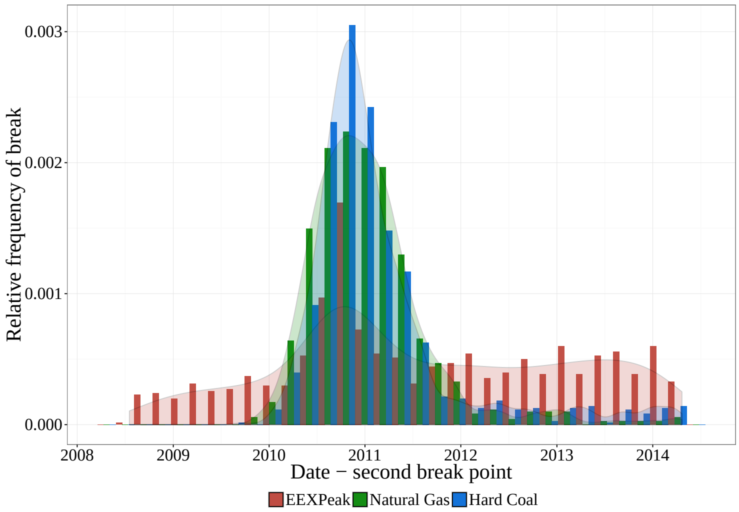

Figure 8: Histogram for the location of the second break

D Impulse response functions for natural gas and hard coal

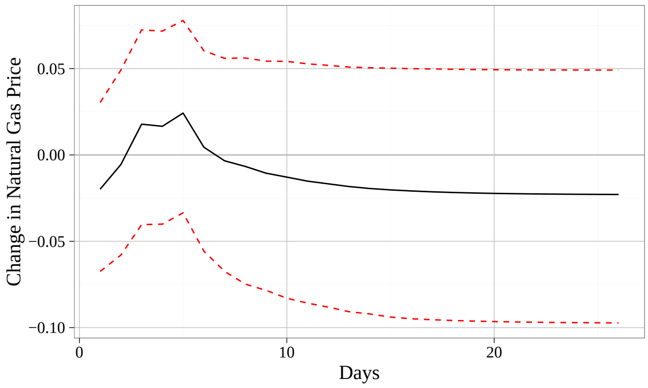

Figure 9: Response of the natural gas price to a shock in the EEXPeak electricity price (dashed red lines indicate the 95% bootstrapped C.I.s)

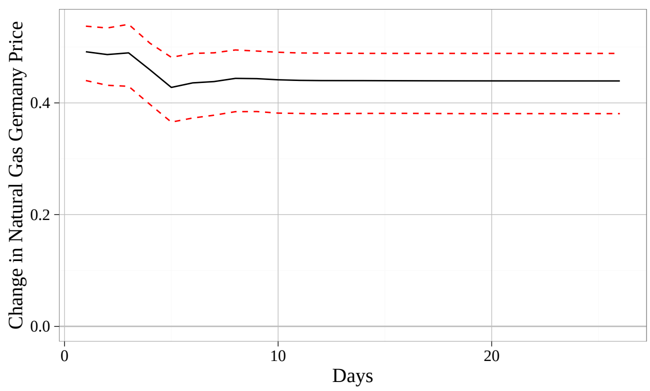

Figure 10: Response of the natural gas price to a shock in the natural gas price (dashed red lines indicate the 95% bootstrapped C.I.s)

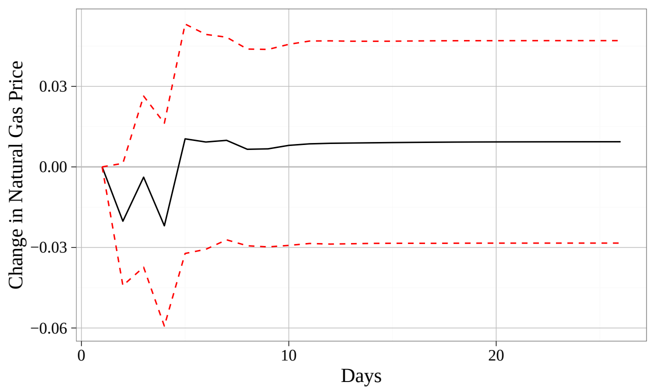

Figure 11: Response of the natural gas price to a shock in the hard coal price (dashed red lines indicate the 95% bootstrapped C.I.s)

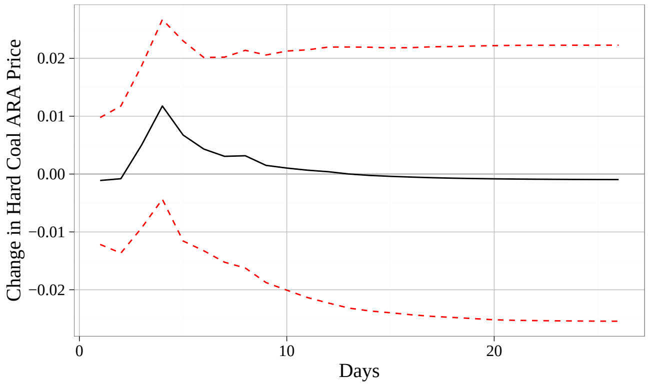

Figure 12: Response of the hard coal price to a shock in the EEXPeak electricity price (dashed red lines indicate the 95% bootstrapped C.I.s)

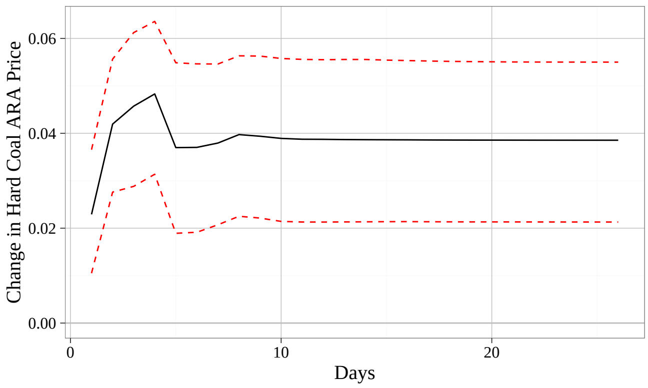

Figure 13: Response of the hard coal price to a shock in the natural gas price (dashed red lines indicate the 95% bootstrapped C.I.s)

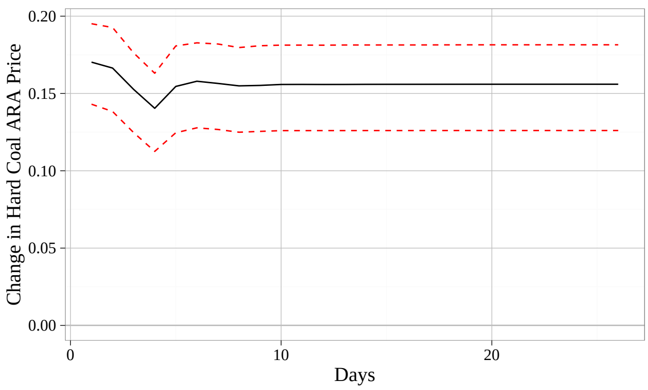

Figure 14: Response of the hard coal price to a shock in the hard coal price (dashed red lines indicate the 95% bootstrapped C.I.s)

E Results of cointegration analysis for different subsamples

Initial period

rank	trace test stat.	10%	5%	1%
$r \leq 2$	3.81	6.5	8.18	11.65
$r \leq 1$	25.52	15.66	17.95	23.52
$r = 0$	88.77^{***}	28.71	31.52	37.22

Table 10: Trace test statistic to determine the cointegration rank for the first period from 28/09/2007 to 19/12/2008.

	α-vector		β-vector	
	Parameter	t-stat	Parameter	t-stat
EEXPeak	-0.4769^{***}	-7.88	1.0000	—
Natural Gas	0.0046^{*}	1.70	-6.6616^{***}	-8.64
Hard Coal	0.0025^{**}	2.20	-0.2421	-0.18

Table 11: Cointegration Parameters for the first period from 28/09/2007 to 19/12/2008

Second period

rank	trace test stat.	10%	5%	1%
$r \leq 2$	0.4	6.5	8.18	11.65
$r \leq 1$	16.92	15.66	17.95	23.52
$r = 0$	80.59^{***}	28.71	31.52	37.22

Table 12: Trace test statistic to determine the cointegration rank for the second period from 22/12/2008 to 07/12/2010.

	α-vector		β-vector	
	Parameter	t-stat	Parameter	t-stat
EEXPeak	-0.2926^{***}	-7.43	1.0000	—
Natural Gas	0.0062^{**}	2.03	-2.2230^{***}	-6.02
Hard Coal	-0.0008	-0.90	2.7142^{**}	2.42

Table 13: Cointegration Parameters for the second period from 22/12/2008 to 07/12/2010

Third period

rank	trace test stat.	10%	5%	1%
$r \leq 2$	0.48	6.5	8.18	11.65
$r \leq 1$	3.66	15.66	17.95	23.52
$r = 0$	152.81^{***}	28.71	31.52	37.22

Table 14: Trace test statistic to determine the cointegration rank for the third period from 08/12/2010 to 15/01/2015.

	α-vector		β-vector	
	Parameter	t-stat	Parameter	t-stat
EEXPeak	-0.3568^{***}	-17.96	1.0000	—
Natural Gas	0.0013	1.37	-0.8660^{**}	-2.05
Hard Coal	0.0009^{***}	3.54	-4.4924^{***}	-6.12

Table 15: Cointegration Parameters for the third period from 08/12/2010 to 15/01/2015

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