Understanding the determinants of electricity prices and the impact of the German Nuclear Moratorium in 2011

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Abstract

This paper shows how the effect of fuel prices varies with the level of electricity demand. It analyzes the relationship between daily prices of electricity, natural gas and carbon emission allowances with a semiparametric varying smooth coefficient cointegration model. Different electricity generation technologies have distinct fuel price dependencies, which allows estimating the structure of the power plant portfolio by exploiting market prices. The semiparametric model indicates a technology switch from coal to gas at roughly 85% of maximum demand. This model is used to analyze the market impact of the nuclear moratorium by the German Government in March 2011. Futures prices of electricity, natural gas and emission allowances are used to show that the market efficiently accounts for the suspended capacity and correctly expects that several nuclear plants will not be switched on after the moratorium.

Keywords: Electricity market, merit order, cointegration, varying coefficient, nuclear moratorium
JEL-Classification: G14, L94, Q41, Q48

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1 Introduction

Electricity is a homogeneous good that cannot be stored at reasonable economic costs. However, the demand is highly seasonal and needs to be satisfied at all times. Hence, it is most efficient to generate electricity with a mixture of various technologies with different properties regarding capital costs and marginal costs. These technologies also differ in terms of input fuels and carbon emissions.

Therefore, how input price variations affect the electricity price critically depends on the marginal technology used; and the marginal technology used depends on the level of the residual demand.[1] The present paper tries to investigate exactly this effect. To illustrate the point, consider the 'merit order', i.e., an ordering of fossil power plants from those with low marginal cost (like lignite or hard coal) to high marginal cost (natural gas). If the residual demand is low (e.g. because electricity demand is low in the night; or because there is a lot of wind feed-in), the marginal power plant will be a coal fired power plant, and we expect that changes in the gas price will not affect the electricity price. This will be the case only if demand is high. The approach in the present paper allows to identify how the fuel price effects vary with the size of the residual demand.

This is analyzed empirically using data from the German electricity market and applying a semiparametric cointegration model. In order to measure how the fuel price sensitivity changes throughout the merit order, it is necessary to use a model that allows the parameters of the fuel price sensitivity to vary freely. The semiparametric varying smooth coefficient model, which was introduced by Hastie and Tibshirani (1993), allows for straightforward analysis of the relationship between fuel price sensitivity and load. The main advantage of the model is that the nature of the varying

[1] The residual demand is the electricity demand minus the feed-in of renewables, like wind or solar power.

effect is directly derived from the data, which means that there is no need for ad-hoc assumptions or restrictive functional specifications. Recent work by Cai et al. (2009) and Xiao (2009) shows that such a model can be used to estimate the nonlinear functional coefficients of a cointegration relationship. The application of this estimator is novel for modeling the dynamics of electricity markets. This method indicates a technology switch from coal to gas fueled power plants at around 60 gigawatt (GW) average non-wind daily peak generation. The estimated input price sensitivities are used to simulate the merit order for different natural gas and carbon price scenarios.[2]

The usefulness of this approach can be illustrated by analyzing a specific policy intervention like the German nuclear power suspension in March 2011. After the incident in Japan's Fukushima nuclear power plant, the German government decided to put the so called 'Nuclear Moratorium' in place. Seven nuclear power plants, all built before 1980, had to be switched off from 03/15/2011 to 06/15/2011 to examine the security of these plants. After the announcement, the market reacted with immediate price increases of electricity, gas and carbon emission allowance futures. Using only these futures prices, the proposed model is able to split the electricity price increase into a fuel price component and a capacity effect. It is also possible to measure the expectations of the market for the period after the end of the moratorium. The results of the event study show that the market accounts for most of the capacity effect during the period of the moratorium and expects that several nuclear power plants remain closed. This expectation proved to be correct as all affected nuclear power plants were permanently decommissioned after the end of the moratorium.

The approach in this paper relates to two distinct strands of the literature on empirical modeling of energy prices. The first strand focuses solely on the electricity

[2]Carbon prices refer to EU emission allowance certificates under the European Emission Trading Scheme phase II.

market and tries to resemble the stochastic characteristics of the typical price patterns. Driven by capacity constraints, hourly and daily prices have a high volatility and spikes. There are also hourly, daily and monthly seasonalities that reflect demand patterns of consumers and industry. The two most prominent approaches are the 'Mean Reverting Jump Diffusion Model' and the 'Markov Regime Switch Model', which are both described by Weron et al. (2004). These models can also be extended by additionally accounting for fundamental factors like load (see Mount et al. (2006), Kanamura and Ohashi (2007)). However, this class of models has the drawback that the relationship between the electricity price and input fuel prices is not analyzed.

The second strand of literature consists of studies that broadly analyze the interdependencies between different energy commodities, but fail to account for the aforementioned specific fundamentals of the electricity market. Mohammadi (2009) uses a vector error correction model (VECM) to analyze the long-term relationship between fuel prices and electricity prices in the United States. Mjelde and Bessler (2009) indicate that fossil fuels are weakly exogenous and electricity prices adapt to re-establish the equilibrium. Similar results hold for the European electricity markets. Bosco et al. (2010) employ a set of robust tests to show that European electricity time series have a unit root and are cointegrated. Electricity prices seem to share a common trend with gas prices, but not with oil prices. Ferkingstad et al. (2011) also find that gas prices have strong instantaneous and lagged causal effects on electricity prices, while coal and oil prices are less important. Furthermore, coal, oil and gas prices are weakly exogenous. Fell (2010) finds evidence that the effect of fuel prices varies with the level of demand. The author estimates a VECM for the Scandinavian electricity spot market and several inputs. The short-term impact of the carbon price on the electricity price is higher in off-peak hours than in peak hours. Coulon and Howison (2009) account for this effect by directly modeling different parts of the supply stack.

The actual bids are split into clusters, which are governed by different fuels.

The present paper advances the current literature by showing how exactly the natural gas and carbon price sensitivities vary with load. It fills the gap between models that focus on idiosyncratic effects of the electricity market and models that focus broadly on interdependencies between energy markets. The remainder of this paper is organized as follows. Section 2 describes the data sets that are used for the analysis. Section 3 outlines the semiparametric varying coefficient cointegration model and discusses the empirical results. This part includes the semiparametric estimates of the gas and carbon price sensitivity functions as well as the predicted merit order simulation for different input price scenarios. In Section 4, the proposed semiparametric model is used to analyze the market impact of the German nuclear moratorium in March 2011. The conclusion is given in the final section.

2 Data

This study focuses on electricity, natural gas and carbon prices in Germany. The data consists of daily observations from 2008/04/01 to 2010/09/29. All price time series were obtained from the European Energy Exchange (EEX). This analysis uses day-ahead base, peak and off-peak electricity prices on weekdays. The peak block covers the hours from 8 am to 8 pm, while the off-peak block covers the remaining time. The base block is the daily average price. Daily day-ahead EEX gas prices are quoted from July 2007 onwards. Both Gaspool and NetConnect Germany (NCG) contracts are traded, but I choose NCG because of the higher liquidity in this market. NCG gas prices are denominated in Euro/MWh and will be used as an indicator for the gas market as a whole. For carbon prices, the EEX Carbix index of the EU Emission Trading Scheme phase II is used.[3] All prices are transformed into their natural logarithms.

The choice of price time series used for the analysis is driven by the consistency of both the geography of the German market and the exchange itself. However, the liquidity of the natural gas and carbon market at the EEX remains an issue for this study, which could potentially affect the results. While the Belgian natural gas hub Zeebrugge or the Dutch Title Transfer Facility (TTF) are sometimes considered more important markets with a higher liquidity, it is a priori not clear whether they are better proxies for the German natural gas price. Furthermore, due to a high convergence of European natural gas prices, as shown by Renou-Maissant (2012) or Asche et al. (2013), the choice of the natural gas price time series does not have a relevant impact on the results.

Lignite, coal and oil prices are not included for several reasons. First, the oil fueled electricity generation capacity in Germany is rather small, as it is shown in Table 1. Moreover, the trading and transportation properties of the coal market do not match the daily frequency setup of this study. Lignite is not actively traded and is usually not the marginal technology, which also holds for nuclear power. Adjustments for electricity ex- and imports as well as reservoir power stations can be neglected, because the observed relationship between load, input prices and electricity prices implicitly accounts for their influence. Several comparable studies, including Fezzi and Bunn (2009) and Zachmann and von Hirschhausen (2008), choose a similar approach and focus on the cointegration relationship between electricity, gas and EU emission allowance prices. The analysis of detailed cross-commodity relationships for a system of all different energy commodities is not the aim of this study, but can be found in Ferkingstad et al. (2011) and Mjelde and Bessler (2009).

[3] The gas prices are taken from the trading day that is closest to delivery to match the trading structure of the electricity market. Carbon spot prices are taken from the same trading day as the gas prices. The delivery day of gas and electricity contracts is the same.

Despite the fact that coal markets are biased towards over-the-counter trading and long-term contracts, there are some proxies for spot coal prices in northwest Europe, such as the McCloskey Coal Marker for the Amsterdam-Rotterdam-Antwerp (ARA) region. However, in order to achieve a coherent framework for the event study, it would be necessary to have a full set of actively traded futures for monthly, quarterly and yearly contracts at the EEX. During the period of the announcement of the moratorium, the spot coal price showed a strong co-movement with both natural gas and carbon emission allowance futures prices, which all increased substantially less than electricity prices. This observation indicates that the coal price did not reflect additional information, and therefore, including coal prices into the analysis of the moratorium would not change the main conclusions. However, as thoroughly argued by Dyckman et al. (1984) and Armitage (1995), the market model and data are very important for the event study methodology due to the fact that the choice of the respective approach may have an impact on the final results.

Germany's diversified technology and fuel mix is shown in Table 1. Electricity from renewable energy sources enjoys a preferred feed-in policy. The remaining load is covered by other technologies and cross-border exchange. Nuclear and lignite fueled plants satisfy the base load, while coal and especially gas fueled power plants cover the peak demand during the day. Generators have to buy EU emission allowances for their carbon emissions.

ENTSO-E provides hourly load data for Germany.[4] Wind forecasts and realized wind production were obtained by aggregating publically available data from the major transmission system operators (TSO), Amprion, 50Hertz and Transpower.[5] Wind

[4]ENTSO-E is the abbreviation for the European network of transmission system operators for electricity. Data is publically available from `www.entsoe.eu`.

[5]The data can be downloaded from: `www.amprion.net/en/wind-feed-in`, `www.50hertz.com/en/1983.htm` and `www.transpower.de/site/en/Transparency`.

Table 1: The German generation portfolio by technology

Technology	Installed Capacity (in MW)
Wind	25,848
Nuclear	20,441
Lignite	20,375
Coal	16,158
Gas	13,094
Solar	10,392
Oil	1,826
Hydro	1,678
Waste	496
Total	110,307

Source: German Federal Ministry of Economics and Technology, 2010.

power production from EnBW has been neglected because of the unavailability of forecasts and the small capacity.[6] Daily wind in-feed and load data was derived by averaging the quarter-hourly and hourly data. Day-ahead load forecasts are necessary to model day-ahead electricity prices. I assume that the realized load is the best proxy for this variable, because there is no publically available and generally accepted load forecast. The realized load is adjusted by the official wind production forecasts of the major TSOs. This adjusted load is called residual load. Summary statistics of the price and load variables are given in Table 2.

For the event study of the impact of the nuclear moratorium, a range of different EEX future contracts are used for a period from 2012/02/28 to 2012/04/18. The analysis includes monthly electricity futures settlement prices with delivery in April, May and June 2011, quarterly futures with delivery in the second, third and fourth quarter of 2011 and yearly futures for 2012 and 2013. The analyzed electricity and gas prices are futures with the same delivery period. The carbon price is the EU emission

[6] EnBW accounted for 1.86% of the total German wind power production in August 2010. Data was obtained from `www.enbw-transportnetze.com`.

allowance future for delivery in mid-December of the corresponding year.

Table 2: Summary Statistics

Variable	Unit	Mean	Median	Minimum	Maximum	Std. Dev.
Base Electricity	€/MWh	53.71	47.68	17.06	131.40	18.71
Peak Electricity	€/MWh	65.03	55.92	33.15	177.49	24.45
Off-peak Electricity	€/MWh	41.67	38.73	-11.25	87.08	13.61
EU Emission Allowance	€/t CO2	16.30	14.53	8.02	28.75	4.74
NCG Gas	€/MWh	17.91	17.14	6.90	32.04	6.82
Base Residual Load	MW	53,449	53,446	37,773	63,978	4,332
Peak Residual Load	MW	59,303	59,394	41,445	69,255	4,619
Off-peak Residual Load	MW	46,973	46,951	33,566	60,699	4,309

3 Semiparametric varying coefficient model

This section analyzes the relationship between natural gas, carbon emission allowances and electricity prices. Given the fact that electricity is generated with different technologies, the relationship between fuel prices and the electricity price should depend on the marginal technology used. It is necessary to assume that fuel price changes are passed through to electricity markets. In this case, the carbon sensitivity for coal driven parts should be higher than for gas. The dependence on gas prices should be higher for periods with high load.

Thus, I use a semiparametric varying-coefficient model, which was introduced by Hastie and Tibshirani (1993) as a generalized class of regression models. It measures explicitly how the fuel price sensitivity varies with load, which means that the model directly accounts for the underlying merit order. It is very flexible, because it does not assume any functional specification of how the fuel price sensitivity varies, but estimates it directly from the data. The model is given as

$$Y_i = \beta(Z_i)'X_i + u_i \tag{1}$$

which seems to be rather specific. However, the model is very flexible, because Z is a vector of so-called effect modifiers. The beta coefficients vary freely as a smooth function depending on the effect modifier. This function does not need any further specification and is estimated only from the data. The model proposed by Hastie and Tibshirani (1993) is a static approach that is not necessarily capable of estimating parameters in a time series context.

The literature on energy markets suggests that fuel prices and electricity prices are cointegrated. There is a unilateral effect from fuel prices to electricity prices in all markets. These results are robust for different regions and model setups.[7] Thus, the existence of a cointegration relationship is relevant for the following analysis and also has to be examined in this article. The Johansen test indicates that there is exactly one cointegration relationship and that both gas and carbon prices are weakly exogenous. These prices do not adapt to the long-term equilibrium, indicating that the electricity price follows the natural gas and carbon prices in a unilateral relationship. Thus, it is possible to estimate this relationship in a single equation model with the electricity price as endogenous variable. As the Johansen cointegration analysis and the obtained findings are standard in the literature, the results of this preliminary step are presented in Appendix A.

Recent studies by Cai et al. (2009) and Xiao (2009) expand the semiparametric approach and analyze the properties of similar varying coefficient models for non-

[7] Mohammadi (2009) finds that there is one cointegration vector in his model for annual electricity, gas and coal prices in the United States. The error correction term is only significant for electricity. Mjelde and Bessler (2009) use weekly data and find that only electricity and uranium prices adapt to re-establish the equilibrium in the long-run relationship. Using a different methodology, Ferkingstad et al. (2011) find a strong causal link from gas prices to electricity prices, while the German electricity market does not have a causal effect on any fuel market. Fezzi and Bunn (2009) analyze daily spot prices and show that gas and carbon prices drive the electricity price in the UK. Furió and Chuliá (2012) use forward prices of Spanish electricity, Brent crude oil and Zeebrugge natural gas. Similarly to the other studies, they also find a cointegration relationship where causation runs from fuel prices to the electricity market.

stationary time series and cointegration settings. Xiao (2009) proves that a kernel estimator of the varying cointegration coefficients is super-consistent. A kernel estimator is used to estimate this regression by locally weighing all observations with $K\left(\frac{z_t - z}{h}\right)$. The estimator of $\widehat{\beta}$ is defined as

$$\widehat{\beta}(z) = \arg\min_{\beta} \sum_{t=1}^{n} K\left(\frac{z_t - z}{h}\right)\{y_t - x_t'\beta\}^2 \tag{2}$$

In this paper, the kernel estimator and bandwidth selection of the semiparametric varying smooth coefficient model is implemented as given in Li and Racine (2007) and in the np package by Hayfield and Racine (2008). The semiparametric varying smooth coefficient model is then given as $y_t = \beta(z_t)'x_t + u_t$. The electricity price is defined as y_t, while x_t is a matrix of a constant and of gas and carbon prices. The regression coefficient $\beta(z_t)$ is a vector of unspecified smooth functions of z, which is the residual load.[8] In this model, the gas and carbon price dependence of the electricity price varies with the effect modifier z. This means that the cointegration coefficients change throughout the assumed underlying merit order.

I estimate different models for base, peak and off-peak electricity prices to account for different underlying fundamentals. The semiparametric cointegration coefficients for gas and carbon are shown in Figure 1. These functions measure the input price sensitivity of the electricity price depending on the residual load.[9]

A visual inspection shows that the parameters vary throughout the merit order and that there are two distinct parts. The first part has a higher carbon sensitivity, while the second part has a higher gas sensitivity. The transition point lies at around 55 GW average daily residual load for the base electricity price and at around 60 GW average

[8]In Xiao (2009), the process z_t is required to be stationary, which is the case for all residual load processes of the base, peak and off-peak blocks. See Table 3 for the according unit root tests.

[9]Due to the estimation procedure, parameters at the fringe of the load spectrum are unstable and therefore omitted in the graphs.

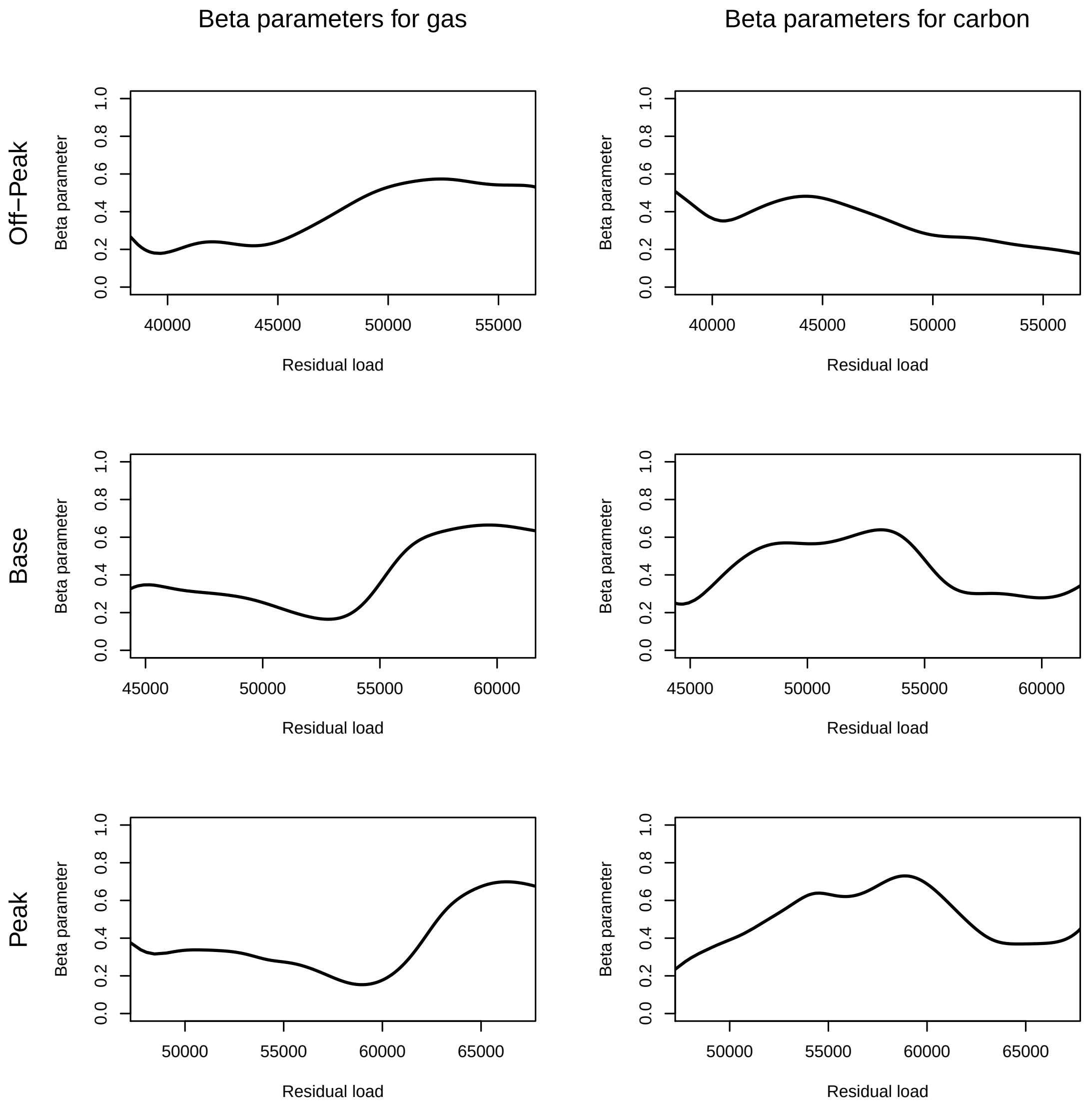

Figure 1: Semiparametric cointegration parameter estimates of fuel prices

Notes: This figure shows the estimated semiparametric cointegration coefficients for off-peak, base and peak electricity prices. The parameters are a smooth function that depends on the residual load in MW. The coefficients for natural gas are displayed in the left column and the parameters for carbon emission allowances are in the right column.

residual load for the peak block. The position of the shifting coefficients reflects the German generation portfolio. Nuclear, lignite and coal based electricity production has a total capacity of approximately 57 GW. These technologies are generally assumed to have lower marginal costs than gas based production. The model indicates that the gas driven part of the merit order has a generation capacity of approximately 10 GW. This estimate is also highly consistent with the power plant portfolio, as there is a total gas fueled capacity of around 13 GW in Germany.

One needs to be careful with an economic interpretation of pass-through rates in this model. Gas and carbon prices are used as a proxy for input prices as a whole. Thus, the direct effect of each variable itself might be misleading. Rickels et al. (2010) find a positive effect of the coal and oil prices on the carbon price, which may be caused by a common factor of general demand for energy. To measure a meaningful pass-through rate, I determine how the electricity price increases when the input prices as a whole increase by one percent. The mean of the sum of the parameter vectors is 0.745% for off-peak, 0.835% for base and 0.906% for peak. The first and third quartiles are within bounds of 0.05 percentage points below and above the point estimates. These values can be interpreted as the pass-through rate multiplied by the portion that fuel costs contribute to the total marginal costs. Given this interpretation, it makes sense that the estimate is higher for peak, because the fuel costs are relatively more important. The results of this analysis suggest that fuel price changes are passed through.

As a robustness test, the comparable parametric VECM estimates of the cointegration vector are 0.51 for gas and 0.36 for carbon (see Table 4). These estimates are also consistent with the results of Fezzi and Bunn (2009). Using a similar setup for the English market, they find cointegration parameters of 0.66 for gas and 0.32 for carbon. The differences might be driven by a higher ratio of gas production in the

UK.

The QQ-plots in Figure 2 show a good fit of the semiparametric model. It is able to resemble the pricing behavior for normal price levels, but underestimates the highest prices. This probably happens due to a scarce capacity effect that causes a price premium that cannot be explained by fuel price changes.

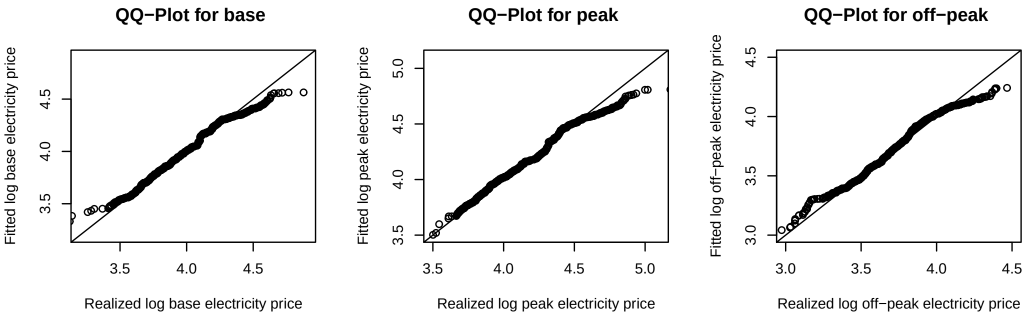

Figure 2: QQ-plot for the fit of the semiparametric model

The estimates of the semiparametric model can be used to predict the changes of the merit order for different gas and carbon price scenarios. Load-varying beta parameters translate into flexible shifts of the merit order. Figure 3 shows the estimated base electricity prices depending on load and input prices. The graph on the left illustrates equal gas and carbon prices that vary from 10 Euro to 25 Euro, which is a realistic scenario for the observed period. The right graphs show the merit order for varying gas prices while holding the carbon price fixed. Due to the semiparametric estimates, the gas price has a stronger impact on the electricity price if the load is high.

The model is capable of explaining the observed electricity prices with a flexible and simple approach. The relationship between electricity, natural gas and carbon prices is motivated by the underlying power plant portfolio. In the next section, the model is used to analyze the impact of an unexpected and sudden change of the power plant portfolio.

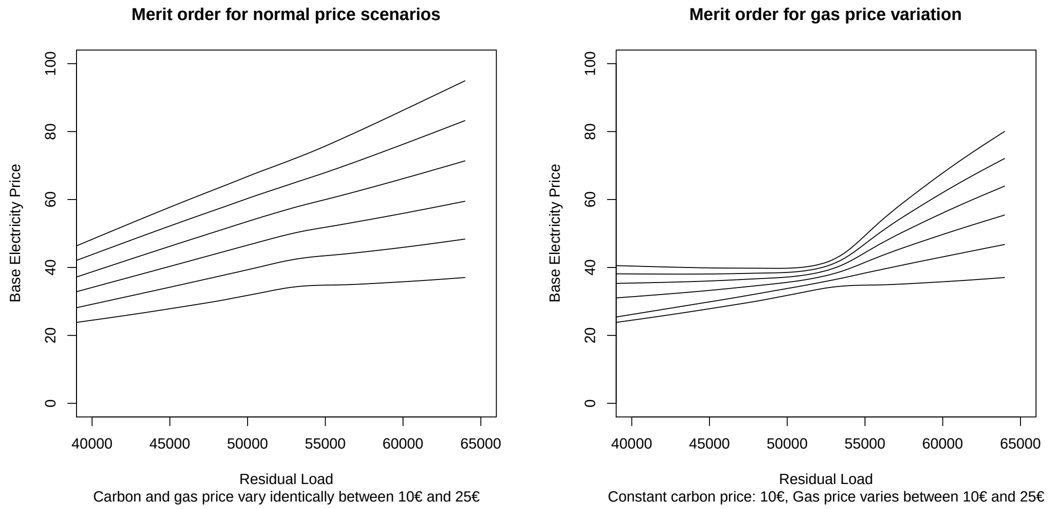

Figure 3: Simulated merit order for different natural gas and carbon price scenarios

Notes: This figure illustrates the fitted merit order conditional on varying gas and carbon prices. The fitted base electricity price (in Euro/MWh) is derived using the semiparametric cointegration coefficients shown in Figure 1. The chart on the left shows the merit order for gas and carbon prices varying identically between 10 and 25 Euro per MWh and per ton, respectively (in steps of 3 Euro). For the chart on the right, the carbon price is fixed at 10 Euros per ton and the gas price varies between 10 and 25 Euros per MWh.

4 Analysis of the German Nuclear Moratorium in 2011

On Friday, 11 March 2011, a heavy earthquake and tsunami hit Japan and severely damaged the nuclear power plant in Fukushima. Following these disastrous events, the German government surprisingly decided to put a nuclear suspension in place. The decision for a moratorium of three months length was announced publically on the evening of Monday, 14 March 2011. This policy intervention immediately removed seven nuclear power plants from the market.

In this section, I conduct an event study in order to assess the impact of the nuclear moratorium. According to Binder (1998), event studies are used to test if a market efficiently incorporates information and to analyze the event's price impact on some securities. Classical event studies in finance focus on measuring the abnormal returns around a firm specific or economy wide event of interest. MacKinlay (1997) gives an overview about event study methods, which all start by defining the event of interest and the event window, during which the impact of the event is measured. The event of interest is the announcement of the moratorium and the event window is chosen to be 10 trading days before and 25 trading days after the announcement.

The impact of the moratorium on the German electricity price can be assessed either for the spot or the futures market. Looking at the German base electricity day-ahead spot market first, the price fluctuated in a range between 45 and 60 Euro per MWh without showing a clear trend in March 2011. However, due to the large variation of spot prices, it is not possible to rule out an effect of the nuclear moratorium. Generally, the influence on the day-ahead market was less distinct because the suspended capacity was comparable to the normal fluctuations of renewable electricity production, which had a high availability during the time of the announcement of the moratorium. Thus, the price effect on the day ahead-market was small and short-lived as concluded by the European Commission (2011). Looking at cross-border electricity trade flows, the immediate impact of the moratorium is obvious for the period surrounding the commencement. According to the report of the Bundesnetzagentur (2011), Germany turned from being a net-exporter of 4.1 GW to an net-importer of 1 GW, effectively compensating for the nuclear capacities by imports from the neighboring European countries.

However, only analyzing the direct impact on the spot market has two distinct drawbacks for a comprehensive event study of the moratorium. First, the real price impact of the moratorium may be concealed by the high variance of spot prices or factors like the large fluctuation of electricity production from renewable energy sources. Second, it is not possible to measure the expectations of the market regarding the question whether the moratorium will be permanent.

Therefore, the following part of the event study focuses on the futures market, which is well suited to analyze the impact of the moratorium because futures prices reflect the expectations of all market participants. Furthermore, the derivatives markets of the EEX have a sufficiently high liquidity as the trading volumes are about two to five times higher than at the spot market. Given the high importance of the futures market, most institutions such as the EEX (2011) and the European Commission (2011) focus on futures prices to analyze the impact of the moratorium.

The electricity futures traded at the EEX reacted with a steep price increase, which is shown in Figure 4. Given an instant daily price increase of roughly 15%, the mere existence of a moratorium effect is obvious for the electricity futures. However, also the gas and carbon futures prices rose, probably because the market expected an increasing demand for fossil fuels, which are used to offset the suspended nuclear capacities. As a consequence, the event study focuses on analyzing the impact of the different influences that cause the electricity prices to rise. The method proposed in this study allows to determine whether the market efficiently accounts for the new information.

In theory, there are two separate shifts of the merit order for the according electricity futures with delivery between March 2011 and June 2011. First, the supply curve is shifted left by about 6 GW, because nuclear generation capacity with low marginal costs is removed from the system. This effect is called the capacity effect of the moratorium. Second, the increased gas and carbon futures prices result in an upwards shift of the merit order.

The event study is conducted in the following way. In order to isolate the capacity effect for a certain electricity futures contract, I compare the observed electricity futures price and the predicted merit order for the contract before and after the mora-

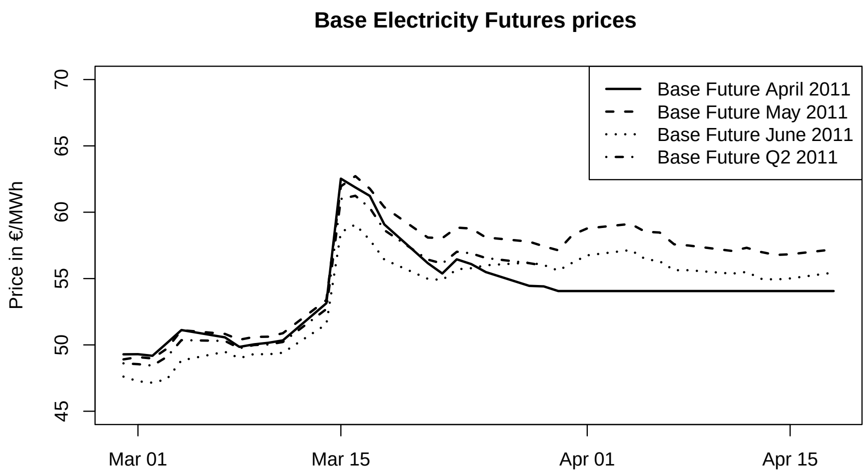

Figure 4: Base electricity futures prices at the time of the announcement of the nuclear moratorium

Notes: This figure shows the EEX market reaction for base electricity futures that are directly affected by the nuclhear moratorium. The moratorium was announced on the 14 March 2011.

torium. The semiparametric cointegration model, as discussed in Section 3, is used to predict the merit order, i.e. the counterfactual electricity price function conditional on residual load.[10] Due to the varying beta coefficients, the observed natural gas and carbon emission allowance futures prices are sufficient to derive such a merit order curve for an electricity futures contract.[11] As the predicted merit order only accounts for the change in gas and carbon futures prices, it is possible to derive the capacity effect of the moratorium. First, the merit order of the electricity futures contract is predicted using the observed settlement prices of the according natural gas and carbon futures on a trading day before the moratorium. Then, the settlement price of the electricity future on the same trading day is used to determine the implied expected demand,

[10]Generally, cointegration is seen as a long-term framework, but in this context it is reasonable to assume that the stable long-term relationship is relevant for the price expectations at the futures market.

[11]The event study uses unadjusted futures prices in levels. The model is calibrated with data from the day-ahead market with seven days per week to match the delivery structure of the base futures.

which is defined as the residual load that is necessary to justify the observed electricity futures price. This is achieved by calculating the intersection of the predicted merit order and the actual observed electricity futures settlement price. In the second step, the same procedure is repeated for electricity, gas and carbon futures prices observed on a trading day after the moratorium. The difference of the implied expected demand before and after the moratorium is the capacity effect.

This procedure is illustrated in Figure 5, which shows as an example how the capacity effect is derived in this study. The capacity effect is determined for the Q2 2011 base electricity futures contract and the period between March 9 and March 24. The merit order shown in this figure is calculated with the semiparametric model using the natural gas futures prices for delivery in Q2 2011 and the carbon emissions allowance futures price for delivery in mid-December 2011 as inputs. The dashed bold line is the predicted merit order derived from the futures settlement prices traded on March 9. The implied expected residual load for the setup in Figure 5 can be calculated by taking the intersection of the merit order and the observed electricity futures settlement price on the same trading day. This expected residual load for Q2 2011 amounts to 47.5 GW on 9 March 2011, which is close to the 2008 - 2010 average of 48.3 GW. Driven by the moratorium, the gas and carbon futures prices rise and shift the Q2 2011 merit order upwards, as it is shown by the bold line representing the merit order for the gas and carbon futures prices traded on March 24. This gas and carbon price effect accounts for an electricity price increase of less than 3 Euro. However, from March 9 to March 24, the Q2 2011 electricity futures settlement price rose from 49.75 Euro to 56.90 Euro. This observed change of the electricity futures price is used to determine the capacity effect of the nuclear moratorium by looking at the merit order on each of both trading days and asking which residual load would justify the actual electricity futures price. The difference between this implied residual

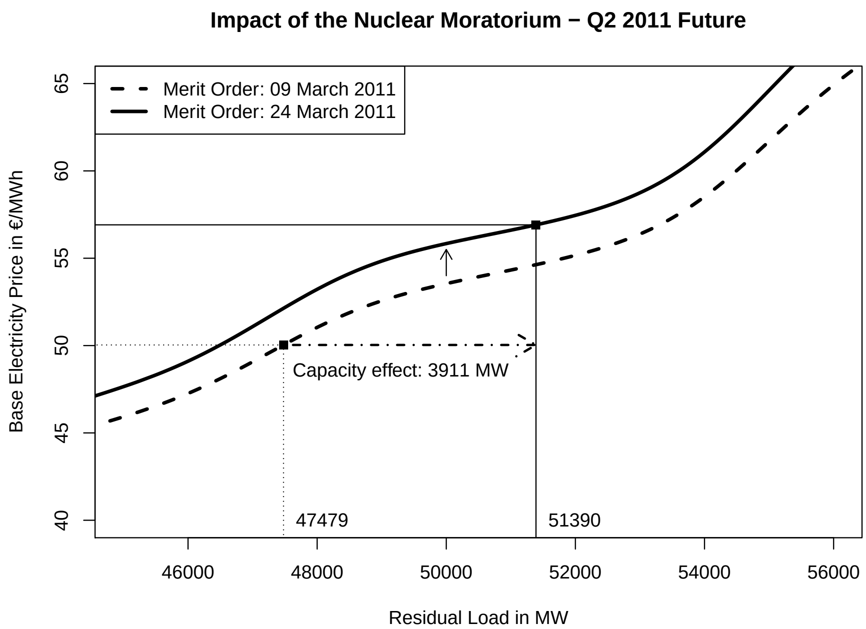

Figure 5: Derivation of the capacity effect of the nuclear moratorium

Notes: The merit order is derived by using the previously calibrated semiparametric model as well as gas and carbon futures settlement prices on a specific trading day. Due to the rising gas and carbon futures prices, the merit order shifts upwards from March 9 to March 24. While the fuel price effect accounts for an electricity price increase of less than 3 Euro, the actual futures price rose by 7.15 Euro. The capacity effect is determined by calculating the residual load that would justify the actual electricity futures prices on each of both trading days and then taking the difference between the implied residual load before and after the moratorium.

load before and after the moratorium is the capacity effect. It can be interpreted as the additional demand that would be necessary to drive the electricity price to the observed level if the nuclear moratorium had not been imposed. For the setup shown in the graph of the Q2 2011 future, the capacity effect amounts to 3.9 GW.

The proposed approach allows to measure the capacity effect, but is based on the assumption that futures prices mainly reflect expected spot prices and market conditions. Analyzing only the futures market without the calibrated market model would not allow to directly link the observed price developments to the capacity effect.[12]

The analysis in Figure 5 displays only the capacity effect for one single futures contract and for the comparison of two trading days. Thus, in the next step, the same procedure is used to calculate the capacity effect for different electricity futures and the full range of trading days in the event study window. Figure 6 shows the development of the capacity effect over time and for futures contracts with different times to maturities. For example, in order to calculate the moratorium's capacity effect for the Q2 2011 futures contract traded on March 24, I compare the implied expected demand for the contract on this trading day with the implied expected demand for the same futures contract on all trading days before the announcement of the moratorium. Finally, the average of these capacity effects between March 24 and each of the trading days before the moratorium is displayed in Figure 6 as the capacity effect for the Q2 2011 contract on March 24.

The top panel of Figure 6 displays the capacity effect for directly affected futures.

[12]The results derived with the approach in this study are consistent with the findings of Fritz (2012) using a different setup in this working paper. Fritz (2012) estimates a VECM for European energy futures prices, namely EEX base electricity prices, Title Transfer Exchange (TTF) natural gas prices, Intercontinental Exchange (ICE) coal prices and EEX carbon emissions allowances. The results regarding the cointegration properties are similar to Section 3, finding one cointegration relationship. Within the VECM framework using futures prices only, the author finds an electricity price increase, which cannot be explained by fuel prices, that is of the same magnitude as estimated in Figure 5 using the semiparametric approach. However, the setup in Fritz (2012) does not allow to express the price increase as a capacity effect (in GW) due to the setup of the model using futures prices only.

On Monday, 14 March 2011, the first trading day after the Fukushima events, the prices of the electricity, gas and carbon futures rise. However, the capacity effect, which measures the abnormal price increase of electricity futures, shows no indication of previous information about the moratorium. There is no evidence for a capacity effect before 15 March 2011. Then, in direct response to the moratorium, all futures contracts immediately account for the shut capacity of about 6 GW. The market efficiently reacts to the moratorium by adding a capacity effect premium to the electricity price in order to reflect the missing generation capacity. In the following days, the capacity effect declines first, but remains at a rather stable level after this drop. This decline might have been caused by the fact that the market agents did not anticipate a nuclear moratorium and thus needed some time to develop sound forecasts. After a few trading days, the market agents expect that a part of the capacity effect will be mitigated by dynamic factors like the flexibility of the power plant portfolio or international transmission.

The framework also allows measuring the market's expectations for the time after the end of the moratorium in June 2011. The middle and bottom panel of Figure 6 show the capacity effect for several futures with delivery after the moratorium. For the quarterly future with delivery in Q3 2011, the development of the capacity effect reveals an unsteady reaction, which is lasting for a few trading days, before sound expectations have developed. Then, the market expects a capacity effect of roughly 3-4 GW for the time after the moratorium. The capacity effect for the following quarter is at a very similar level, but more stable over time. The yearly futures for 2012 and 2013 also reveal a more settled picture. There is no panic reaction and the markets quickly adjust to a stable level of around 1 GW missing nuclear capacity.

Generally, the capacity effect for futures with delivery during and directly after the moratorium is rather similar. Thus, there is an impact that is expected to be

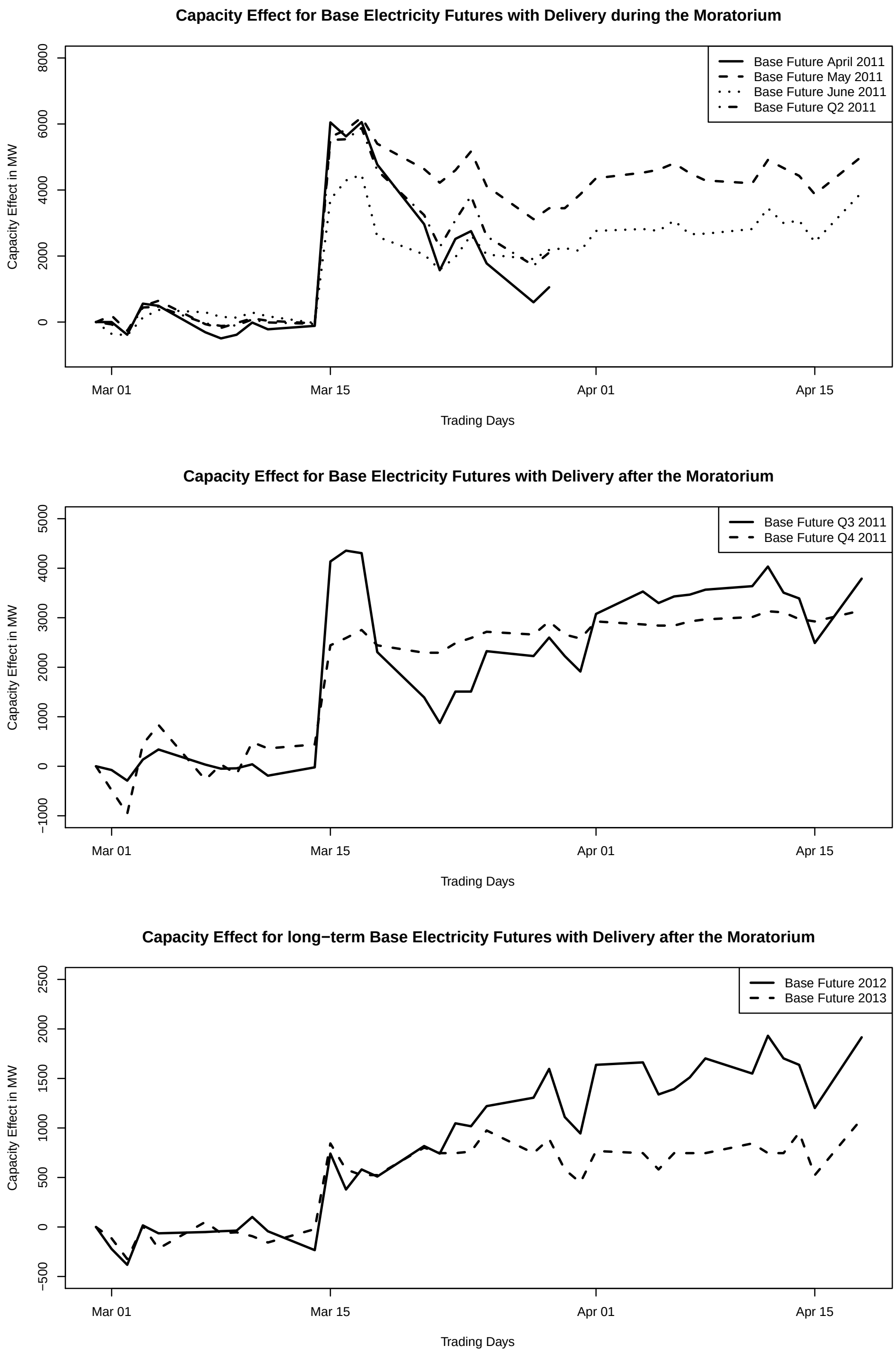

Figure 6: Implied capacity effect of the nuclear moratorium

Notes: This figure shows the implied capacity effect (in MW) that is caused by the nuclear moratorium. Only the futures illustrated in the top panel are directly affected by the moratorium. The capacity effect is calculated with the same procedure that is depicted in Figure 5.

permanent. It is difficult to quantify the expected number of nuclear power plants to remain closed down as there is some uncertainty introduced by dynamic effects. These effects could be a change of the maintenance schedule, endogenously added new generation capacity, changes of international transmission and demand responses. This dynamic adjustment process mitigates some of the capacity effect. Second, weighted expectations for different political scenarios might be reflected in the prices. If market participants think that several scenarios are realistic, the estimated capacity effect will reflect an average expectation that might not be a realistic scenario itself.

Given these considerations, there are two possible explanations for the decaying capacity effect: (1) that the moratorium of 6 GW has an expected capacity effect of only 1 GW in 2013 due to dynamic adjustment effects, or (2) that the market expects that the probability of an extension of the moratorium decreases with the time to maturity and is relatively low for 2012 or 2013.[13]

However, there is still consistent evidence for the existence of a capacity effect for all futures with delivery after the end of the moratorium. Thus, one can conclude that the market on average correctly expects an extension of the moratorium with several nuclear power plants remaining closed down after the announced end in June 2011.

5 Conclusion

There are two main contributions of this paper. First, it shows that the relationship between the input fuel prices and the electricity price varies with load and reflects the underlying merit order. This result is potentially useful for other markets with

[13]The finding that the capacity effect decays with the time until delivery might also be partially driven by the well-known Samuelson (1965) effect that commodity futures with a longer time to maturity are less volatile. In this case, both the electricity, gas and carbon futures for 2012 and 2013 would react less to new information than futures for 2011. However, this can also be explained economically, as the long-term futures are not directly affected by the moratorium and additionally would allow more time for dynamic adjustment effects.

different production technologies and inputs. One example are commodity markets, where local conditions lead to different mining or extraction technologies.

Second, the paper provides a framework to assess the impact of the German nuclear moratorium in 2011. The market incorporates the new information efficiently and correctly expects that several power plants will remain shut off after the moratorium. Furthermore, it anticipates that dynamic adjustment processes will mitigate some of the capacity effect. However, these results are not necessarily applicable for additional plant closures, which could affect the security of supply or lead to substantial capacity premium effects.

The approach in this paper could be improved and extended in several ways. It would be desirable to include other fuels to get a more granular picture of the nonlinear fuel price effects. It would also be interesting to test and compare the fuel price effects for various markets with different dominating technologies. Accounting for a possible scarce capacity premium, which seems to exist, would also improve the model.

Due to the semiparametric approach, the demand elasticity is not included explicitly. However, Fezzi and Bunn (2010) show that it is preferable to model demand as an endogenous variable. The analysis of the nuclear moratorium focuses on the German futures market, but does not include the day-ahead market or indirect price effects on other European markets. The impact on these markets and the response of input fuel prices to the moratorium provide an interesting area for future research.

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A Appendix

Table 3: Augmented Dickey Fuller unit root tests

Variable	Level			1st diff.		
	statistic	p-value	lags	statistic	p-value	lags
Base Electricity	-2.25	0.19	9	-11.73	0.00	8
Peak Electricity	-2.17	0.22	9	-11.65	0.00	8
Off-peak Electricity	-2.58	0.10	9	-12.35	0.00	8
NCG Gas	-0.45	0.52	1	-19.63	0.00	1
EU Emission Allowance	-0.65	0.43	0	-10.98	0.00	5
Base Residual Load	-3.82	0.00	9			
Peak Residual Load	-3.12	0.03	15			
Off-peak Residual Load	-3.01	0.03	10			

Notes: The null hypothesis of the ADF test is that there is a unit root in the considered time series. Lag lengths are determined by the Akaike Information Criterion (AIC). Whether to include a trend or constant was decided by checking the significance of the trend/constant parameters at a 5% significance threshold.

Table 4: Johansen cointegration analysis of electricity, gas and carbon prices

Panel A. Cointegration tests

Rank	Trace test statistic	p-value
Base electricity, gas, carbon		
0	120.48	0.000
1	15.56	0.200
2	3.93	0.435
Peak electricity, gas, carbon		
0	103.08	0.000
1	15.82	0.187
2	4.05	0.417
Off-peak electricity, gas, carbon		
0	169.89	0.000
1	15.27	0.215
2	3.81	0.454

Notes: The Johansen test is used to test for the existence and rank of a possible cointegration relationship between the three I(1) variables electricity, gas and carbon. The constant is restricted to lie in the cointegration space, as there is no indication for trends in the data. The lag length is determined by the Schwarz Information Criterion (SIC). The trace statistic for rank j tests the null hypothesis of rank $r = j$ against $r > j$.

Panel B. Analysis of the cointegration parameters

	α-Vector		β-Vector	
	Parameter	t-stat.	Parameter	t-stat.
Base	-0.297	-10.58	1	-
Gas	0.012	1.06	-0.51	-9.29
Carbon	-0.002	-0.27	-0.36	-4.50

Notes: The α-parameters indicate if and at which speed the variable of interest reacts to a disequilibrium in the long-term relationship. In the equations for gas and carbon, the α-parameters are not significant and thus, the gas and carbon prices are treated to be weakly exogenous. The estimates of the β-vector are significant, which shows that both gas and carbon prices are part of the stable long-term relationship and important drivers of the electricity price.