Institute of Energy Economics
at the University of Cologne

EWI Working Paper, No. 11/06

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

by
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July 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 vector error correction model and a semiparametric varying smooth coefficient model. The results indicate that the electricity price adapts to fuel price changes in a long-term cointegration relationship. 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. It is used to analyze the market impact of the nuclear moratorium by the German Government in March 2011. Futures prices show that the market efficiently accounts for the suspended capacity and 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

ISSN: 1862 3808

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†I am grateful to Felix Höffler, Christian Growitsch, Marc Oliver Bettzüge, Jörg Breitung, Caroline Dieckhöner, Jürgen Kruse and Johannes Viehmann for their helpful comments and suggestions.

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 the first step, the cointegration relationship is established and a vector error correction model (VECM) is used to show that gas and carbon prices are weakly exogenous. This means that fuel prices do not adapt to the long-term equilibrium, indicating that the electricity price follows the fuel prices in a unilateral relationship. In the second step, a nonlinear single equation cointegration framework measures 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

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

for straight-forward analysis of the relationship between fuel price sensitivity and load. The main advantage of the model is that the nature of the varying 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 fuel price sensitivities are used to simulate the merit order for different gas and carbon price scenarios.

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 for electricity futures and fuels. Using only the realized electricity and fuel 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.

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 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 VECM to analyze the long-term relationship between fuel prices and electricity prices in the US. 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. (2010) 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 fuel 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 outlines the empirical methodology, i.e. the vector error correction model (VECM) and the semiparametric smooth varying coefficient model. Section 3 describes the data set. The empirical results of the cointegration analysis are reported in Section 4. The results and implications of the smooth varying coefficient model are discussed in Section 5. This part includes the semiparametric estimates of the fuel price sensitivity function and the predicted merit order for different fuel price scenarios. In Section 6, the market impact of the German nuclear moratorium of March 2011 is analyzed in an event study. The conclusion is given in the final section.

2 Empirical Methodology

The empirical analysis is divided into three parts. First, it analyzes the existence of a cointegration relationship between fuel prices and the electricity price with a multivariate time series approach. In the second step, a semiparametric smooth varying coefficient model is used to estimate how the cointegration parameters vary with load. Third, these results are used to analyze the market impact of the German nuclear moratorium in 2011.

The preliminary data analysis reveals a cointegration relationship between the time series of interest. Thus, a vector error correction model (VECM) is employed to analyze the effects between the fuel prices and the electricity price. Cointegration means that each of the variables is nonstationary by itself, but a linear combination of these integrated variables is stationary. The VECM can be derived from the vector auto regressive model (VAR), which is a multivariate dynamic regression model. The specification in this study follows Johansen and Juselius (1990). Consider the p-dimensional VAR model of the order k

$$X_t = \Pi_1 X_{t-1} + ... + \Pi_k X_{t-k} + \varepsilon_t \tag{1}$$

where ε_t is a vector of independent identical normally distributed innovations. After taking first differences with $\Delta = 1 - L$, the model can be expressed as

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k} + \varepsilon_t \tag{2}$$

with $\Gamma_i = -(\mathrm{I}-\Pi_1 - \ \ldots \ - \Pi_\mathrm{i})$, $i = 1, ..., k-1$ and $\Pi = -(\mathrm{I} - \Pi_1 \ \ldots \ -\Pi_\mathrm{k})$. The rank of the matrix Π determines the long-run relationship. The Johansen test, which is used to test for the rank of the matrix, is employed in the empirical part of this study. If the matrix Π has the full rank p, the vector process X_t is stationary and a normal VAR for the level of the variables can be used. If the rank of the matrix is 0, there is no long-run relationship and the model above is equal to a VAR in differences. If the rank is greater than 0 and smaller than p, there is a cointegration relationship of rank r. In this case, there are $p \times r$ matrices α and β such that equation $\Pi = \alpha\beta'$ holds. Multiplying the r cointegration vectors β by the vector process X_t gives the stationary term $\beta' X_t$. The vectors α are called adjustment vectors. In a VECM, there are two ways of price interdependency. Short-term effects of the variables are captured similar to the vector autoregressive model of differences. The long-term effects enter the model with the term ΠX_{t-k}.

However, Johansen's linear parametric VECM approach cannot directly account for the structure of the merit order or varying fuel price effects. For this purpose, a semiparametric varying smooth coefficient model is more suitable. 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 shown that it is feasible to draw conclusions about the power plant portfolio, because different marginal technologies have distinct fuel price dependencies. 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.

The semiparametric smooth varying coefficient model is able to directly estimate the fuel price sensitivities. 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 preliminary analysis shows that the gas and carbon prices are weakly exogenous, which means that the system can be modeled with a single equation framework. Thus, I use a semiparametric varying-coefficient model, which was introduced by Hastie and Tibshirani (1993) as a generalized class of regression models. The model is given as

$$Y_i = \beta(Z_i)' X_i + u_i \tag{3}$$

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. However, the model proposed by Hastie and Tibshirani (1993) is a static approach that is not necessarily capable of estimating a cointegration vector in a time series context. Recent studies by Cai et al. (2009) and Xiao (2009) expand this approach and analyze the properties of similar varying coefficient models for nonstationary 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

$$\widehat{\beta}(z) = \arg\min_{\beta} \sum_{t=1}^{n} K\left(\frac{z_t - z}{h}\right) \{y_t - X_i'\beta\}^2 \tag{4}$$

In this paper, the kernel estimator and bandwidth selection of the semiparametric varying smooth coefficient model is implemented as given in Li and Racine (2006) and in the np package by Hayfield and Racine (2008). The electricity price is defined as y_t, while x_t consists of a constant and fuel prices (gas, carbon). The regression coefficient $\beta(z_t)$ is a vector of unspecified smooth functions of z. The fuel price dependence of the electricity price varies with the effect modifier z, which is the adjusted load.[2] In the semiparametric model, the function $\beta(z_t)$ changes throughout the assumed underlying merit order and measures how the fuel price sensitivity, measured by the cointegration coefficients, varies with the adjusted load.

[2] In Xiao (2009), the process z_t is required to be stationary, which is the case for all adjusted load processes of the base, peak and off-peak blocks.

3 Data

This study focuses on electricity, gas and carbon prices in Germany. The data consists of daily observations from 2008/04/01 to 2010/09/29. Detailed electricity prices are available 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.

Coal or 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. Including these fuels leads to more than one cointegration relationship, which is consistent with the results in the literature. 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. (2010) and Mjelde and Bessler (2009). Technically, several cointegration relationships make it infeasible to estimate a meaningful single equation semiparametric cointegration relationship. Given these considerations, the following models are restricted to include only gas and carbon as fuels. This focus on two major drivers leads to parsimonious models that are still able to explain the electricity price well.

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.

[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.

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.

Table 1: The German generation portfolio by technology (German Federal Ministry of Economics and Technology, 2010)

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

ENTSO-E provides hourly load data for Germany. Wind forecasts and realized wind production were obtained by aggregating publically available data from the major transmission system operators (TSO), Amprion, 50Hertz and Transpower. Wind power production from EnBW has been neglected because of the unavailability of forecasts and the small capacity.[4] Hourly wind data was derived by averaging the quarter-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.

For the event study of the impact of the nuclear moratorium, EEX futures prices are used. The analyzed electricity and gas prices are futures with the

[4]EnBW accounted for 1.86% of the total German wind power production in August 2010.

same delivery period. The carbon price is the EU emission allowance future for delivery in mid-December of the corresponding year.

4 Johansen's Cointegration Analysis

This section establishes the empirical cointegration relationship between the variables of interest and explores how the fuel prices affect the electricity price. The results are also a preparatory work for the semiparametric model in the next section.

The stationarity of the time series is tested with the Augmented Dickey Fuller (ADF) test. The null hypothesis of the ADF test is that there is a unit root in the considered time series. Lag lengths are determined by optimizing 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. The results of the unit root tests are shown in Table 2. The tests provide evidence for the hypothesis that all prices are nonstationary in levels, but have stationary first differences. Thus, I conclude that all price time series are integrated of order one, i.e. $I(1)$.

Table 2: ADF unit root test

Variable	Level			1st diff.		
	statistic	p-value	lags	statistic	p-value	lags
Base	-2.25	0.19	9	-11.73	0.00	8
Peak	-2.17	0.22	9	-11.65	0.00	8
Off-peak	-2.58	0.10	9	-12.35	0.00	8
Gas	-0.45	0.52	1	-19.63	0.00	1
Carbon	-0.65	0.43	0	-10.98	0.00	5

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 optimal lag length is determined by analyzing the AIC and the Schwarz Information Criterion (SIC). The trace statistic for rank j tests the null hypothesis of rank $r \leq j$ against $r > j$.

Table 3: Johansen cointegration test for base electricity, gas and carbon

Rank	Trace test statistic	p-value
0	120.48	0.000
1	15.56	0.200
2	3.93	0.435

For all electricity prices and all lag lengths, there is evidence for only one cointegration vector. Table 3 shows the result for the setup with base, gas and carbon and with a lag length determined by the SIC. Additional pairwise cointegration tests show that the electricity prices are cointegrated with both the gas and the carbon prices. However, the gas and the carbon price do not seem to be cointegrated with each other.

Table 4: 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

Table 4 reports the cointegration parameters for the same setup as the cointegration test shown in Table 3. For robustness reasons, several VECMs for different optimal lag lengths and electricity prices are estimated. The constant is restricted to lie in the cointegration space. All models show that the α-parameters are significant in the equations of the electricity prices. These 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 for all possible setups. Thus, the gas and carbon prices are treated to be weakly exogenous in the model. Only electricity prices adapt to the long-term equilibrium while gas and carbon prices do not tend to this equilibrium relation. The estimates of the β-vector are significant for all setups. This shows that both gas and carbon prices are part of this stable long-term relationship and important drivers of the electricity price.

These results are consistent with the literature. Mohammadi (2009) finds that there is one cointegration vector in his model for electricity, gas and coal. The error correction term is only significant for electricity. Mjelde and Bessler (2009) also 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. (2010) 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) show that gas and carbon prices drive the electricity price in the UK. Generally, these studies indicate that the relationship of electricity and fuel prices seems to be consistent for different regions. There is a strong unilateral effect from fuel prices to electricity prices in all markets.

However, testing the Granger causality suggests a bidirectional relationship between the fuel prices and the base electricity price, which contradicts the estimated long-term relationship. The lag length of the tested VECM is determined by the AIC to account for short-run effects. The relationship between the variables can be illustrated graphically with an impulse response analysis. The functions in Figure 1 measure the impact of an exogenous price shock of one variable for a period of 20 weekdays. Each shock has the magnitude of one standard error. Bootstrapped confidence intervals indicate the 2.5% and 97.5% quantiles. These impulse responses show that the electricity price has a small significant short-term effect on the gas price. However, this effect diminishes quickly. On the other hand, the carbon price only affects the electricity price after several days. Once the shocks have settled, the effects are consistent with the cointegration relationship. The Granger causality and impulse responses indicate that short-run effects may outweigh the long-run relationship for one or two weeks.

The impulse response functions in Figure 1 also show that the impact

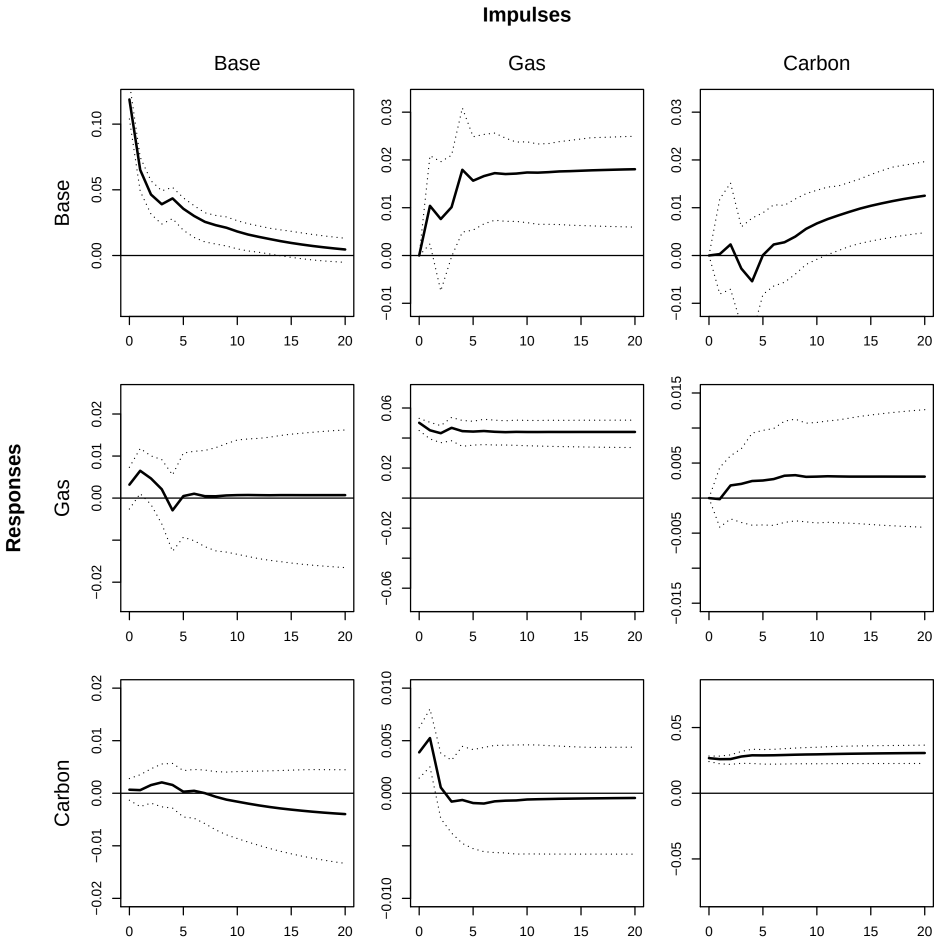

Figure 1: VECM orthogonal impulse responses

of an electricity price shock on the electricity price itself decays quickly. Electricity shocks are probably driven by capacity effects that do not have effects over longer horizons. The electricity price does not have a persistent significant effect on fuel prices. However, gas and carbon price shocks have a strong and positive long-term impact on the electricity price. Gas price changes do only slightly affect the price of emission allowances. Similarly, the carbon price does not have a significant impact on the gas price, which is meaningful as the model concentrates on the long-term component and both fuel prices are not pairwise cointegrated.

The variance decomposition also shows that fuel prices drive the electricity price in the longer term. It measures how much of the forecast error variance of a variable can be attributed to exogenous shocks of the other variables in the same model. For a period of 30 weekdays, fuel prices account for 40% of the base price variance. For 250 weekdays, fuel prices account for 85% of the variance of the electricity price. However, for the same horizon, only 2% of the variance of the gas and carbon prices can be explained by the respective remaining variables. This means that there is a strong unilateral link from fuel prices to the electricity price. In the next section, this link is analyzed with a methodology that allows accounting for the diversity of the power plant portfolio.

5 Semiparametric varying coefficient model

The previous analysis, based on Johansen's procedure, finds exactly one cointegration relationship and indicates that fuel prices are weakly exogenous. These results make it possible to estimate this relationship in a single equation model with the electricity price as endogenous variable. Therefore, a more flexible model is applied in this section.

Recall that the semiparametric varying smooth coefficient model is given as $Y_t = \beta(Z_t)'X_t + u_t$. In this equation, Y_t is the electricity price and 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. This means that the fuel price dependence of the electricity price varies with the residual load z.

Due to the estimation procedure, parameters at the fringe of the load spectrum are unstable and therefore omitted in the graphs. 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 2. These functions measure the fuel price sensitivity of the electricity price depending on the residual load.

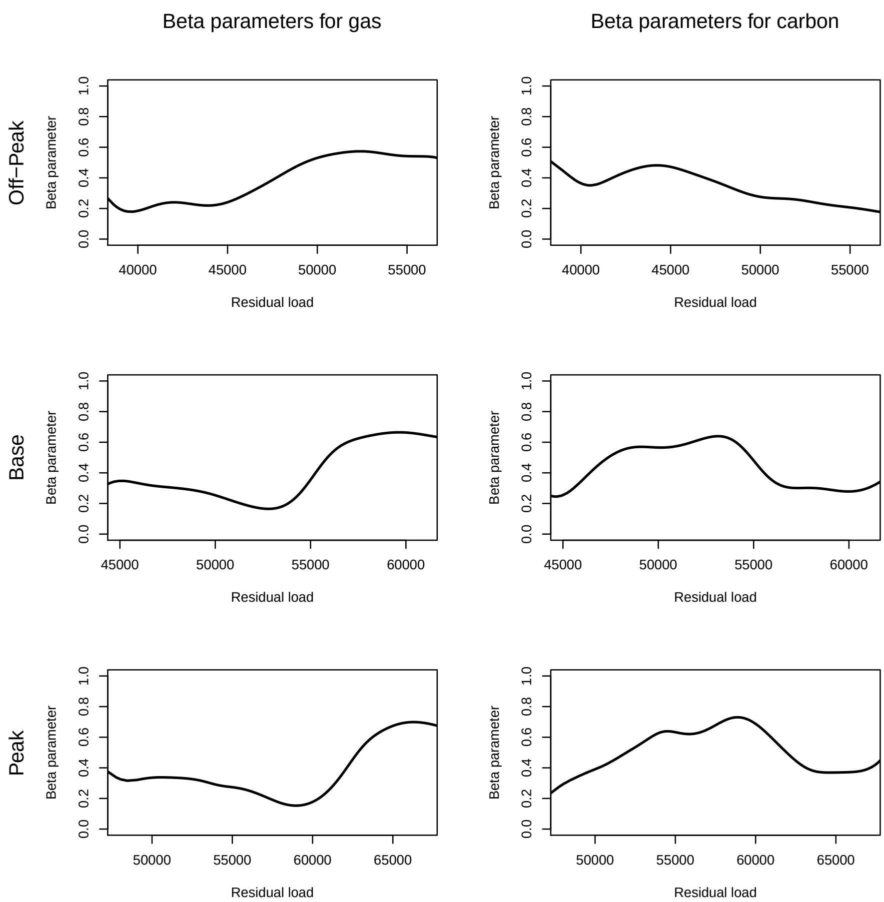

Figure 2: Semiparametric cointegration parameter estimates of fuel prices

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 break lies at around 55 GW average daily residual load for the base electricity price and at around 60 GW average residual load for the peak block. The estimated position of the structural break 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 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 3 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.

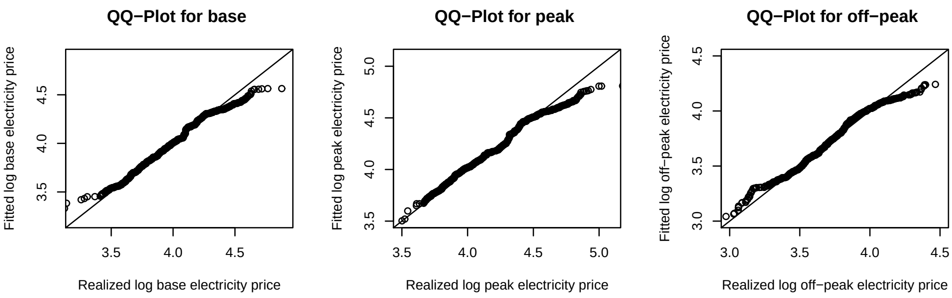

Figure 3: QQ-plot for the fit of the semiparametric model

The estimates of the semiparametric model can be used to predict the changes of the merit order for different fuel price scenarios. Load-varying beta parameters translate into flexible shifts of the merit order. Figure 4 shows the estimated base electricity prices depending on load and fuel 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.

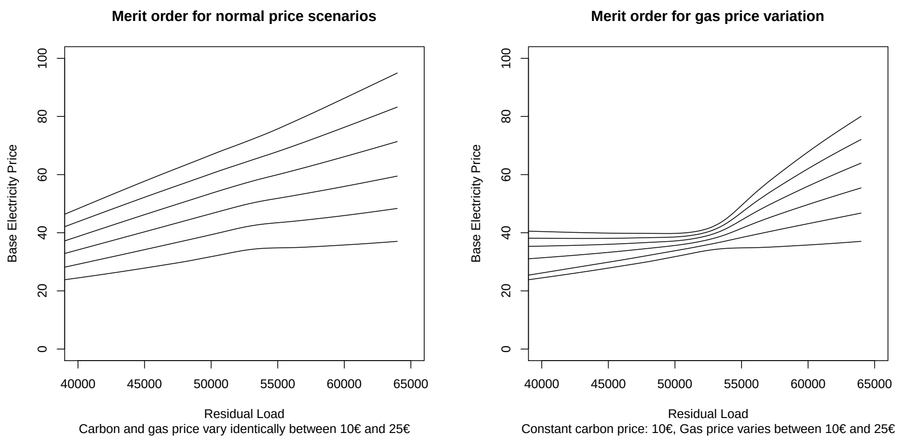

Figure 4: Estimated merit order for different fuel price scenarios

The model is capable of explaining the observed electricity prices with a flexible and simple approach. The relationship between electricity and fuel 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.

6 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 decided to put a nuclear suspension in place, the so-called "Nuclear Moratorium". On the evening of Sunday, 13 March 2011, the German Chancellor Angela Merkel still denied the plan to shut down German nuclear power plants in reaction to the events in Fukushima. During the following Monday, Vice Chancellor Guido Westerwelle stated that it was a possible option to put a moratorium in place. The decision for the moratorium was announced publically on the evening of Monday, 14 March 2011. This policy intervention immediately removed seven nuclear power plants from the market. The EEX reacted with a steep price increase of electricity, which is shown in Figure 5. Similarly, also the gas and carbon prices rose, probably because the market expected an increasing demand for fossil fuels, which are used to offset the suspended nuclear capacities.

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. Given an instant daily price

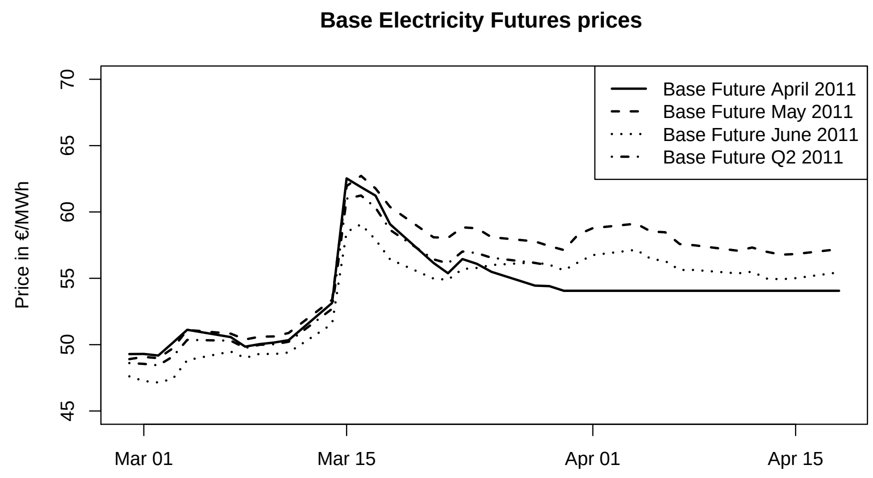

Figure 5: Electricity price impact of the moratorium

increase of roughly 15%, the mere existence of a moratorium effect is obvious. As a consequence, this 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 fuel prices result in an upwards shift of the merit order.

The semiparametric cointegration model analyzes the impact of each of these effects separately, which means that it can quantify the implicit capacity effect only from futures prices. Generally, cointegration is seen as a long-term framework, but in this context, the prices adapt rather quickly within a few days. It is also reasonable to assume that the stable long-term relationship is relevant for the price expectations at the futures market. Thus, the analysis using cointegration parameters is reasonable for this event study.

The event study uses prices in levels, which is possible as the results of the two sections before also hold for unadjusted prices. 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.

The event study is conducted in the following way. In order to isolate the capacity effect, I compare the merit order and realized electricity prices before and after the moratorium. First, the merit order is calculated with the prices of gas and carbon futures of a trading day before the moratorium. Then, the according settlement price of the electricity future for the same delivery period is used to obtain the implicit expected demand. This is achieved by calculating the intersection of the merit order and the electricity price. In the second step, the same procedure is repeated for futures prices taken from a trading day after the moratorium. The difference of the implicit expected demand before and after the moratorium is the capacity effect.

The estimated merit orders for the Q2 2011 base electricity contract traded on March 9^{th} and 24^{th} are shown in Figure 6. The implicit expected average demand for Q2 2011 is 47.5 GW residual load on 9 March 2011, which is close to the 2008 - 2010 average of 48.3 GW. Driven by the moratorium, the fuel prices rise and shift the merit order upwards. However, the electricity price rises more than the increase of fuel prices can explain, which means that there is a capacity effect. This is expected as the moratorium removes some nuclear generation capacity from the market. The new implicit demand results from the intersection of the new electricity price and the new merit order. It can be interpreted as the demand that would be necessary to drive the electricity price to the observed level if the nuclear moratorium had not been imposed. Thus, the capacity effect of the moratorium is the difference between the implicit demand before and after the moratorium. For the setup shown in the graph of the Q2 2011 future, the capacity effect amounts to 3.9 GW.

Figure 7 shows the development of the capacity effect for different directly affected electricity futures over time. Each line in the graphs represents the capacity effect in comparison to a different day before the moratorium. On Monday, 14 March 2011, the first trading day after the Fukushima events,

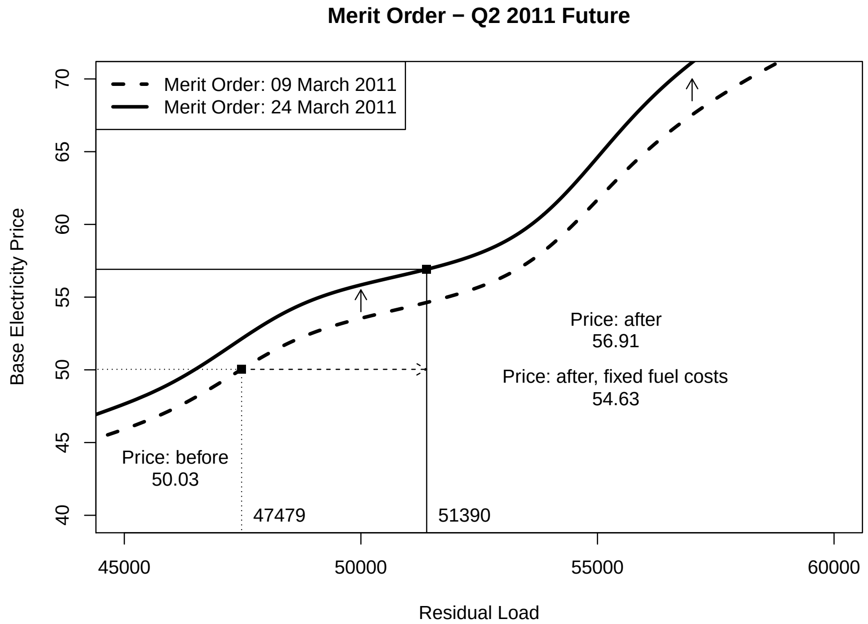

Figure 6: Shift of the merit order due to the moratorium

the prices of both the fuel and electricity 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. Figure 8 shows the

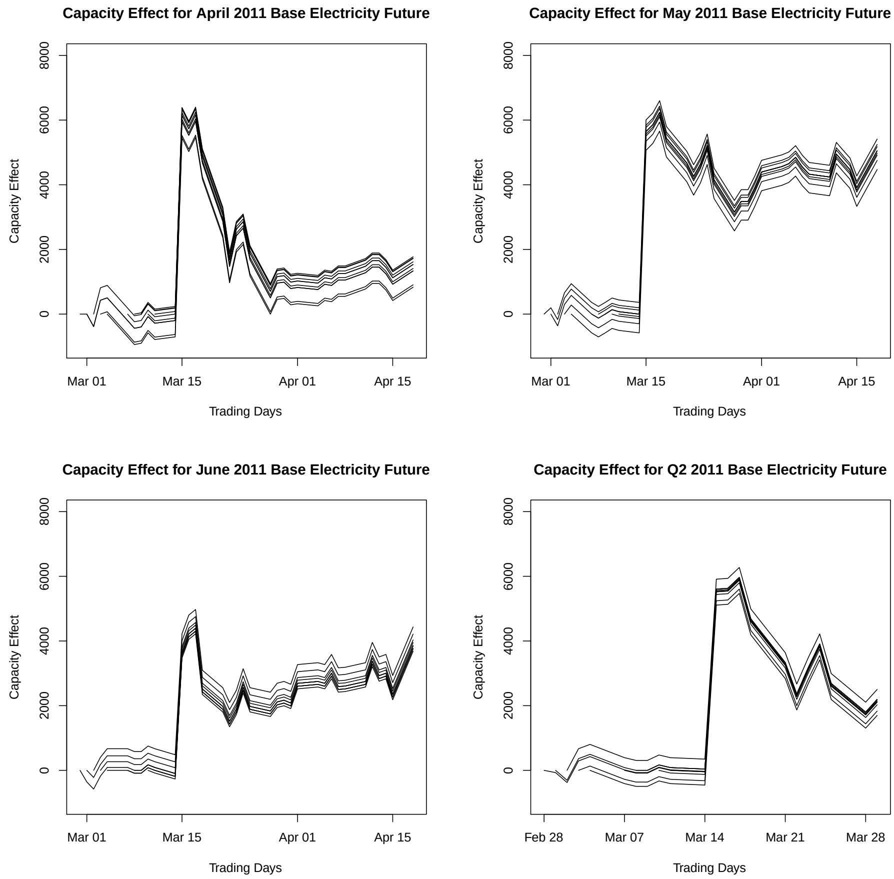

Figure 7: Capacity effect for monthly and quarterly base electricity futures with delivery during the moratorium

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.

Some of the observed effects might also be driven by the well-known Samuelson effect (1965) that commodity futures with a longer time to maturity are less volatile. In this case, both the electricity and fuel futures for 2012 and 2013 react less to new information than futures for 2011. However, in the model described above, the ratio of electricity price change versus fuel price change is relevant when calculating the intersections for the capacity effect. As long as the Samuelson effect is similar for the commodities concerned, there is no bias introduced by analyzing futures with different times to maturities.

Generally, the capacity effect for futures with delivery during and after the moratorium is rather similar. Thus, there is an impact that is expected to be permanent. It is difficult to quantify the 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. However, one can still conclude that the market on average expects several nuclear power plants to remain closed down after the moratorium.

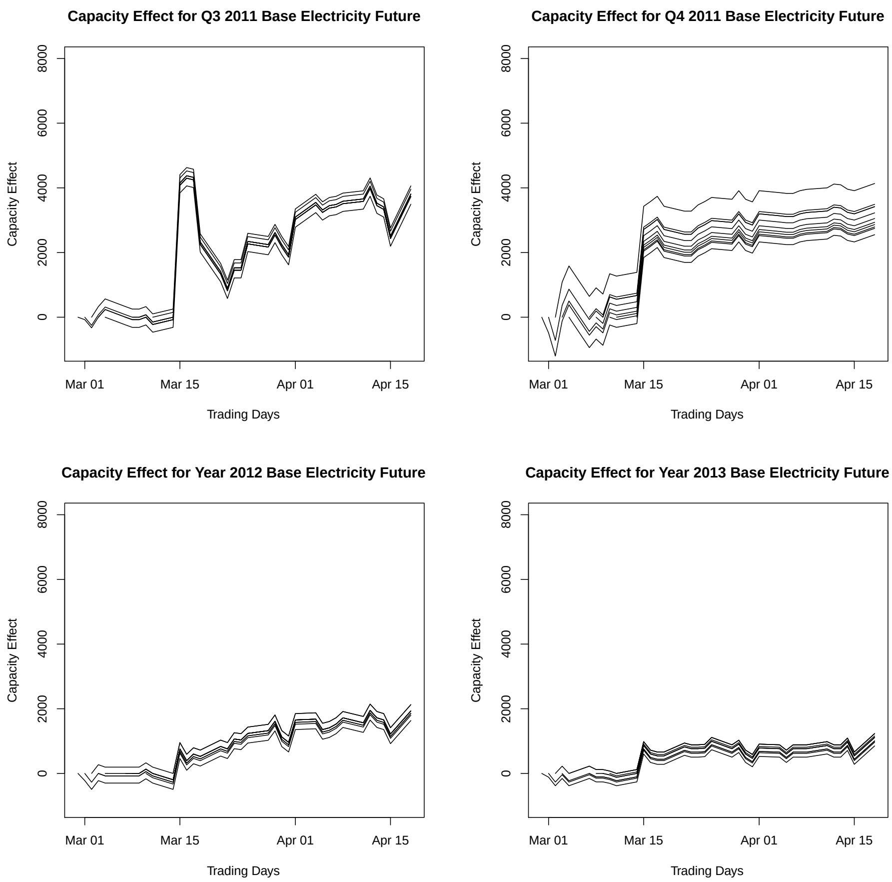

Figure 8: Capacity effect for base electricity futures with delivery after the moratorium

7 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 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 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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