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A PARSIMONIOUS FUNDAMENTAL MODEL FOR WHOLESALE ELECTRICITY MARKETS - ANALYSIS OF THE PLUNGE IN GERMAN FUTURES PRICES

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A parsimonious fundamental model for wholesale electricity markets - Analysis of the plunge in German futures prices

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ABSTRACT

The German market has seen a plunge in wholesale electricity prices from 2007 until 2014, when base futures prices dropped by more than 40 percent. In this paper we determine the fundamental components of electricity futures prices and quantify their impact on the price drop as well as on operation margins. Our methodology is based on a parsimonious model in which the supply stack is approximated by piecewise linear functions. A fundamental futures price estimate can then be given by averaging up the hourly equilibrium prices over the futures contract's delivery period. It turns out that the parsimonious model is able to replicate electricity futures prices and discover non-linear dependencies in futures price formation. We quantify which of the factors fuel prices, emission prices, renewable feed-in, conventional generation capacities, and demand developments contributed most to the observed price slide.

KEYWORDS

Futures Prices, Bid Stack, Fundamental Factors, German Electricity Market, Price Modeling, Efficient Markets, Market Expectations, Piecewise Linear Function, Investment Decision

INTRODUCTION

Capacity planning in competitive electricity markets is a challenging task especially when no capacity markets are in place. Optimal decisions depend on directly observable factors such as commodity prices and available power plant technologies, but also on uncertain and vague future prospects such as political and socio-economic developments. German power plant operators have experienced this at their expense, since the large investment boom in the years 2006 to 2008 has been followed by a drop of wholesale market prices by almost 40 percent. The prices of Phelix Base Year Futures contracts for the year 2014 with delivery in Germany was quoted at 61 EUR/MWh at the end of 2007 and dropped to almost 37 EUR/MWh by the year 2013. By presuming efficient capital markets, all available information and market participants' expectations are included in the futures market prices. Frequently in the public and political debate the futures price slide is attributed to the unexpected increase in renewable generation due to excessive subsidies. The impact of increasing production from renewable energy sources (RES) on electricity market prices is discussed extensively in the academic literature. Among others by [1], [2] or [3] for the German market, by [4] for the Spanish Market or [5] for the Danish Market. Yet most of these works focus rather on implications for spot price pattern in general, without empirical verification of the theoretically derived results. Besides the increasing RES, essentially originated by the Renewable Energy Act, a number of political decisions are affecting the German energy market, notably the European Union Emissions Trading System (EU ETS), established in 2005 and the nuclear phase-out. The mandated phase-out is a result of decades of controversial public discussions and the events around the nuclear accident in Fukushima in 2011. Another relevant development in light of electricity price formation over the period from 2007 to 2013 in Germany are the increasing

efforts across Europe to advance international energy trading. The target is to harmonize European electricity prices and reduce grid congestions by use of market coupling, eventually flow-based.
The focus of the present paper is to investigate to what extent the unanticipated growth in renewable generation and other fundamental drivers explain the price drop in German electricity prices between 2007 and 2013. We thereby focus on electricity futures prices to abstract from the stochastics of actual realizations of renewable infeed and demand. An appropriate methodology for this purpose has to provide accurate forecasts of electricity futures prices based on market data and other publicly available information. A method that functions with only a parsimonious number of input parameters is favorable since it reduces the number of assumptions regarding market expectations and keeps the results interpretable. At the same time such a parsimonious model may be used for further purposes such as valuating derivatives, including power plant assets treated as real options.

In this context, a related steam of research is the analysis of risk premia in electricity futures markets, e. g. [6], [7], [8]. Analyses about risk premia usually do not explicitly focus on delivering price estimates but on reproducing and interpreting the price markups in futures prices that are attributable to risk aversion of market participants. In this literature stream, the difference between fundamental price estimates and actual prices is interpreted as a risk premium. Considering the huge price changes observed in the market over the last decade, the focus of the present paper is rather put on replicating these price changes as driven by fundamental factors, than on estimating risk premia which we believe to be an order of magnitude smaller than the fundamental price changes.
Our modeling approach belongs to the general class of equilibrium models. We abstract from behavioral aspects and aim to model the prices as the results of a market mechanism which intercepts aggregate supply and demand functions. Fundamental information, e. g. power plant capacities, are incorporated to model the supply and demand side. The inclusion of such fundamental information is particularly advantageous when price developments over longer time spans are investigated. Additionally the modeling of the supply curve accounts for non-linearities in the formation of energy prices, which is especially relevant for the German electricity market with its heterogeneous supply. Classical, so called *parameter-rich fundamental models* (cf. [9]) are based on a detailed representation of the supply stack and employ complex optimization routines. E. g. [10–12] present applications for such models to the German electricity market, but primarily focus on the identification of strategic behavior and price mark-ups. The major drawbacks of parameter-rich fundamental modeling approaches are a high complexity as well as computational burden and significant data requirements. In contrast, our methodology aims to avoid a detailed representation of the supply stack and find a reasonable approximation with only a parsimonious number of inputs and assumptions. Among others, [13] refer to models that – with varying degree of detail and complexity – explicitly approximate the supply curve with the adjective ‘structural’. Usually fundamental modeling approaches work with the assumption of companies bids being equal to the variable costs of power production. The bid curve is then represented by the ordered costs of production. In this sense the term bid curve is synonymous to supply stack, supply curve or merit order curve.
Within the class of *structural approaches* used to forecast electricity prices, different representations of the bid stack exist. One of the first examples is [14], who uses a fixed parametric function. Later works consider dependencies of the bid stack e. g. on available capacity [15] and on fuel prices, including emission costs [13, 16–19]. The inclusion of dependencies on capacities and on fuel prices allow insights into the causal relations of electricity price formation. The mentioned approaches for the bid stack usually utilize simplifying assumptions,

e. g. constant heat rates per fuel type [16], or [18] cluster the bids from each technology. The authors of the latter represent the bid stack as an inverse cumulative distribution function and link the parameters of different distributions to fuel prices. This procedure implies different heat rates for different generating units in the market, e. g. older generation units. [13] propose to model the stack structure as a piecewise exponential function that allows to approximate the heterogeneity of generator efficiencies per fuel type. This approach allows to accounts for possible future changes in the order of the supply stack. The approach presented in this paper uses an approximation of the supply curve by a piecewise linear function which can be calibrated based on weak assumptions on efficiencies per fuel type.

The contribution of the article at hand has thus three main dimensions: (I) The introduction of a fundamental modeling approach approximating the supply curve with piecewise linear segments that works with parsimonious assumptions and inputs. (II) The use of this model in a case study for Germany that presumably is the first systematic analysis of fundamental influences driving the drop in wholesale electricity markets prices between 2007 and 2014. Contrarily to other recent works, we do not focus exclusively on the analysis of the impact of renewables but quantify the impact of several fundamental factors on the electricity price development. (III) Assessing the operation margins of generation technologies, we additionally identify the major misjudgments of companies during the 2006 to 2008 investment hype.
The article is structured as follows. Chapter 2 describes the modeling approach and its mathematical formulation. Chapter 3 describes the input data and the validation of the model. Chapter 4 uses the model to analyze the drop in wholesale electricity prices in Germany and discusses the results. Chapter 5 delivers a conclusion and an outlook to further research perspectives.

METHODOLOGY

Our modeling approach bases on the assumption of efficient futures markets in line with [20]. Applying the martingale property - valid under risk neutrality and thus neglecting the possible impact of risk aversion - we use expected spot prices to derive fundamental expectations on futures prices. More precisely, since electricity futures contracts are unconditional contracts on electricity deliveries within a period T_1 until T_2, the futures price F_{t,T_1,T_2} equals to the average of the expected spot prices S_T over the same period under the information I_t available at time t. The actual market delivers prices for discrete (hourly) price intervals, as does our parsimonious fundamental model. Hence our estimate for the futures price is given by:

$$F_{t,T_1,T_2} = \frac{1}{T_2 - T_1} \sum_{T=T_1}^{T_2} E[S_T | I_t] \quad (1)$$

Future price changes can only occur in that model if the expected spot prices change. Price volatility consequently only results from changed information and expectations. Differences between expected and actual futures price may then be attributed to differences between expectations and realizations as well as fundamental factors that are not included in the model, e. g. fixed costs, or other factors like risk aversion, behavioral aspects et cetera.

In the following the model of the electricity spot market is defined. In general terms, the spot price of electricity S_t at time period $t \in T$ is a function of time-varying, uncertain fundamental factors $S_T = f(x_{i,t}, K_{i,t}, L_t, \ldots)$, such as prices of fuels and carbon emissions x_t , available generation capacities K_t , or the residual load L_t. Commonly structural fundamental models determine the market price as the equilibrium between supply and demand, e. g. [14] or [13]. These approaches reflect the market mechanisms of generators submitting bids to a central market operator. The market operator aggregates the bids to a bid curve sorted in increasing order. Intersecting the bid stack with the (residual) demand yields a fundamentally estimated spot price of electricity for each time period observed.

We model a number of conventional production technologies $i \in I$, such as lignite, coal, and gas, which can be used to produce electricity by converting fuels into power. Each technology has an associated fuel whose price is given by $x_{i,t}$. Technologies are further defined by an emission factor ε_i representing their fuel's carbon intensity and their thermal efficiency η_i. In addition, operation and maintenance costs are given by $c_{i,other}$ for each technology. The variable production costs are calculated by the formula given in (2).

$$c_i = \frac{x_{i,t} + \varepsilon_i \cdot x_{CO2,t}}{\eta_i} + c_{i,other} \tag{2}$$

In order to account for differences in plant age, retrofitting activities, and other factors, we define the heat rate (inverse efficiency) of each technology as a linear function over the installed capacities of this technology, i.e. $\eta_i \in (\eta_{i,min}, \eta_{i,max})$. The highest efficiency $\eta_{i,max}$ represents the most efficient, state-of-the-art generation plant whereas $\eta_{i,min}$ reflects the least efficient plant in the market. The production costs of each technology are thus described as a range $c_i \in (c_{i,min}, c_{i,max})$. Following from the assumption of cost-based bids, the individual bidding function $b_{i,t}$ for each technology i is then a monotonous piecewise linear function increasing in S_t. The capacity which is available to the market is the total installed capacity $K_{i,total}$ reduced by must-run capacity $K_{i,t,CHP}$. The total capacity is adjusted by an availability factor $\upsilon_{i,t}$, which is a relative measure for scheduled, e. g. maintenance, and unscheduled unavailabilities, e. g. outages. Must-run capacities notably result from combined heat and power production (CHP). Due to heating demand constraints, the operation of CHP units is at least partly independent of market prices. This production is consequently also subtracted from demand.

$$K_{i,t} = K_{i,total} \cdot \upsilon_{i,t} - K_{i,t,CHP} \tag{3}$$

For the bidding quantity $b_{i,t}$ given spot price S_t we then have:

$$b_{i,t}(S_t) = \begin{cases} 0 & , \quad S_t < c_{i,min} \\ K_{i,t} \cdot \dfrac{S_t - c_{i,min}}{c_{i,max} - c_{i,min}} & , \quad c_{i,min} < S_t < c_{i,max} \\ K_{i,t} & , \quad S_t > c_{i,max} \end{cases} \tag{4}$$

The aggregated bidding function b is the sum of the individual technologies' bidding functions b_i. The sum of continuous monotonous piecewise linear functions retains these properties, hence b is likewise piecewise linear, continuous, and monotonous.

$$b = \sum_{i=1}^{I} b_i \tag{5}$$

While the bidding functions b and b_i describe a relation of offered capacity dependent on the electricity price, the bid stack B gives the electricity spot price on a given demand. Thus we define B as the inverse of b. B is a monotonous piecewise linear function, however it is not necessarily continuous.

$$B = b^{-1} \tag{6}$$

The residual load D_t is the demand for electricity L_t reduced by fluctuating renewable energy production of wind W_t and photovoltaics P_t, power supplied by must-run generators $K_{t,CHP}$ and the net imports (FTB_t: foreign trade balance). Fluctuating renewable energy sources have marginal production costs of zero. The electricity supplied by such sources is thus used with priority and may be directly subtracted from demand. The same holds for CHP must-run capacities, which are forced by heat demand restrictions to produce electricity. Their electricity production is bid at minimum price to ensure its use independent of market conditions. Given interconnections between electricity grids of different regions, imports and exports have to be considered. Taking the foreign trade balance FTB_t as given, it is subtracted in Eq. (7) in order to obtain the domestic electricity demand that has to be produced in the modeled region.

$$D_t = L_t - W_t - P_t + FTB_t - \sum_I K_{i,t,CHP} \tag{7}$$

For practical applications, the net imports have to be estimated as a function of exogenous quantities like renewable infeed and demand, in order to allow application of the model outside historical spot prices. The approach applied here is detailed in the subchapter 'Data'. Subsequently, the electricity spot price at time t is then given by the marginal costs at the intersect between supply and demand $S_t = B(D_t)$.

The piecewise linear bid stack described above can be used to derive further properties of electricity prices. The bid stack consist of a number of segments $m \in M$. Due to the monotonicity of the bid stack, each segment is defined by an electricity price interval $\left(S_{m,min}, S_{m,max}\right)$ and a corresponding load interval $\left(D_{m,min}, D_{m,max}\right)$. This relationship is bijective, making the segments disjoint in demand and price. For the analysis of futures prices, we define the absolute frequency H_m, which represents the number of times $t \in T$ at which load D_t falls into a certain demand interval $\left(D_{m,min}, D_{m,max}\right)$. Dividing H_m by T yields the relative frequency h_m,

$$h_m = \frac{1}{T} \sum_t \mathbf{1}_{D_t \epsilon \left(D_{m,min}, D_{m,max}\right)} \tag{8}$$

For each segment m, one or several of the technologies $i \in I$ are setting the price if their marginal production costs fall into the interval's price range. This is the case if and only if $\left(S_{m,min}, S_{m,max}\right) \subseteq \left(c_{i,min}, c_{i,max}\right)$. We define I_m as the subset of technologies I which are price-setting in m. The property implies that when the production costs of such a technology change, so does the price range of segment m. If more than one technology is setting the price, the impact is divided by their number $|I_m|$. $\eta_{i,m}$ corresponds to the mean efficiency of technology i in segment m. With these definitions, the electricity futures price $F_{t,T1,T2}$ appear as follows.

$$F_{t,T1,T2} = E\left[\sum_{m \in M} \sum_{i \in I_m} \left(h_m \cdot \left(\frac{x_i + \varepsilon_i \cdot x_{CO2}}{\eta_{i,m}} + c_{i,other}\right) \cdot \frac{\mathbf{1}_{i \in I_m}}{|I_m|}\right)\right] \tag{9}$$

APPLICATION

Data

For reliable simulation results, the model requires accurate and consistent input data. The data for the developed model is collected from the sources indicated in Table 1. The Table also provides an overview how the expectations for future years are determined.

Table 1. Data sources

Data	*Source*	*Specification*	*Expectations*
Load	entsoe.eu	Hourly load values	Adjusted historic Profile
Demand	iea.org/statistics	Energy Supplied	Extrapolation
Electricity Price	energate.de	Phelix Futures Base	Corresponding futures price
Coal Price	dito	API#2 (CIF ARA)	dito or last quoted product
CO_2	dito	EU Allowances (EUA)	dito
Gas price	dito	Gas-TTF	dito
Wind and Solar	eex-transparency.com	Ex-ante production	Profiles, Netztransparenz.de
Unavailability's	dito	Non-usability	Extrapolation
Cross Boarder Flow	transparency.entsoe.eu	Commercial Schedule	Regression analysis
Capacities	bmwi.de	Production capacities	BMU Leitstudie[1]
CHP production	dito	Electricity production	Extrapolate historic pattern

The expectations for *commodity price* are based on the relevant futures products for the German market, e. g. API#2 for coal or TTF for gas and equals to the average of the contract prices observed in the last three month (previous quarter), e. g. the price expectation for 2008 corresponds to the average of the API#2 cal-2008 prices between 1th of October 2007 and 31th of December 2007.[2] The corresponding yearly aggregated data is given in Table 2.

Table 2. Input data overview (*Mean Front-year prices)

Information basis Expectations for:	***Actual 2008***	***Actual 2013***	***Q4-2007 2008***	***Q4 2007 2014***	***Q4 2012 2013***	***Q4 2013 2014***	***Unit***
Demand	613.5	582.6	620.6	643.8	597.2	603.7	TWh
Solar	4.7	30.3	2.9	5.9	34.5	36.6	TWh
Wind	37.3	48.5	35.8	53.9	53.0	56.3	TWh
Coal Price	8.91*	14.14*	11,18	10,19	14,01	8,70	€/MWh
Gas Price	16.26*	27.48*	25,74	27,31	29,80	29,37	€/MWh
EAU	19.58*	7.94*	22,41	24,92	7,65	4,90	€/t

Table 3 shows the expectations concerning the *capacities* and the *technical parameters* used for the approximation of the bid stack. Due to significant differences in the efficiencies of gas-fired power plants we distinguish open-cycle (OC) and combined-cycle gas (CC) power plants. The capacities are adjusted to account for planned and unscheduled *non-usability* of conventional power plants. Based on historical non-usability data, availability factors for the major conventional power plants are calculated as quotient between unavailable and installed capacities [21]. The availabilities show yearly, weekly and daily cycles. The expected non-

[1] Myopic expectations have also been tested but do not affect the results strongly.

[2] To find longer term expectations and overcome the data limitations for contracts far away from deliver time, we took the first (up to 10) days from the following year as approximation for the expectations.

availabilities are created by extrapolating those cycles from historical data (see Appendix, Figure 1).

Table 3. Actual and expected Capacities in GW and Technical Parameters

Information basis *Expectations for:*	*Actual* *2008*	*Actual* *2013*	*Q4 2007* *2008*	*Q4 2007* *2014*	*Q4 2012* *2013*	*Q4 2013* *2014*	*Min* η_i	*Max* η_i	$c_{i,other}$ *€/MWh*
Run-of-river hydro	5.4	5.6	4.8	5.0	5.7	5.6	-	-	0
Biomass	3.9	6.4	3.4	5.2	6.2	6.4	-	-	0
Nuclear[3]	21.6	12.1	21.5	12.7	12.7	12.1	33%	36%	0.50
Lignite	22.4	23.1	22.7	21.5	24.2	23.1	29%	43%	2.00
Coal	29.6	29.2	31.1	29.5	29.8	29.2	32%	46%	2.50
PSHP [4]	4.7	4.7	4.7	4.7	4.7	4.7	75%	80%	0.40
Gas (CC)	18.2	22.2	20.1	26.0	21.8	22.2	40%	60%	1.20
Gas (OC)	4.6	4.6	5.1	5.1	4.6	4.6	25%	36%	1.20
Oil	5.4	2.9	4.1	4.1	4.2	2.9	24%	44%	1.20
Miscellaneous[5]	5.6	7.6	3.1	3.3	6.6	7.6	-	-	-
Sum	**121.3**	**118.3**	**120.6**	**117.1**	**120.4**	**118.3**	**-**	**-**	**-**

The yearly electricity production from *must-run CHP* is distributed over the year based on typical average heating-degree profile, since must-run CHP production is largely driven by heating demand, which in turn is temperature-dependent [21].

The *hourly load values* are the average absorbed energy from installations connected to the distribution and transmission grid. Those values do not represent the overall demand, e. g. "(…) industry's own production for own consumption and some parts of German railways are not included (…) as well as grid losses" [22]. Physical fundamentals require the consumption and grid losses to be equal to the electricity production at any point in time. Therefore the hourly load values are scaled to the electricity produced per month according to IEA statistics. The scaling is partly additive to represent a base load consumption from e. g. self-consumption of industry and partly quadratic for the amount of grid losses.[6] Yet under the assumption of adaptive expectation formation, the expectations about *future demand* may be derived from historical data as follows: We calculate the average growth rate from the yearly IEA data of the previous three years (see [23]). This growth rate is used to extrapolate the current annual demand to a future value, which is then used to calibrate a historical load profile.

Historical hourly profiles are also used for the *renewable feed-in* from wind and solar power generation facilities. The annual quantities for the expected wind and solar power production are taken from the midterm forecasts of the German TSOs (cf. from see Table 1). The use of historical hourly profiles allows to capture the short-term variations in load and feed-in without setting up detailed stochastic models. This is obviously only valid if the historical profile

[3]For 2007, the capacity expectations reflect the state of information after the first nuclear phase-out decision from 2002. They do not reflect market actors potentially anticipating the 2010 decision to extend nuclear plant lifetimes. By 2012/2013, the events around the Fukushima accident had led to a repeal of the lifetime extension and an accelerated nuclear phase-out, which is reflected in the expectations.

[4]Pumped-storage hydro plants are modeled as generation technology which is fuelled at the variable costs of coal plants (lower) and open cycle gas (upper bound). Thus the opportunity costs of pumping and turbine are based on the implicit assumption that pump storages are partly filled during times where different base load plants are price setting. We also abstract from modeling reservoirs and assume dispatch to be driven by market prices.

[5]Miscellaneous capacity includes multi-fuel fired plants that cannot be assigned unambiguously to one fuel type (e. g. mix of oil and coal), waste and small proportions of marsh gas, landfill gas, sewage, and other fossil plants. The fuel prices for Miscellaneous are assumed to equal the mean prices for coal, gas and oil power plants.

[6]$L_t = L_t^{entsoe} + \frac{L^{iea} - \sum_{i=1}^{T} L_i^{entsoe} - G^{iea}}{T} + \frac{G^{iea}}{\sum_{i=1}^{T} {L_i^{entsoe}}^2} \cdot {L_t^{entsoe}}^2$ (G: Grid losses, L: Demand $\neq D$ residual Demand)

provides a representative sample. Since the historical sample consists of 8760 hourly values, this should generally be the case.

To the best of our knowledge no long-term expectations for *cross-border trading* activities are available. From a market perspective, cross-border trading depends on the price level difference between the respective countries. Since our analysis aims to forecast prices, cross-border trading cannot be based on electricity price expectations. Therefore we employ a regression analysis in order to derive expectations about cross border flows from German market fundamentals. Higher exports are expected during times of high renewable feed-in, low demand and/or high base load plant availabilities in the exporting county:

$$FTB_t = \beta_0 + \beta_1 L_t + \beta_2 P_t + \beta_3 W_t + \beta_4 \upsilon_t^{lignite} + \beta_5 \upsilon_t^{nuclear} + r_t \tag{10}$$

The multiple regression analysis identifies significant influences from wind W_t and solar infeed P_t, load level L_t and the availability of base load plants - nuclear and lignite - υ_t .

Table 4. Regression results for Foreign Trade Balance based on Data from 2012-13[7]

$\boldsymbol{\beta_0}$	Intercept	-15814.188***	Multiple correlation coeff.	0.7180
$\boldsymbol{\beta_1}$	Demand [MW]	-0.087***	R-squared	0.5156
$\boldsymbol{\beta_2}$	Solar [MW]	0.348***	Adjusted R-squared	0.5154
$\boldsymbol{\beta_3}$	Wind [MW]	0.366***	S.D. dependent var	2500.8419
$\boldsymbol{\beta_4}$	Available Lignite [%]	142.466***	Observations	17544
$\boldsymbol{\beta_5}$	Available Nuclear [%]	105.014***		

R-squared determines the explained variance of FTB by the regression equation.
The multiple correlation coefficient is equal to the square root of R-squared, thus the correlation between FTB and the linear regression estimates that includes an intercept $\beta_0 + \beta_1 L + \cdots$, see Eq. (10).
Significances are computed using standard errors obtained through the Newey-West procedure
Significances at the 0.01 level are labeled with (***), 0.05 level with (**) and 0.1 level with (*).

Model Validation

In the first step the model is validated to ensure that the results from the model are capable to replicate observed futures prices. Therefore we run the model for historic years based on information (expectations) from different years and compare the results with the actual Phelix Base Load Future prices for the corresponding product. Table 5 sums up the results.

Table 5. Annual base price estimates using the fundamental model and actual futures prices

Information basis *Expectations for:*	*Q4 2007* *2008*	*Q4 2007* *2014*	*Q4 2012* *2013*	*Q4 2013* *2014*	
Fund Price	61.28	63.42	46.84	36.13	EUR/MWh
Phelix Base Future	60.05	61.30	46.55	37.64	EUR/MWh

In absolute terms, the fundamental model is able to replicate the observed market prices, implying that expectations about fundamental factors drive electricity futures prices to a large extend. Except the front-year contract 2014 all simulated prices exceed the historical values by 1-2 Euros.[8] An assessment of the input data shows a sharp drop in fuel prices which may not have been fully reflected in electricity prices. Additionally the expectations concerning the

[7] Due to data availability reasons, the regression analysis is based on cross border flows from 2012 until 2013.
[8] Results for additional years irrelevant for the following analyses are not stated in the table but lie on similar levels between 1 and 2 EUR/MWh absolute difference between the observed and predicted prices.

annual electricity demand 2014 are considerably lower in 2013 compared to earlier years. As described in the previous chapter, measures for the load data are subject to statistical inaccuracy and load is typically difficult to predict. At the same time the expected electricity demand has a considerable impact on market prices. Therefore we compute a sensitivity of the fundamental prices with respect to changed assumptions on demand expectations. Based on data from 1990 until 2013, the year-ahead uncertainty in annual electricity demand is calculated as the standard deviation of the difference between year-ahead expected and actual demand. This demand uncertainty is found to be approximately 2.5 percent of annual demand which is similar e.g. to the results by [23]. Table 6 reports two sensitivity runs with demand expectations modified by one standard deviation of the forecast error (i.e. 2.5 percent) up and down. This leads to price variations in the order of +/- 2 EUR/MWh. Hence the fundamental model is able to replicate the observed futures prices up to the uncertainty range caused by demand uncertainty.

Table 6. Base price expectations under varying electricity demand expectations

Information basis *Expectations for:*	*Q4 2007* *2008*	*Q4 2007* *2014*	*Q4 2012* *2013*	*Q4 2013* *2014*	
Fund Price low demand	59.50	61.58	45.40	34.14	EUR/MWh
Fund Price high demand	63.33	65.51	48.27	38.18	EUR/MWh

CASE STUDY

Results

Our investigation of the German electricity futures prices from 2007 to 2014 aims to explain the price drop by use of the previously introduced fundamental bid stack model. Therefore we investigate a number of fundamental factors and determine their contribution to the price drop. To do so, we use the market expectations from 2007 and successively update each factor separately to the value of its 2013 expectation. In that way we can identify how each factor influences the base price level under ceteris paribus conditions. Table 7 shows the results.

Table 7: Results of the price plunge investigation

	Year 2014	*Absolute Change*	*Relative Change*
Phelix Base Futures in Q4 2007	61,30		
Fundamental Price (Expt. Q4 2007)	63,42		
Updated Expectations to Q4 2013			
Load	59,19	-4,23	-6.70%
RES	60,39	-3,03	-4.80%
Fuel Prices	60,63	-2,79	-4.40%
EUA Price	49,16	-14,26	-22.50%
Capacities	63,89	+0,47	0.70%
All = Fund. Price (with Expt. Q4 2013)	36,13	-27,29	-43.00%
Phelix Base Futures in Q4 2013	37,64	-23,66	-38.60%

Based on expectations from Q4 2007, our model yields an expected 2014 futures base price of 63.42 EUR/MWh, while our model predicts a fundamental price of 36.13 EUR/MWh based on expectation from Q4 2013. This represents a fundamental price reduction by 27.29 EUR/MWh. In contrast the actual observable reduction in the cal-2014 futures price equals

23.66 EUR/MWh. Thus the model predictions exceed the actual price drop by about 15 percent. Given the long time to maturity for the initial price expectations and the number of simplifications this remains a remarkable accuracy.
To derive the impact of expectation changes, we separately update the following fundamental factors: demand, renewable infeed, fuel prices except emissions, carbon certificates, and conventional capacities. These factors together represent all the expectations for the demand and the supply side included in the fundamental model. The results indicate that the change in price of carbon emissions has the largest impact, as it reduces the electricity futures base price by 14.24 EUR/MWh. The second and third largest impacts come from demand and renewable infeed, adding up to a combined effect of 7.26 EUR/MWh. Fuel price developments except carbon contribute 2.79 EUR/MWh, while changed expectations regarding conventional capacities actually induce a slightly higher electricity price – this is at least partly due to the revised German nuclear phase-out after the Fukushima catastrophe. The sum of these individual impacts is 23.84 EUR/MWh. This number is lower than the combined impact of 27.29 EUR/MWh when all factors are updated simultaneously to the new information basis. This result implies the presence of non-linear superposition effects, notably between the drop in residual demand and the drop in carbon prices. The former makes hard coal and lignite more frequently the marginal fuel while the latter affects particularly the variable costs of these technologies.
In addition to the development in power prices, the impact of these developments on the *profitability of conventional generators* is also of interest –in particular for an ex-post assessment of the investment decisions taken in the 2006 to 2008 period. Notably an investor is not affected by a plunge in electricity prices if his input factor costs are simultaneously reduced and the operation margin of the power plant remains unaffected. We therefore investigate the development of the operation margins of the modeled technologies. We disregard again restrictions regarding ramping and other operating constraints in line with the assumptions of the parsimonious price model.[9] Since the focus is on new investments, we consider for each technology the plants with maximum efficiency. The results are given in Table 8.

Table 8. Results for expected operation margins (OP) for the year 2014 (new power plants)

Tech Type	**OP [€/MW]**	**Reduction 2007-2013 [%]**					
	2007-2008	Total	Load	RES	Capacities	EUA	Fuel_non_EUA
Nuclear	498.122	-48%	-7%	-5%	-5%	-25%	1%
Lignite	190.621	-31%	-15%	-11%	-10%	15%	2%
Hard Coal	115.751	-44%	-21%	-15%	-14%	3%	18%
Gas (CC)	34.488	-86%	-38%	-29%	-25%	-25%	-4%
Gas (OC)	247	-100%	-95%	-63%	-79%	-42%	-14%

The operation margins in 2007 decrease from base- to peak-load technologies – as expected, given that capital expenditures are higher for base technologies. Nuclear and lignite power plants are able to earn respectable six-figure operating margins per MW, while Gas (OC) rarely operates even under these comparatively high electricity prices. By 2013, the margins of all technologies drop by 31 to 100 percent.

The analysis of the impact from single factors (information updates) shows differences between the impact on profitability and on electricity prices. The drop in carbon prices from

[9] Without doubt, the operating constraints reduce the achievable operating margins, but their impact should not vary extremely over the time span considered. Since increased renewable feed-in makes the residual demand more volatile, the impact of operating constraints on profitability has more likely increased than decreased.

2007 to 2013 actually increases profitability for emission-intensive lignite plants significantly. Hard coal additionally profits from a price slide on the steam coal market. Other base load plants, notably nuclear and lignite, slightly gain from increased gas prices. Here the fundamental model highlights how their production spread benefits from gas price increases whenever gas-fired plants are the price-setting technology. The developments regarding residual demand, i.e. decreased load and increased renewable infeed expectations, hurt all plants significantly. The effect is larger for mid- and peak-load plants, who are pushed out of the supply stack in some hours of the year by what is known as the merit-order effect [2]. Similarly, the addition of base load generation capacities between the simulated years (despite the accelerated nuclear phase out) decreases profits for all plants due to lowering effects on electricity base prices. Comparing the total effects with the sum of the single factor impacts indicates that there are strong non-linear effects affecting the operation margins. E.g. hard coal plants lose 44 percent of their operation margins when all effects are considered simultaneously, whereas the (hypothetical) sum of individual effects adds up to minus 19 percent. This is especially due to the super-additive of the quantity effects of load, RES and capacity changes. All factors individually reduce the hours where expensive technologies like Gas (OC) set the prices. Taken together, hardly any hours with high prices remain and operating margins collapse.

Discussion

The analysis of the drop in German electricity base futures prices indicates a strong influence of fundamental factors. With our parsimonious fundamental model, we are able to replicate the changes in expectations observed in the futures market. The investigation of the individual fundamental factors indicates different levels of impact, while the sum of the single impacts is lower than their combined effect. This implies a super-additive relationship which may be attributable to the non-linear structure of the bid stack. Depending on the residual load level, the price-setting technology may change, and hence a shift in a certain fuel's price can have a large, small, or non-existent impact on electricity prices. The same argument with a somewhat different twist holds for changes regarding load and RES feed-in, whose price impact especially depend on the change in probabilities for residual load being located in steep parts of the bid stack.

Contrarily to previous works, (e. g. [2] or [3]), who focus solely on the integration of RES, our results indicate that while RES play an important role, they are not the largest driver of falling electricity prices in German. The model results show that emission prices are quantitatively the most important driver of the futures electricity price in Germany between 2007 and 2013. This can be explained by the fact that emission prices impact the production costs of most conventional power plants, which results in changes of the supply stack's shape in most intervals. Recently [24] quantified the impact on electricity prices in Germany between 2006 and 2010 if no emission trading system or renewable energy support schemes were in place. The authors rather focus on the quantity reduction of emissions then on price effects and found a positive interaction effect for the German electricity market between higher RES injection and lower CO2 Emissions. A valid question in this context is whether the measurable impact of emission prices on electricity prices (as found in the present work) may interact with RES additions, as investigated by, e. g.[1], [25] or [26]. Their analysis into the interactions between RES support and emission trading supports the argument that additional RES feed-in substitutes electricity from fossil fuels and thus reduces the demand for emission certificates, which in turn leads to decreasing emission prices. Bases on a scenario analysis in an simulation model [25] state a likely significant effects from RES deployment an Allowance prices for the EU 12 Member states. The authors found a maximum reduction of emission prices due to RES injection in 2007 by 15 EUR/tCO_2 up to 100 EUR/tCO_2 in 2010. In an ex post analysis [26] try to explain the price decline of EU allowances from 30 EUR/tCO_2 in

2008 to less than 5 EUR/tCO_2 in 2013. Their key result is that 90 percent of the emission price variation remains unexplained. The extent to which RES deployment reinforces the emission prices plunge is empirically limited by around 2.3 percent of the total price variation. In contrast to simulation based investigations of interaction effects between RES feed-in and emission prices the empirical ex post analysis implicate only moderate influence. In line with the latter results we believe that RES capacity additions in Germany are from minor importance for emission prices, concluding that the measurable effects from CO_2 found in this paper are not altered by the mentioned interaction effects between RES additions and emission prices.

Compared the previously discussed factors, changes in the capacities of conventional power plants are of minor importance for the drop in electricity base prices. The reinforced linkage between European countries (market coupling) and convergence of individual electricity markets towards a European Single Market may explain why capacity scarcity is no serious threat for the intermediate future. However, this can partly be attributed to the fact that the German electricity market is currently characterized by overcapacities. The regional distribution of demand and contested grid extensions, which our model does not consider, may nevertheless create necessities for capacity extensions in certain areas.[10]

To complete the discussion about the impact factors, our analysis highlights the uncertainties regarding the load and their impact on futures prices. While the impact on the overall electricity price level is limited, its high influence on operation margins makes it an important factor to consider for market participants. Our analysis finds demand as the largest single impact factor on profitability. We assess that market participants should be aware of this uncertainty and its implications, since current policy goals could focus efforts on energy efficiency investments, which would have a depressing effect on the total load level.

A wide range of additional potential factors can explain changes in market participant's expectations and thus the drop in wholesale electricity prices. A related work with a more general scope is done by [29], who conducts a qualitative analysis about the German 'dash for coal'. In addition to fundamental factors, the author discusses further factors, e. g. technological developments, political decisions or public acceptance that can generally influence expectations of energy market participants. In the light of additional explanatory factors we refer to the academic work on risk premia in energy markets (see 'Introduction') that puts focus on more strategic and behavioral aspects of market participants.

SUMMARY AND OUTLOOK

The parsimonious fundamental model for wholesale electricity markets is able to explain the development of base futures prices in the wholesale energy market with remarkable accuracy. The model is used to analyze the impact of various fundamental factors on electricity futures prices in the German market. The findings show that the drop in the German electricity futures prices from 2007 until 2014 can be attributed to changed expectations regarding fundamental factors. The emission price reduction is thereby found to quantitatively be the most important explanatory factor for the decrease in power prices. Yet the loss in profitability of new built power plants is to be attributed in the first place to the lower than originally expected electricity demand. Contrarily to common perceptions in the public debate, the higher

[10] The impact of the Fukushima earthquake on German electricity prices received attention in the academic literature. [27] shows that the Fukushima effects had boosting impact on German spot electricity prices. The authors make no analysis on futures market prices but discuss possible longer-term influences due to the possible speed-up of the renewable energy integration in Germany after the nuclear phase-out. [28] conclude that Fukushima and the resulting nuclear phase-out in Germany had brief price effects on futures markets. We similarly conclude that market participants anticipated the phase-out in their longer term considerations.

than expected RES feed-in comes only second in terms of its impact on power plant profitability.

The parsimonious model with a piecewise linearization of the bid stack has advantages which make it suitable for further research applications and possible extensions:

(1) The parsimonious nature allows the use of more frequent data updates, e. g. in order to also forecast spot prices and use day-ahead information instead of forecasting futures prices with year-ahead information. Even intraday prices may be investigated. Since no detailed information about the available intraday flexible capacity exist, it might be of interest to use the piecewise linearization for the intraday supply stack. (2) The simplicity and low computational times of the model support extensions with sophisticated uncertainty modeling or multi-market setups. One such extension could be the inclusion of stochastic processes and distribution assumptions for the input factors. This would also allow the use of the model for an ex-ante evaluation of real options and other derivatives. A particular emphasis should however been given to causal dependencies among uncertainties, e. g. between demand and emission prices. (3) The combination of an analytical formulation and the potential to use numerical Monte-Carlo simulations allow using the model for investigations of stochastic market equilibria.

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APPENDIX

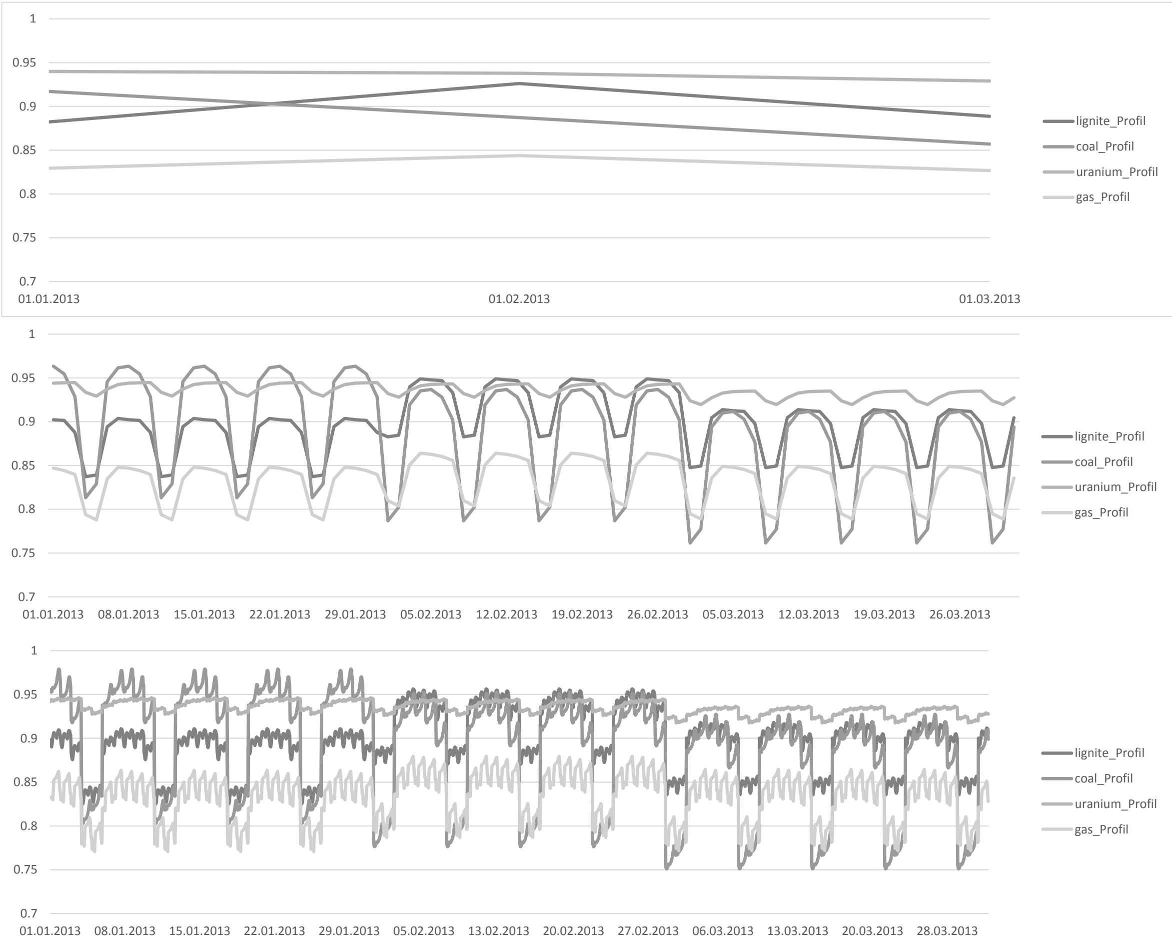

Figure 1. Top to down: superposition of yearly, weekly and daily cycles of available capacities per fuel type (Source own calculations based on EEX transparency data 2012 and 2013.