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Modelling German electricity wholesale spot prices with a parsimonious fundamental model: Validation and application

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Modelling German electricity wholesale spot prices with a parsimonious fundamental model – Validation and application

HEMF Working Paper No. 01/2018

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January 2018

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Open-Minded

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by Philip Beran*, Christian Pape and Christoph Weber

Abstract

Increasing shares of fluctuating renewable energy, the integration of European electricity grids and markets as well as new technologies induce continuous change in the European energy system. Due to these changes, fundamental electricity system and market models that have been developed and applied in the past are dealing with an increasing number of details inducing correspondingly huge data needs. The complexity of these called parameter-rich models (cf. Weron, 2014) leads to limited transparency, also on the impact of data on results, and makes model backtesting rather cumbersome. At the same time, the validity of future scenarios based on non-validated models is dubious. To complement these highly complicated models, more reduced models may be helpful both for transparency and for backtesting. In this paper, we apply a parsimonious fundamental modelling approach to determine hourly German day-ahead power market prices and production volumes. The methodology approximates the supply stack by a piecewise linear function and considers fundamental information, e.g. power plant capacities and availabilities, fuel prices, must-run production and cross-border exchange. We reduce complexity by considering technology classes, uncoupled time periods and only one market area. Between 2011 and 2015, German day-ahead prices declined by 38% and various reasons have been identified in literature, namely a drop in emission certificate prices, the expansion of renewable energies (RES) or lower fuel prices. However, the decision of the German government to shut down nuclear power plants after the Fukushima nuclear disaster happened at the same time and received too little attention as it rather by itself could have led to an increase in prices. The parsimonious model is able to reproduce the hourly historical prices (2011-2015) with a MAE of 5.6 €/MWh and accurately reproduces the electricity production volumes for most thermal production units. In a case study, we investigate a counterfactual scenario without accelerated nuclear phase-out in Germany after the Fukushima nuclear disaster in 2011. The results indicate that German day-ahead power prices would have fallen by additional 3 €/MWh if the nuclear phase-out would have not occurred. Since coal- and gas-fired production as well as additional imports have substituted production from nuclear power plants, their usage would have dropped in the counterfactual scenario.

Keywords: Electricity markets, Fundamental modelling, Nuclear phase-out

JEL-Classification: Q41, Q48

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1 Introduction

Increasing shares of variable RES, the integration of European electricity markets and technological development induce continuous change in the European electricity system. Widely used parameter-rich models aim to cope with these developments by including an increasing number of details (e.g. multiple, interconnected countries, variety of (new) generation technologies, manifold technical restrictions and costs or regulatory frameworks). However, the operation of these models requires considerable amounts of data and is therefore prone to errors in the data handling or delivers biased results if the input data is inaccurate. Since reward is low and the effort is high, backtesting results for this type of model class are rather scarce in literature (cf. e.g. the backtesting results provided by Bublitz et al. (2014), Bublitz et al. (2017), Everts et al. (2016), Hirth (2018)). At the same time, the validity of future scenarios based on non-validated models is dubious. Therefore, models based on reasonable simplifications may be helpful both for transparency and for backtesting. This type of models is often referred to as structural models or parsimonious fundamental models (cf. Weron, 2014; Kallabis et al., 2016) and are characterised by reduced complexity and assumptions on data aggregation.

In this paper, a parsimonious fundamental model for the German day-ahead spot market is developed, validated and applied. The modelling is based on the ideas by Kallabis et al. (2016) and Pape et al. (2016). We validate the model for years 2011-2015 with respect to prices and production quantities and discuss strengths and weaknesses of the parsimonious approach. During that period German day-ahead prices declined by 38%. Various reasons have been identified in literature. Bublitz et al. (2017) apply both an agent-based and a regression model to investigate the contribution of different fundamental drivers to the German spot market price decline between 2011 and 2015. They find carbon and coal prices to be the main reason for the price drop (in total of almost 11 €/MWh of the electricity price). Hirth (2018) analyses the individual contribution of fundamental factors using the model EMMA for the years 2008-2015. He concludes that the largest factor depressing prices is the expansion of RES (-24% of base price 2008). Everts et al. (2016) use a similar method based on a fundamental model to investigate changes in spot prices between 2008 and 2014. They find the decline in emission prices to have the strongest effect on German day-ahead prices (ca. -6 €/MWh). The same applies for Kallabis et al. (2016), who investigate future prices between 2007 and 2014 and conclude that emission prices have a higher decreasing impact on electricity future prices than RES additions or decreasing fuel prices. We contribute to the existing literature by developing the model from Kallabis et al. (2016) and Pape et al. (2016) for application to day-ahead market data. The corresponding hourly description of the market modelling makes detailed data work crucial. Besides price validation we focus on production volumes and foreign trade balance as well as

indications about CO₂ reduction. We demonstrate that the parsimonious nature is well suited to investigate policy or other fundamental impacts in counterfactual case-studies, such as the nuclear phase-out decision in Germany. In response to the Fukushima nuclear disaster, the German Federal Government decided to phase-out nuclear power until 2022 and to immediately shut down eight nuclear power plants. This political intervention meant a reduction of 8.4 GW generation capacity and thus directly influenced German electricity industry.¹ The effect of the German nuclear phase-out has been discussed in several studies with different focuses. Studies that were published immediately after the moratorium are ex ante analyses that focus on the feasibility of the (complete) nuclear phase-out from the perspective of security of supply. Kunz and Weigt (2014) provide an overview and conclude that the nuclear phase-out has rather moderate effects. Depending on the investigated time span, studies report price effects of up to +10 €/MWh after the phase-out.² Recently, Grossi et al. (2017) investigate residual load and spot prices before (2009 and 2010) and after (2012) the phase-out. They estimate an increasing price effect of 8.7% that is partly driven by market power and find that the price effect is strongest in off-peak hours. Some of the above mentioned ex post analyses on the electricity price drop have also determined the counteracting phase-out effect. Bublitz et al. (2017) find a 8.4% effect compared to prices in 2011, Everts et al. (2016) an effect of 11.8% in comparison to prices of 2006 and Hirth (2018) determines a price increase of 22% under ceteris paribus conditions compared to the 2008 electricity spot price level.

The remaining article is structured as follows. Section 2 introduces the parsimonious fundamental model and explains model adaptations. In Section 3, the used data is presented and a model validation for German day-ahead market prices and production volumes is conducted. Subsequently validation results, shortcomings and advantages are discussed. In Section 4 the model is applied in a counterfactual case-study to investigate the impact of the German nuclear phase-out decision. Section 5 discusses general implications for model aggregation and validation and Section 6 concludes and outlines possible further research.

2 Model

The modelling approach in this article is based on the works of Kallabis et al. (2016) and Pape et al. (2016). While former apply the model for analysis of the futures markets and latter are focussing on intraday markets, we merge both model specifications and adjust the model for the German day-ahead spot market. Starting point is the simple supply stack model featuring an

¹ The seven oldest and nuclear power plant “Krümmel” were shut down. Effectively, the decline in generation capacity was 6.3 GW in 2011, because the nuclear power plants “Brunsbüttel” and “Krümmel” haven’t been online for a while due to technical problems.

² Among others Traber and Kemfert (2012) analyse the development until 2020, Fürsch et al. (2012) determine merit-order effects until 2030 under consideration of the phase-out and D’haeseleer et al. (2013) focus on implications on the transmission grid until final German nuclear phase-out in 2022.

ascending supply curve derived from marginal costs of power production and a virtually inelastic demand. This approach is refined by approximations on varying power plant efficiencies, CHP and pumped storage plants. In addition, detailed data on load, renewable infeed, capacities, imports and exports and availabilities are used.

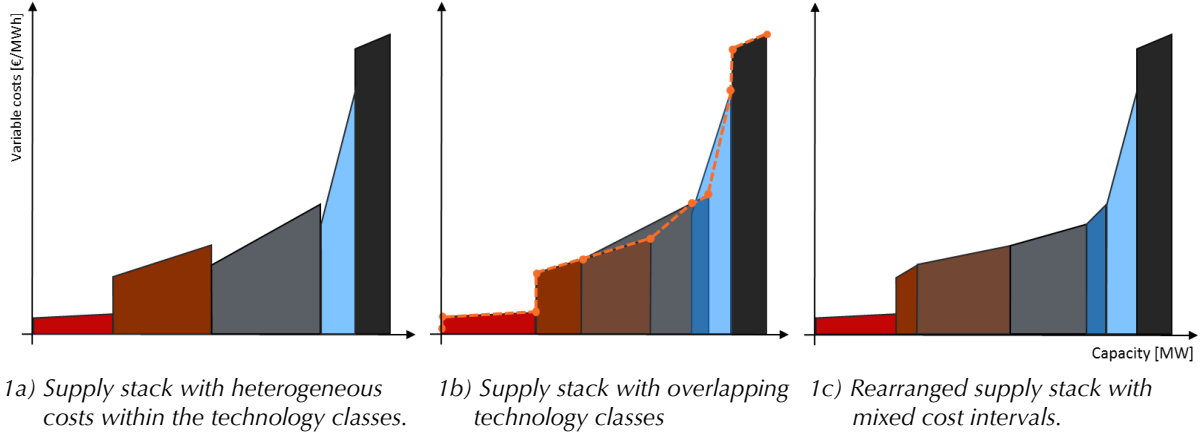


Figure 1: Piecewise linear supply curve

2.1 Core model

The starting point for the modelling is to define the aggregated bid stack B at time t as the inverse function of the individual bidding function b_t^{-1} of each technology class pl (cf. Eq. (1)).

$$B_t = b_t^{-1}(D_t) \text{ with } b_t(S_t) = \sum_{pl \in PL} b_{pl,t} \quad (1)$$

To take care of the heterogeneity within the technology classes arising from varying power plant age, retrofit-measures and technical issues, we consider minimal η_{pl}^{min} and maximal η_{pl}^{max} power plant efficiencies resulting in variable cost ranges $[c_{pl,t}^{min}, c_{pl,t}^{max}]$. Variable production costs are determined by Eq. (2) considering power plant efficiencies $\eta_{pl} \in [\eta_{pl}^{min}, \eta_{pl}^{max}]$, fuel costs $c_{pl,t}^{fuel}$, CO₂ emission allowance price $c_t^{CO_2}$ and additional variable costs c_{pl}^{other} .

$$c_{pl,t} = \frac{c_{pl,t}^{fuel} + EF^{fuel} * c_t^{CO_2}}{\eta_{pl}} + c_{pl}^{other} \quad (2)$$

It is assumed that market participants bid their marginal costs and therefore aim to produce whenever the spot price S_t is above their variable costs (Eq. (3); cf. Kallabis et al., 2016). If the market price is within the cost interval $c_{pl,t}^{min} \leq S_t \leq c_{pl,t}^{max}$ of a technology, the bidding quantity of the technology interval is assumed to be proportional to the relative distance between interval bounds and the market price $(S_t - c_{pl,t}^{min}) / (c_{pl,t}^{max} - c_{pl,t}^{min})$.

$$b_{pl,t}(S_t) = \begin{cases} 0 & , \quad S_t < c_{pl,t}^{\min} \\ AvCap_{pl,t} \cdot \frac{S_t - c_{pl,t}^{\min}}{c_{pl,t}^{\max} - c_{pl,t}^{\min}} & , \quad c_{pl,t}^{\min} \leq S_t \leq c_{pl,t}^{\max} \\ AvCap_{pl,t} & , \quad S_t > c_{pl,t}^{\max} \end{cases} \quad (3)$$

The available capacity $AvCap_{pl,t}$ of technology class pl is determined as the available share of the total installed capacity $Cap_{pl,t}$ of technology pl (Eq. (4)). The availability factor $Av_{pl,t}$ takes into account scheduled and unscheduled power plant outages.³

$$AvCap_{pl,t} = Av_{pl,t} \cdot Cap_{pl,t} \quad (4)$$

The demand side is represented by the residual load D_t described in Eq. (5) (cf. Kallabis et al., 2016). The residual load at time step t is the actual electricity demand L_t minus wind W_t and solar PV_t feed-in, corrected also for the foreign trade balance TB_t and the must-run production from CHP plants CHP_t^{MR} . The approach for estimating the must-run CHP production is described in Section 2.2. The foreign trade balance TB_t is based on actual observations and is given if one subtracts the electricity exports from electricity imports at time t .

$$D_t = L_t - W_t - PV_t - TB_t - CHP_t^{MR} \quad (5)$$

The electricity spot market price at time t then results from the marginal costs at the intersection of supply and demand, $S_t = B_t(D_t)$.⁴

2.2 Model adaptation and production quantities

To establish a modelling framework that is able to represent relevant aspects of the German day-ahead market and to accurately reproduce prices and production volumes based on a parsimonious number of input data, we extend the core model in several ways. One point is that we extend the model so that it is capable to determine the production volume for each technology class. Given the parsimonious, piece-wise model structure this is rather straight-forward for a given supply stack. Yet here a second modification comes into play. In order to model day-ahead market results, the hourly availabilities have to be used to describe changes in the supply stack due to plant outages and planned maintenance. Thereby it is important to consider only the information that was available when the bids to the day-ahead market were submitted.

³ The availability factor $Av_{pl,t}$ is defined as $Av_{pl,t} = 1 - \frac{Unav_{pl,t}^{sched} + Unav_{pl,t}^{unsched}}{Cap_{pl,t}}$ where $Unav_{pl,t}^{sched}$ and $Unav_{pl,t}^{unsched}$ are the scheduled and unscheduled capacity outages of technology pl in time step t (cf. Pape et al., 2016).

⁴ In times with negative residual load, the market price S_t is set to -10 €/MWh (cf. Pape et al., 2016).

A further modification is related to CHP-production. As in the models of Kallabis et al. (2016) and Pape et al. (2016), we consider temperature dependent must-run production from CHP. Before we can determine the actual production quantities, we therefore need to specify the CHP approximation (cf. Pape et al., 2016). In contrast to the stepwise functional relationship between the hourly average temperature and the level of must-run utilization used in Pape et al. (2016), we suggest a monotonically decreasing function $f^{MR}(temp_t)$ (cf. Eq. (6)) to avoid jumps and to smoothen the temperature driven CHP must-run utilization.

$$f^{MR}(temp_t) = \begin{cases} 1 & temp_t < 2 \text{ }^\circ\text{C} \\ 1.0\bar{7} - 0.03\bar{8} \cdot temp_t & 2 \text{ }^\circ\text{C} \leq temp_t \leq 20 \text{ }^\circ\text{C} \\ 0.3 & temp_t > 20 \text{ }^\circ\text{C} \end{cases} \quad (6)$$

If temperatures are below 2 °C, heating demand is high and therefore all must-run power plants are assumed to be producing – further increases in heat demand at very low temperatures are assumed to be covered by heat boilers. In warm hours with temperatures above 20 °C we assume that heating demand is low and only 30% of the inflexible CHP power-plants are producing (e.g. for industrial heating processes). In order to correctly represent the annual heating demand, the temperature driven seasonality is scaled in Eq. (7) to yearly CHP must-run production $y_{pl,t}^{CHP MR}$ per technology class pl .

$$y_{pl,t}^{CHP MR} = \frac{f^{MR}(temp_t)}{\sum_{t \in year} f^{MR}(temp_t)} \cdot y_{pl,year}^{CHP MR} \cdot \frac{Cap_{pl,t}^{CHP MR}}{Cap_{pl,year}^{CHP MR}} \quad (7)$$

The total must-run CHP production (cf. Eq. (8)) in time step t is subtracted from electricity supplied in Eq. (5). Thereby we further distinguish CHP capacities and production into production from flexible and inflexible power plants. The latter have no variability of their electricity production at given heating demand while former have some flexibility to produce additional electricity which may be bid into the spot electricity market.

$$CHP_t^{MR} = \sum_{pl \in PL^{CHP}} y_{pl,t}^{CHP MR} \quad (8)$$

Non-must-run CHP is assumed to have the same cost structure than non-CHP capacities and thus is added up and included into the bidding quantity $b_{pl,t}$. Eventually, the overall production volume $y_{pl,t}$ of a technology class pl at time t is made of two parts due to the modelling of the CHP must-run as stated in Eq. (9).⁵

$$y_{pl,t} = b_{pl,t} + y_{pl,t}^{CHP MR} \quad (9)$$

⁵ In case of a technology class pl without CHP capacity $y_{pl,t}^{CHP MR}$ becomes 0 MWh.

We consider nine different generation technology classes: biomass, coal, lignite, gas (distinguished into combined-cycle-gas (CCG) and open-cycle-gas (OCG)), oil, nuclear, run-of-river, pumped-storage and miscellaneous.⁶ Due to subsidies and German laws (notably the guaranteed priority infeed), renewable generation capacities from biomass and run-of-river hydro are assumed to have marginal costs of zero. CHP generation is available for biomass, coal, lignite, CCG, OCG, miscellaneous and oil.

Pumped-storage power plants have to be considered differently. As these power plants consist of at least two reservoirs connected by a turbine and a pump, they will pump water into their reservoirs in hours with low electricity prices and aim to produce during high (peak) prices to maximize their profit. Since we are simulating time steps without coupling, we assume pumped-storage power plants to turbine with marginal costs based on expected average cost of charging based on coal-, oil- and gas-fired power plants. Current consumption of pumps is considered exogenously in the overall load L_t .⁷

The model aims to replicate the German electricity prices and domestic production by considering only one market area – basing hence the entire model on information aggregated to one market area. For this reason, the parsimonious model makes use of the net foreign trade balance. When applying the parsimonious fundamental model as part of an ex post analysis, available historical data can be used. In applications for future scenarios or case studies (cf. Chap. 4) the foreign trade balance is not available and therefore needs to be derived separately. To the best of our knowledge, there are no public forecasts for scheduled commercial flows available. For that reason, we develop a multiple regression model similar to Kallabis et al. (2016) in Eq. (10). In addition to the approach by Kallabis et al. (2016), we include temperature and emission prices to the regression model. The inclusion of temperature as an explanatory variable is notably motivated by the importance of electric heating which varies in different countries (e.g. high share in France). Emission prices will affect trade balances not only through variable cost of local plants but also through changes in the overall merit-order and resulting reversed flows. E.g. the Netherlands are likely to import less when gas plants become more competitive. This approach, when applied to single years in the past, leads to an adjusted R^2 of 60% on average. This is a substantial improvement over the previous specification.

⁶ The collective class of miscellaneous is also divided into two classes. Power plants assigned to the first miscellaneous class have low variable costs derived by variable costs of biomass, lignite and coal. This class represents capacities that include multi-fuels with partly subsidies or plants that profit from other cost reductions. The second miscellaneous class has variable costs derived from coal, gas and oil plants and represents more expensive generation capacity, e.g. mixed gas and oil fuels.

⁷ A detailed list of all considered power plants and parameters can be found in Appendix A1.

$$TB_t = \beta_0 + \beta_1 W_t + \beta_2 PV_t + \beta_3 L_t + \beta_4 AvCap_{LIG,t} + \beta_5 AvCap_{NUC,t} + \beta_6 CO_{2,t} + \beta_7 Temp_t + \varepsilon_t \quad (10)$$

The multiple regression analysis identifies influences from all considered regressors that are significant at a 99% level except for the CO₂ emission allowance price in 2014. Results in Table 1 indicate an import surplus between 5.0 GW and 19.3 GW as a starting point. Each MW from wind W_t and photovoltaic PV_t as well as each available MW of nuclear $AvCap_{NUC,t}$ and lignite capacity $AvCap_{LIG,t}$ reduce the import level and lead to an export surplus at some point. The most influential driver amongst those investigated is the available lignite capacity. The domestic load L_t , CO₂ emission certificate prices $CO_{2,t}$ and temperature $Temp_t$ increase Germany's electricity imports.

Table 1: Foreign trade balance auxiliary model - regression results for years 2011-2015

Variable	Estimates				
	2011	2012	2013	2014	2015
(constant) [MW]	4985.56	9636.59	16515.74	19304.15	19153.52
Wind-infeed [MW]***	-0.3270	-0.2030	-0.3218	-0.2956	-0.1994
Solar-infeed [MW]***	-0.4461	-0.4538	-0.3977	-0.3587	-0.2674
Load [MW]***	0.0766	0.0669	0.0953	0.0873	0.0684
Available lignite capacity [MW]***	-0.2891	-0.2538	-0.5900	-0.9746	-0.9134
Available nuclear capty. [MW]***	-0.4494	-0.6395	-0.8898	-0.7814	-0.6109
CO ₂ -price [€/t]*** ⁽¹⁾	60.23	-425.50	-695.03	35.07	-497.04
Temperature [°C]***	174.56	103.18	73.42	60.65	57.37
# observations	8760	8784	8760	8760	8760
adjusted R ²	0.6727	0.4273	0.6025	0.7125	0.6000
F-statistics	2572.40	937.35	1897.78	3102.46	1877.76

Each year is estimated based on hourly data. 1% significance level in each regression is marked with ***. Due to autocorrelated and heteroscedastic error terms ε we estimate Newey-West standard errors.
1) CO₂-price is not significant in 2014 regression.

Overall, the presented parsimonious fundamental model for the day-ahead market has two major simplifications compared to full fundamental models. The first reduction relates to the spatial coupling. In full fundamental models, multiple market areas are considered and imports and exports between these regions are determined endogenously. In the parsimonious model, however, only one market area is considered and the foreign trade balance has to be assessed using statistical methods. The second simplification relates to the temporal coupling. Full fundamental models usually model coupled time steps. This allows the consideration of start-up costs and minimal operating times. Hydro and pumped-storage power plants can be included with endogenous operation schedules and shadow prices. The parsimonious model reduces complexity by considering uncoupled time periods neglecting start-up costs and other operating

restrictions. On the other hand, the parsimonious model differentiates generation costs within one technology class, whereas larger system models tend to use constant generation cost per technology class. While full models often tend to use rough availability data, careful research on power plant availabilities is at the core of the parsimonious approach. For ex ante simulations, these detailed times series data may however be replaced by more or less simple distributional assumptions.

3 Validation

3.1 Data

To validate our model with respect to prices and production volumes, we model the German day-ahead market for the years 2011 to 2015. Hereby, we distinguish two data sets. The first data set contains all time series and parameters to run the fundamental model and simulate the German day-ahead market. The second data set is the comparison data set needed for the model validation. Table 2 gives an overview on data and sources used for modelling and validation.

Table 2: Model input and validation data

Model data	Data info	Resolution ⁸	Years	Source
Coal price	API#2 (CIF ARA) front month future	D	2011-2015	Energate
Gas price	OTC TTF day-ahead	D	2011-2015	Energate
Oil price	ICE Brent Index	D	2011-2015	Energate
CO ₂ price	EU CO ₂ emission allowances	D	2011-2015	Energate
Wind feed-in	Day-ahead forecasts	QH	2011-2015	50Hertz, Amprion, Tennet, TransnetBW
Solar feed-in	Day-ahead forecasts	QH	2011-2015	50Hertz, Amprion, Tennet, TransnetBW
Cross-border flows	Day-ahead cross-border commercial schedule	H	2011-2014	ENTSO-E transparency
			2015	ENTSO-E transparency
Load	Day-ahead hourly load values	H	2011-2014	ENTSO-E data portal
			2015	ENTSO-E Power Statistics
	Electricity supplied	M	2011-2015	IEA
Availability shares	Non usability generation (ex ante & ex post)	H	2011-2015	EEX Transparency
	EEX master data power	H	2011-2015	EEX Transparency
Generation capacity	Installed net generating capacity	Y	2011-2014	ENTSO-E (2017), BNetzA (2017)
			2015	ENTSO-E transparency, BNetzA (2017)
	Installed CHP capacity	Y	2011	Eurelectric (2013)
CHP must-run shares	CHP production volumes	Y	2012, 2014	Öko-Institut (2015)
			2011-2015	AGEB (2017)
	Temperature data	H	2011-2015	DWD WESTE-XL
Validation data	Data info	Resolution	Years	Source
Electricity price	EPEX Spot German day-ahead price	H	2011-2015	EPEX SPOT
Production volumes	Yearly net production volumes by technology classes	Y	2011-2015	ENTSO-E Power Statistics, Destatis, BMWi (2017), IEA, Öko-Institut (2014), Öko-Institut (2015)

The day-ahead auction for the joint market area of Germany and Austria closes daily at 12 p.m. Thus, the bidding of market participants is based on information that is available before gate closure.⁹

⁸ The resolution column states the temporal resolution of the original data source: Y=Yearly, M=Monthly, D=Daily, H=Hourly, QH=Quarter-hourly. All time series are edited to become hourly input data for the fundamental model. Missing data are interpolated.

⁹ We assume that day-ahead forecasts for cross-border flows, load as well as wind and solar forecasts to be available to market participants before gate closure even though the actual publication is later. Since

For the residual load in Eq. (5) we use hourly load data from the ENTSO-E transparency platform.¹⁰ This data represents so-called public supply including network feed-in of electricity originating from RES into the distribution grid but it does not contain parts of conventional distributed generation, notably from industrial and traction power stations (ENTSO-E, 2016). ENTSO-E hourly load data only represents approx. 86% of actual load (see Eq. (5)). Therefore, hourly load data is scaled to monthly electricity supply data according to IEA monthly energy statistics. We use an adjusted approach based on Kallabis et al. (2016) and presented in Eq. (11) to scale load L_t at time period (hour) t .

$$L_t = (L_t^{ENTSOE})^2 \cdot \beta_{m(t)}^{GL} + L_t^{ENTSOE} \cdot \begin{cases} \beta_{m(t)}^{Peak} & \text{if } t \in \text{Peak} \\ \beta_t^{Offpeak} & \text{if } t \notin \text{Peak} \end{cases} \quad (11)$$

Grid losses are not linear with respect to the load level and therefore, we consider a quadratic form with a monthly grid loss parameter $\beta_{m(t)}^{GL}$ (cf. Eq. (12)). Furthermore other losses are considered with time-differentiated impact factors β_m^{Peak} and $\beta_m^{OffPeak}$ (cf. Eq. (13)).¹¹

$$\beta_{m(t)}^{GL} = \frac{GL_{m(t)}}{\sum_{i \in M_t} (L_i^{ENTSOE})^2} \quad (12)$$

$$\beta_m^{hType} = \frac{OL_m}{|H_m^{hType}|} \cdot \frac{L_{M(t)}^{ENTSOE, hType}}{L_{M(t)}^{ENTSOE, Base}} \text{ with } hType \in \{\text{peak, off-peak}\} \quad (13)$$

The modelling of must-run CHP production in Eq. (7) requires data on temperature, turbine characteristics and overall CHP production. We follow Pape et al. (2016) and take temperature data as the average temperature of four metropolitan areas in Germany weighted by their population number. To the best of our knowledge no consistent data set on net CHP production and net CHP capacities by technology class are available for years 2011 to 2015. AGEBA (2017) presents yearly CHP production data by technology class neglecting data on micro-cogeneration. We close this gap using Öko-Institut (2015) data. CHP capacities by technology class are available for years 2011 (Eurelectric, 2013), 2012 (Öko-Institut, 2014) and 2014 (Öko-Institut,

EEX transparency data for scheduled and unscheduled unavailabilities contain a notification timestamp, we distinguish sharply regarding data known at gate closure at 12 p.m.

¹⁰ Due to a change in data provision from ENTSO-E there is no consistent day-ahead load forecast dataset available for the period under consideration. We use country package data for the years 2011–2014 and power statistics values for 2015 (cf. also Hirth and Schumacher (2015) on the handling of ENTSO-E load data).

¹¹ Where GL = grid losses, OL = other losses, $m(t)$ = month with hour t within, $M(t)$ = amount of time steps in the corr. month, H_m = peak- or off-peak-hours in the corr. month and $L_{M(t)}^{ENTSOE}$ = sum of load in month $M(t)$. We ascribe 35% of the discrepancy between monthly IEA and ENTSO-E values to grid losses and 75% to other losses.

2015). We extrapolate CHP capacities for years 2013 and 2015 considering the total capacity development of each technology class and assumed CHP production volumes.¹²

To capture capacity changes during the year, we use EEX transparency data. Because this data only represents ca. 74% of conventional generation capacity in Germany (compared to BNetzA data), we scale to year-end values given in official German statistics (BNetzA, 2017) and ENTSO-E yearly statistics and adequacy retrospect (ENTSO-E, 2017; cf. Eq. 14).

$$\text{Cap}_{p,t} = \frac{\text{Cap}_{p,t}^{\text{EEX}}}{\text{Cap}_{p,\text{YE}(t)}^{\text{EEX}}} \cdot \text{Cap}_{p,\text{YE}(t)}^{\text{BNetzA/ENTSOE}} \quad (14)$$

For the model validation with regard to prices and production volumes, suitable comparative data is required. Since we are modelling the German day-ahead market, we use for price validation EPEX Spot day-ahead market auction results for Germany/Austria, which are available in hourly resolution for the years 2011 to 2015. To validate the production volumes, a consistent net production data set by technology class for the years 2011 to 2015 is required. To the best of our knowledge, such a data set does not exist. Among others, BMWi (2017) describe yearly gross production by technology class, IEA (2017) provides monthly net production separated into four production classes while Destatis and ENTSO-E (2017) supply monthly and yearly data on net production. Yet, based on our analysis, we observe varying data quality and class differentiation. Additionally, the data providers treat production from micro-installations and industry processes differently and occasionally report divergent values for the same technology class. Therefore, we create a plausibility checked and harmonised data set for annual net production volumes by technology class based on total gross electricity generation from BMWi (2017) and total net electricity generation from IEA (2017).¹³ The division into the individual technology classes is mainly conducted based on ENTSO-E (2017) data. CHP production is derived from AGEBA (2017), Öko-Institut (2014) and own calculations and assumptions.

3.2 Results

The model validation covers two steps: First, the model accuracy for the German electricity spot market prices for the years 2011-2015 is tested. Second, we compare the fundamental production volumes with the actual generation (cf. Section 3.2.2).

¹² Resulting consistent CHP production from must-run and flexible CHP plants by technology class can be found in Appendix A2.

¹³ The full synthetic electricity balance for Germany for the years 2011 to 2015 can be found in Appendix A2.

3.2.1 Price validation

For the price validation, the descriptive statistics and error measures reported in Table 3 and Table 4 are used.

Table 3: Descriptive statistics on observed and fundamental German day-ahead prices in 2011-2015

		Mean	Min	Max	S.D.	# neg.
2011	Observed	51.12	-36.82	117.49	13.60	15
	Fundamental	51.31	15.04	102.94	11.50	0
2012	Observed	42.60	-221.99	210.00	18.68	56
	Fundamental	44.60	-10.00	203.17	15.67	11
2013	Observed	37.79	-100.03	130.27	16.45	63
	Fundamental	38.47	6.75	94.34	15.11	0
2014	Observed	32.76	-65.03	87.97	12.77	64
	Fundamental	32.84	6.66	72.90	10.25	0
2015	Observed	31.63	-79.94	99.77	12.67	126
	Fundamental	33.06	6.39	76.69	9.43	0
Overall	Observed	39.18	-221.99	210.00	16.63	324
	Fundamental	40.06	-10.00	203.17	14.50	11

Table 4: Error measures parsimonious fundamental model

Errors	ME	MAE	RMSE	R ²
2011	0.19	4.94	6.77	0.75
2012	2.00	6.31	11.72	0.62
2013	0.68	6.95	9.57	0.66
2014	0.08	4.80	6.93	0.71
2015	1.43	5.07	7.05	0.70
Overall	0.88	5.61	8.63	0.73

European and German electricity wholesale markets have seen a price drop of ca. 38% between 2011 and 2015. Despite to its parsimonious nature, our model replicates this price decline accurately. The average MAE over all years reaches 5.6 €/MWh and the explained share of total variance is 73%. The model predicts a price drop of ca. 35% (3 percentage points lower than the actual price drop) leading to a slightly higher fundamental price compared to the observed prices in all years. Based on monthly data, we observe a tendency to slightly overestimate the spot price level in some months (e.g. 2015) and to underestimate in other months (e.g. spring 2014; cf. Figure 2) with no systematic (seasonal) pattern which would have indicated a misspecification of the model.

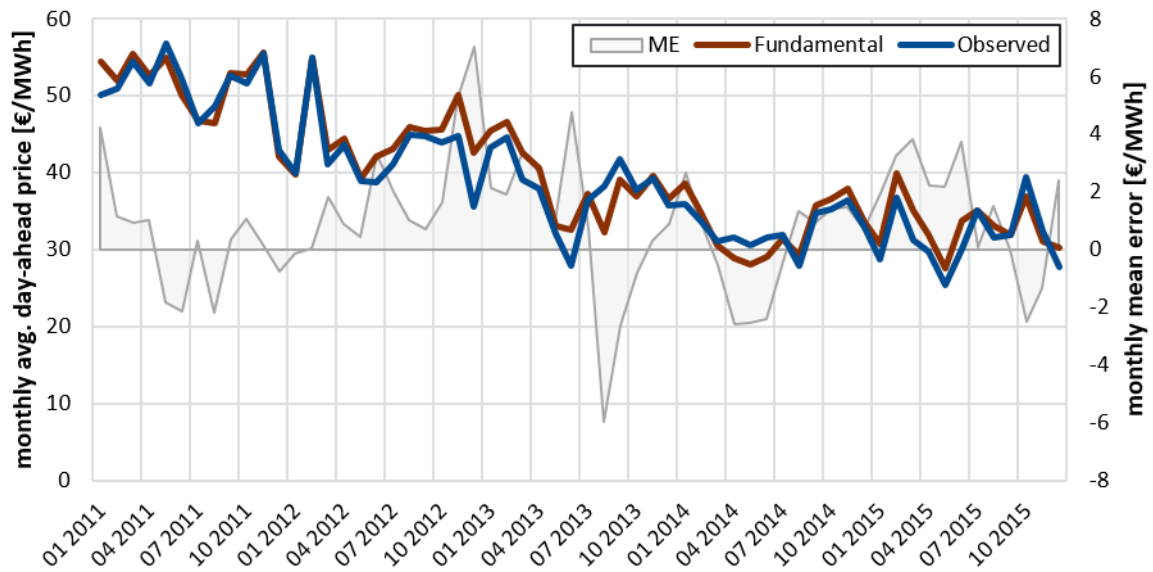


Figure 2: Observed and fundamental monthly average day-ahead prices

The years 2012 and 2013 have the lowest explained variance (R^2 of 62% in 2012 and 66% in 2013), due to more volatile prices and extreme values than the other years. The standard deviation (S.D.) of the modelled prices is lower than the observed level which is in line with other findings. Inter alia fundamental models do not cover effects like strategic bidding, price mark-ups, negative prices or other effects that may increase the price volatility (cf. Weron, 2014; Pape et al., 2017). E.g., negative prices were only reproduced in 11 out of a total 324 observed hours, because negative prices occur in the model during times of negative residual load (cf. Section 2.2). Another reason for lower price volatility in the parsimonious fundamental model is that the model implicitly assumes completely flexible power plants without technical and intertemporal restrictions (e.g. start-up or ramping times; cf. Weber, 2004). Another aspect that is not considered in the parsimonious fundamental model is the provision of positive or negative reserve capacity. Power plants that offer positive or negative spinning reserve capacity have to stay online, which implies that they increase the likelihood of low or even negative prices in individual hours. The histogram of observed and simulated prices (cf. Figure 3) also indicates that the model describes generally well the price distribution, albeit the occurrence of prices below 20 €/MWh is clearly underestimated. This may be attributed to the aforementioned aspects.

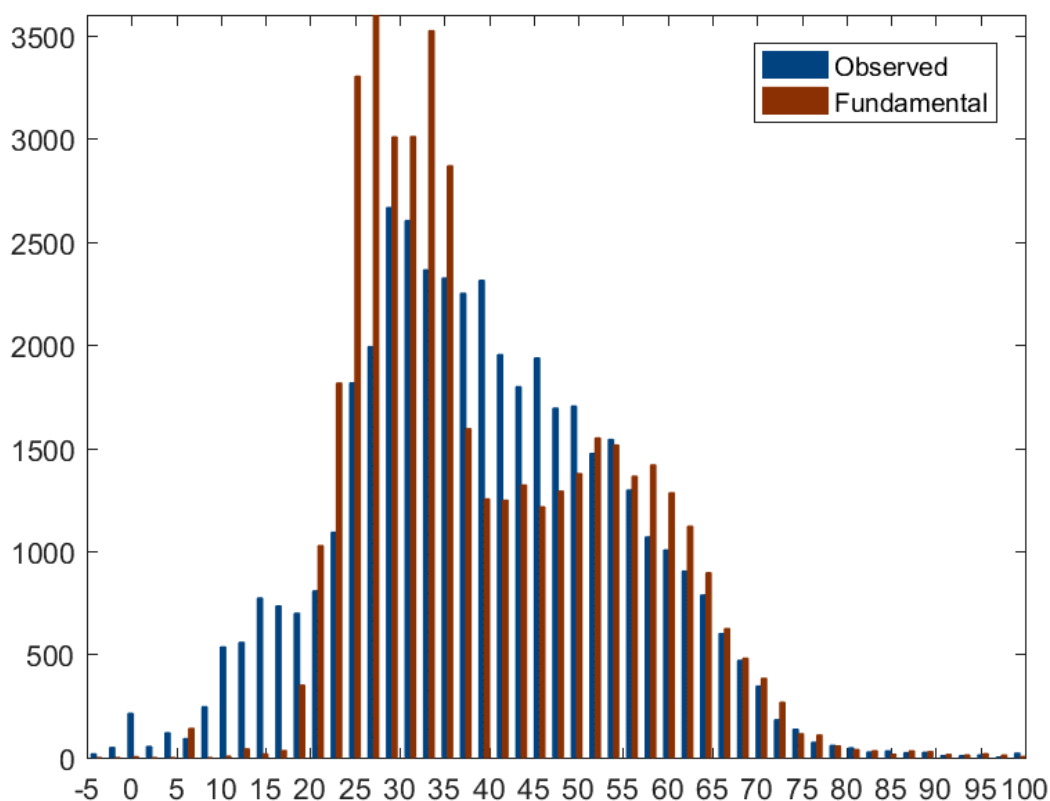


Figure 3: Histogram of observed and fundamental prices

Overall, the fundamental model captures the typical daily structure of electricity spot market prices (Figure 4). However, the model tends to underestimate the valleys in early morning hours and during midday as well as morning and evening peaks, leading to flatter and less volatile price curves. The lowest errors occur in the first and last hour of the day with MAE's of ca. 4 €/MWh and highest errors during noon hours (cf. Figure 5). Especially in the volatile years 2012 and 2013, this error at noon reaches up to 9 €/MWh. Overall, the hourly error yet never exceeds 7 €/MWh (cf. Figure 5).¹⁴

¹⁴ A possible rationale for differing model quality of each year could be a varying data quality. As the high MAE's in years 2012 und 2013 mainly result from the winter period, it is conceivable that the interplay between availability and capacity is not entirely consistent there.

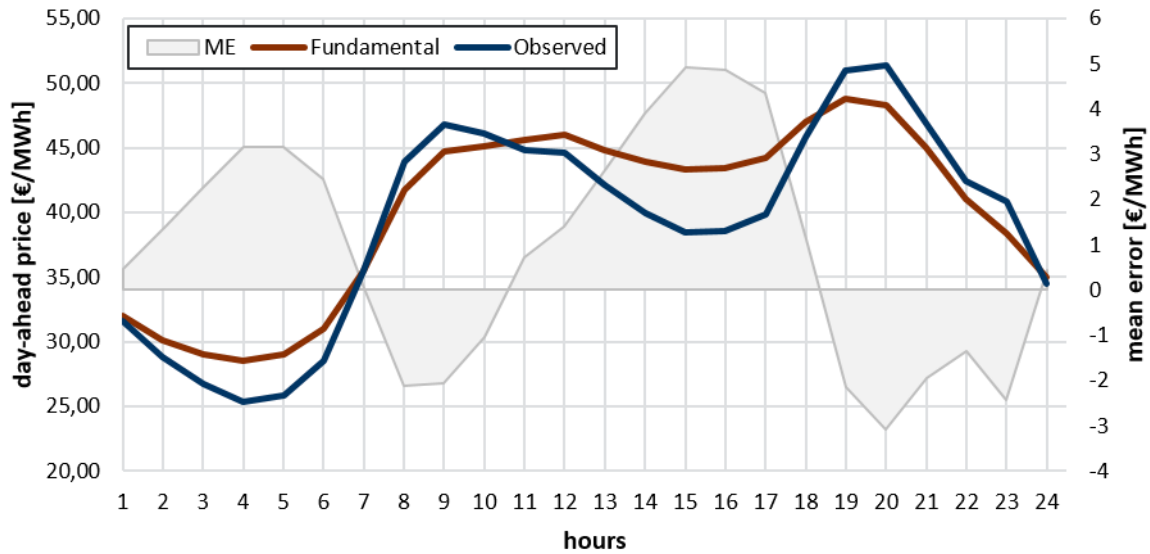


Figure 4: Observed and fundamental hourly average day-ahead prices

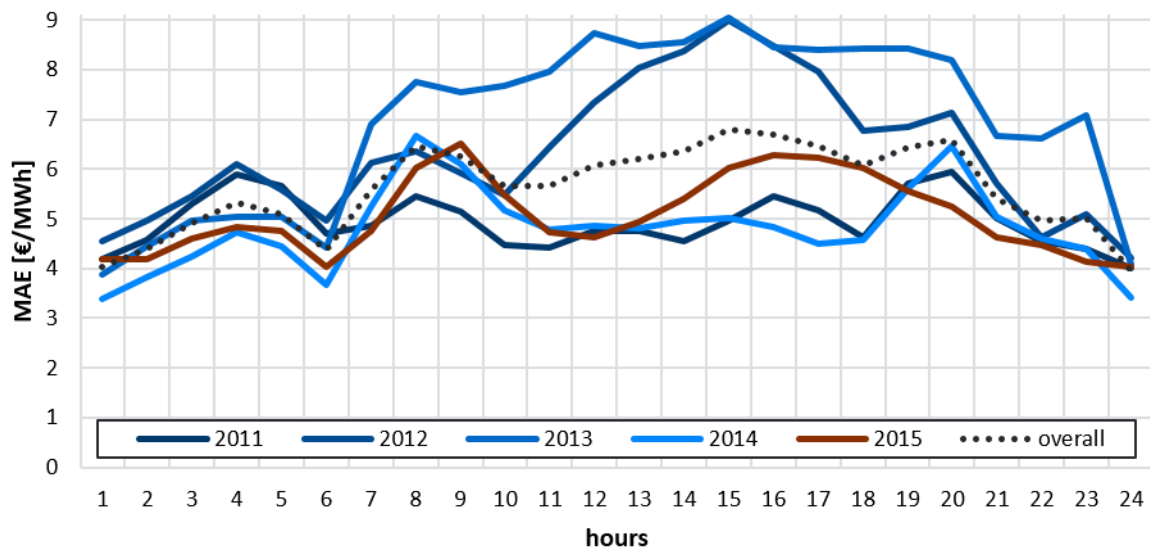


Figure 5: Hourly MAE's for years 2011-2015

3.2.2 Production volumes

As a second validation step, we compare yearly fundamental production volumes with actual observed generation by technology class. Since consistent comparison data do not exist for the investigated period (c.f. Section 3.1), plausibility-checked data is used instead (cf. Appendix A2). One has however to take into account that the data sources used for the comparison provide an ex post indication of the overall electricity market in Germany, whereas the parsimonious fundamental model represents the situation at day-ahead auction. Hence, the fundamental model does not take into account events on the intraday and reserve markets and thus, e.g. the forecast

error of RES. Also redispatch measures are not captured by the model.¹⁵ The fundamental model determines the generation from fossil technology classes nuclear (+2.5%), lignite (+4.9%) and coal (+6.8%) accurately and slightly overestimates their yearly total production volumes (cf. Figure 6 and Figure 7). Annual hydro generation is marginally underestimated by ca. 7.1%. A closer look at this aggregated class reveals a slight overestimated production from run-of-river plants and too low production from pumped-storage plants. The production from biomass assets is significantly overestimated (+15.1%) while gas production is significantly underestimated (-20.3%).¹⁶

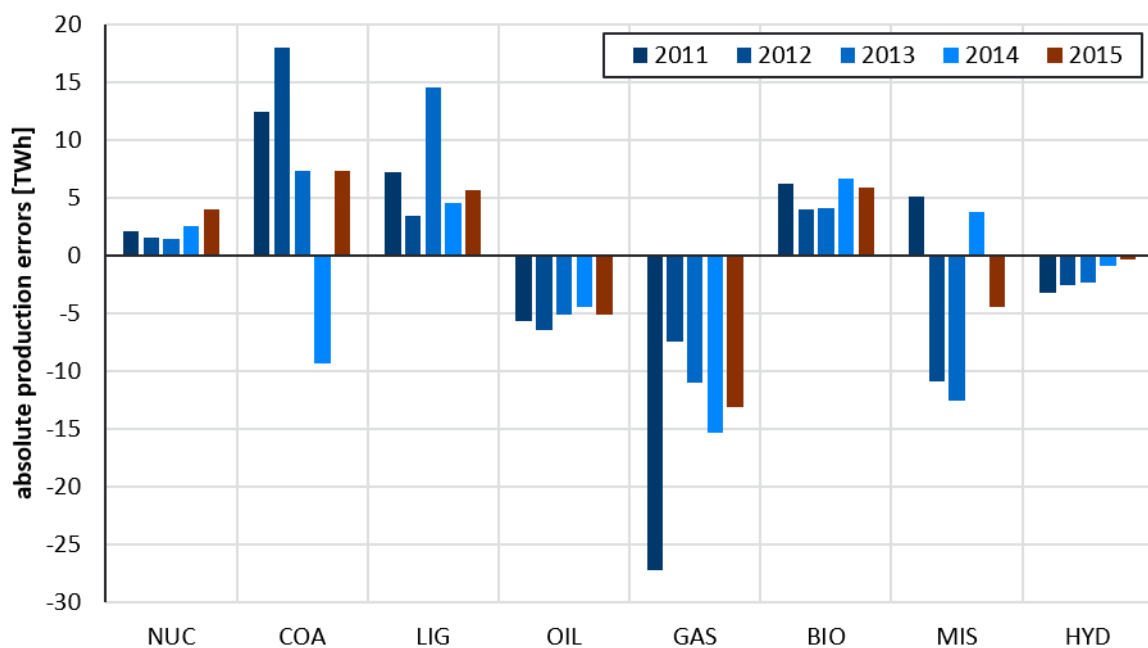


Figure 6: Absolute production volume errors for all years

The underestimation of the production from the relatively expensive technology classes gas and pumped-storage-hydro and the simultaneous overestimation of production from coal and lignite fired power plants can be partly explained by the previously discussed effect of underestimating power plant inflexibilities (cf. 3.2.1). Gas and pumped-storage-hydro plants offer flexibility in reality which is rarely needed in the parsimonious fundamental model, because the actually inflexible cheaper power plants, e.g. coal- and lignite-fired power plants provide flexibility instead. The overproduction from biomass and run-of-river power stations results from their in-

¹⁵ E.g., the average difference in annual production between TSO's day-ahead forecasts and BMWi actual generation is 1.6 TWh for solar- and 3.7 for wind-infeed for the considered period. This leads to a general difference between these two data sets.

¹⁶ The production of the mixed and collective technology class "miscellaneous" is overrated in some years and in others underestimated. Since data sources for the comparison data set as well as the installed capacity are highly volatile over the years, this class will not be considered further in the production volume validation.

transparent costs structure and the retained assumption that they bid with marginal costs of zero €/MWh.

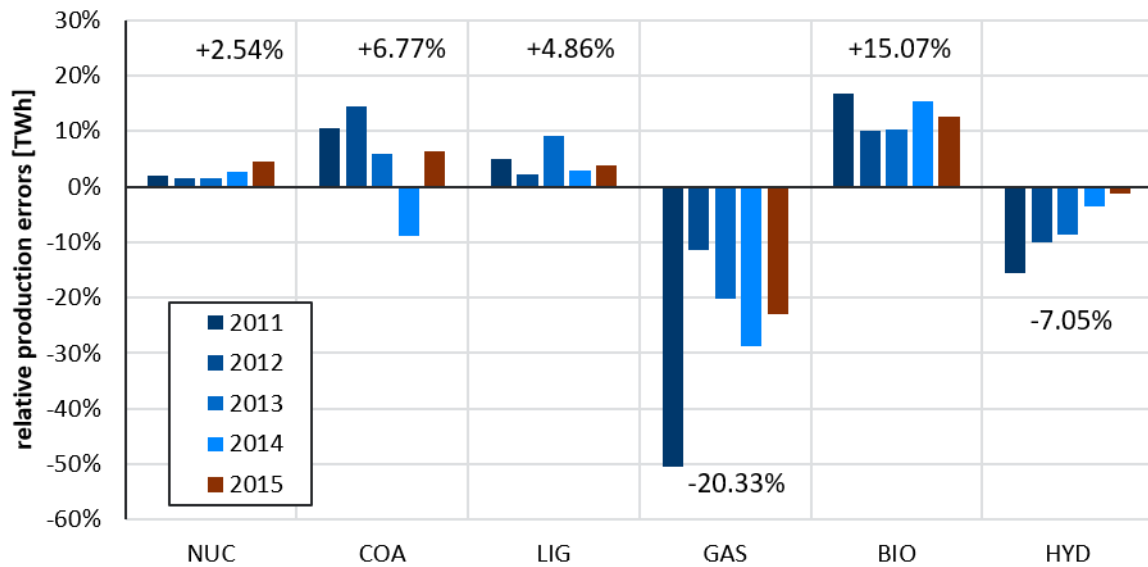


Figure 7: Relative production errors (average numbers indicated for each technology class)

4 Case-Study: German nuclear phase-out

4.1 Counterfactual analysis

The parsimonious fundamental model introduced and validated in this article, is well suited to evaluate the impact of political decisions on the electricity market. One of the biggest political intervention in the German electricity market has been the nuclear moratorium decided by the German government after the Fukushima nuclear accident. In the following, we investigate the impact on the German electricity market if the nuclear moratorium and the immediate phase-out of 8.4 GW nuclear power capacity had not taken place.

Therefore, we conduct a so-called counterfactual analysis for the German nuclear phase-out. A counterfactual analysis in context of a political intervention is a comparison of what actually happened and what would have happened in the absence of the intervention or in the presence of an alternative intervention (c.f. White, 2006). The core of the case-study is an analysis of the German electricity market in the period 2011-2015 without the nuclear phase-out and the immediate reduction of 8 GW of nuclear generation capacity (absence of intervention). In the present case, the installed nuclear power plant capacity and availability are directly affected. Due to continuing technical incidents, the German nuclear power plants Brunsbüttel (771 MW) and Krümmel (1346 MW) had not been in operation for a long time before the Fukushima accident. We assume that this situation would have lasted and that both power plants would have not been available for electricity generation even without the moratorium decision. Eventually we consider hence an additional 6.3 GW of nuclear capacity in contrast to the actual situation in 2011. The

associated power plant unavailabilities are adjusted accordingly and remain unchanged until the Fukushima accident. For the remainder of 2011, the scheduled and unscheduled power plant availability are carefully adjusted for the moratorium. It is assumed that the seasonal maintenance rhythms of nuclear power plants are not affected by the moratorium and can be extrapolated to the decommissioned power plants. For the years 2012-2015, the actual unavailability factor is therefore applied to all nuclear power plants. In addition to these directly affected fundamental factors, the German foreign electricity balance and emission prices would have been indirectly influenced. The intuition is that reduction of low-emission nuclear generation mostly led to increased use of dirty coal generation in the short time. As a result, demand for CO₂ emission allowances and prices increased. Matthes et al. (2011), Kunz and Weigt (2014) as well as Lechtenböhmer and Samadi (2013) among others have investigated this relationship. They conclude that there was only a small price effect of about 2 €/t on the CO₂ emission allowance price (which is within the standard deviation) and that it has vanished within a short time. Therefore, we do not consider any CO₂ effect in this case study. The second, indirectly influenced fundamental factor is the German electricity trading balance. In times of low German electricity prices, Germany tends to export electricity, while it imports in high-price phases. Since we expect the German price structure to have changed as a result of the intervention in the German power plant park, the German foreign trade balance is also affected. Since the foreign trade balance is an exogenous factor in the parsimonious model, it needs to be estimated separately. For this purpose we use a regression model to approximate the foreign trade balance for the counterfactual case (see Section 2.2 and Table 6).

4.2 Results

The results for the counterfactual case for the years 2011-2015 are compared to the validation results (section 3.2.1). A comparison with actual values would lead to biased results since the model inaccuracies would then only be included in the counterfactual and distort the results.

Overall, the price level in the counterfactual case decreases by an average of 3 €/MWh (-7.6%). The electricity price drop in the period between 2011 and 2015 is more pronounced in the case study with 38.7% than in the validation calculation (35.6%). Prices are less volatile in the case-study, i.e. highest prices are lower and lowest prices are higher. In particular, no negative prices occur due to the additional generation capacity. One reason for this is the additional cheap generation capacity and consequently a longer, more shallow part of the supply curve. However, insufficient reproduction of hours with low prices has been identified as a major drawback of the parsimonious fundamental model and thus more negative prices should be expected without the nuclear phase-out. The prices in the counterfactual case are not only lower but the price difference is highly volatile on a monthly basis, ranging from a counterfactual price level

exceeding the validation case one time at the beginning of 2012 (+1€/MWh) to an average monthly difference of -7 €/MWh in November 2011 (cf. Figure 8).

Table 5: Descriptive statistics for day-ahead prices in the validation case and the counterfactual case

		Mean	Min	Max	S.D.	# neg.
2011	Validation Case	51.31	15.04	102.94	11.50	0
	Counterfactual Case	48.39	14.05	89.33	11.35	0
2012	Validation Case	44.60	-10.00	203.17	15.67	11
	Counterfactual Case	41.16	6.45	108.01	13.74	0
2013	Validation Case	38.47	6.75	94.34	15.11	0
	Counterfactual Case	35.87	6.78	90.98	14.07	0
2014	Validation Case	32.84	6.66	72.90	10.25	0
	Counterfactual Case	30.05	6.69	72.37	8.30	0
2015	Validation Case	33.06	6.39	76.69	9.43	0
	Counterfactual Case	29.68	6.59	64.45	7.74	0
Overall	Validation Case	40.06	-10.00	203.17	14.50	11
	Counterfactual Case	37.03	6.45	108.01	13.38	0

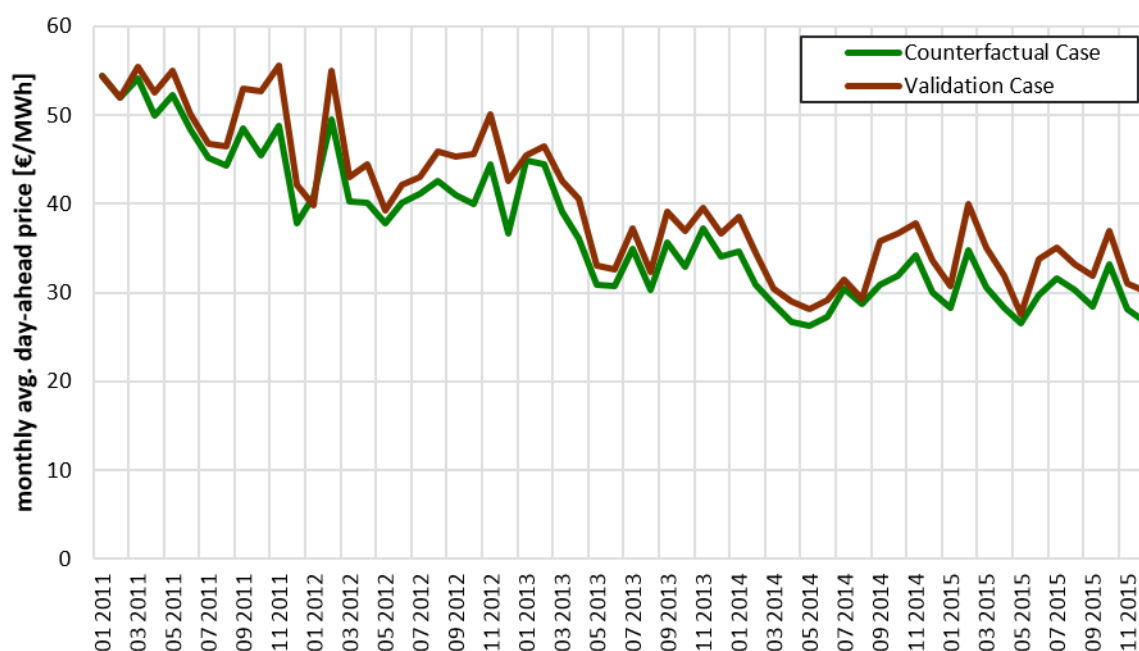


Figure 8: Monthly average day-ahead prices for the validation case and the counterfactual case

The altered generation structure also impacts the German generation mix, with an increase of nuclear production by 46.3 TWh per annum. On the other hand, production from fossil technologies coal (-14.3 TWh), lignite (-4.4 TWh), gas (-4.9 TWh) and others (-0.4 TWh) decreases. In total, this results in a decline of 24.0 TWh in production from combustible fuels. This corresponds to 51% of the additional nuclear energy production. The remaining share of 22.3 TWh additional nuclear production is exported to neighbouring countries.

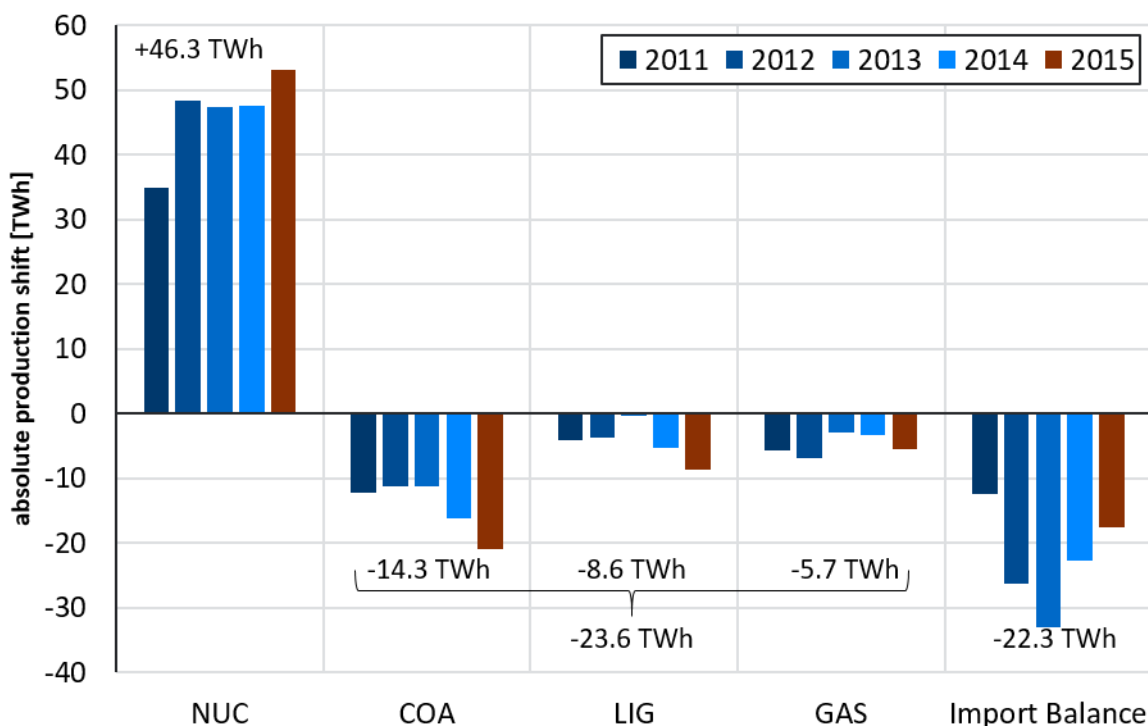


Figure 9: Shift in production volumes: Case-study without nuclear phase-out vs. fundamental validation

The model hence predicts that the accelerated phasing-out of nuclear power in the year 2011 resulted in a price increase of 3 €/MWh on average in the following years. The results indicate that the nuclear phase-out led to less nuclear production (-45.9 TWh) and at the same time increased production from (domestic) fossil fired power plants (+23.6 TWh). The reason for the emerging gap is the reduced German electricity export surplus (-22.3 TWh) in the phase-out case (cf. Table 6). In other words, because Germany would have exported much more electricity without the nuclear phase-out, only every second TWh of electricity not produced by nuclear power plants has led to an increase in German emissions and thus can be tracked to the nuclear phase-out decision. Thus, the nuclear phase-out has had an impact on German emissions and on the fact that Germany will almost certainly miss its 2020 climate targets (SZ, 2017). But given the low carbon and fuel prices, cheap German electricity would have been exported anyway. Curbing sufficiently German emissions would have been difficult even without the accelerated nuclear phase-out.

Table 6: German foreign electricity trade balance according to actual data and in the counterfactual case

[TWh]	2011	2012	2013	2014	2015
Actual (AGEB, 2017)	-6.30	-23.10	-33.80	-35.60	-51.80
Counterfactual	-16.39	-46.55	-67.22	-58.33	-73.09

A comparison of our results to recent studies that have quantified the effect of the German nuclear phase-out on day-ahead prices (Bublitz et al. (2017), Hirth (2018) and Everts et al. (2016)) shows similarities but also differences. Notably all other studies focus on the decomposition of the price drop and thus also quantify effects going in the opposite direction of the phase-out. Bublitz et al. (2017) thereby aggregate the nuclear phase out with other changes in conventional capacities. There are also differences in the considered time periods and in the performed validation. Grossi et al. (2017) identify a 8.7% price effect comparing pre (2009-2010) and post Fukushima (2012) prices. Everts et al. (2016) find a phase-out related effect of 11.8% in the period 2006-2014 whereas Hirth (2018) determines an increase of 22% under ceteris paribus conditions for the nuclear moratorium in the period of 2008 to 2015. The isolation of the effect leads to a higher value, notably due to the non-consideration of the partly compensating changes in imports and exports. Bublitz et al. (2017) investigate the same period as done in this article and obtain rather similar results. They identify a recovery effect on prices in the range of 8.4% (4.3 €/MWh) due to the decrease in power plant capacities (not only nuclear).¹⁷ A further difference is that all the mentioned studies focus on the price effect and do not investigate changes in the generation mix.

5 Implications for model aggregation and validation

Although the model used here is far less detailed than many other fundamental models, it has been possible to obtain good validation results in backtesting studies. This contrasts with most large scale fundamental models where detailed validation results are scarce (cf. also Weron (2014)). This is due to the challenges in backtesting a large-scale model:

The backtesting procedure of a full fundamental model has to be done at least in three steps: The first test includes one country and several time steps. In a second step, a single country with intertemporal constraints is tested. Finally, the backtesting of the full model has to be done. Thus, the increased complexity of these full fundamental models makes model backtesting rather cumbersome and leads to limited transparency, also on the impact of data on results.

The parsimonious approach followed here allows by contrast to use detailed historical information, e.g. on power plant availabilities, to compare modelling and real market outcomes. This allows also to test different hypotheses to complement data that are hardly available (e.g. on CHP operation). A related advantage of the parsimonious model structure is that time series aggregation is not necessary to reach acceptable computation times. Correspondingly the full richness of historical data may be exploited. On the other hand, the degree of technological

¹⁷ Bublitz et al. (2017) report volume-weighted prices which are somewhat higher than the usual (time-weighted) prices. Furthermore, they refer to the starting price level in 2011 when computing relative impacts, whereas our case study refers to the (lower) average price level between 2011 and 2015. Therefore, their decrease in absolute terms is larger than ours.

aggregation may be considered as an inconvenient – although it is partly alleviated by the definition of upward sloping segments in the supply stack.

Yet the most important drawback of the reduced model certainly is that it cannot capture intertemporal interdependencies. Here further work is required to identify adequate simplifications - which may be inspired from outcomes of larger models and/or historical observations. Conversely intertemporal interdependencies also pose large challenges to the time aggregation in larger models – and without detailed validation aggregation approaches should also be subject to critical scrutiny.

Finally, an important possibility for complementary use of parsimonious and parameter-rich models is when it comes to model the interplay between regions and countries in Europe. The regression-based approach to model exchange used here may also be an option for detailed models of the German energy system. On the other side, longer term analyses using the parsimonious model certainly benefit from a detailed modelling of the exchange flows based on a multi-region fundamental model that goes beyond a pure extrapolation of historically observed statistical relationships.

6 Conclusion

This paper introduces a parsimonious fundamental model for the German day-ahead market that has significantly reduced complexity through aggregated technology classes, uncoupled time periods and only one market area. The model is validated for the years 2011-2015 and it is shown that the model reproduces spot prices and annual production volumes accurately.

Despite the aforementioned limitations, the parsimonious model is a simple and validated approach for simulating the German day-ahead market and offers potential for numerous applications in future research on policy pathways and for cross-validation of results obtained with more detailed models.

In a case study, we apply the model to investigate the effects of the nuclear phase-out decision in the German day-ahead market. We find that day-ahead prices would have decreased additionally by 3 €/MWh on average. Thus, the political intervention has counterbalanced the price drop by approximately 7.6%. At the same time, the output from coal, lignite and gas fired power plants would have been lower, while the German overall production and German net power exports would have increased significantly without the nuclear phase-out decision.

This leads to three major findings: Firstly, the political intervention slowed down prices by about 7.6% on average. Secondly, the high CO₂ emissions of the German energy industry can only partly be ascribed to the nuclear phase-out. As a direct result of the phase-out, only 23.3 TWh of electricity have been replaced by other domestic generation – currently mostly fossil fuels.

Finally, we find a high interaction with the foreign trade balance which is modelled based on a simplified regression model.

When assessing policy measures, we hence advice to be aware of the drawbacks of consulting untested or insufficiently backtested models. Even though backtesting is time-consuming and reward has been low in the past, it is essential to identify errors made in the past and to avoid them in the future. Despite its parsimonious nature, the data work for the presented model setup was challenging due to potential biases that may be caused by inaccurate input data or data of low quality. Well documented, publicly available and transparent datasets would ease this process and make model results more comparable.¹⁸

Further research may focus on additional model improvements, e.g. enhanced modelling of intertemporal restrictions for pumped-storage power plants or including implications from reserve markets. In addition, the model may be used for the analysis and assessment of further policy interventions, as well as for future scenarios, e.g. investigations of a potential German coal phase-out or the further effects of the ongoing nuclear phase-out until 2022. Another application of the parsimonious fundamental model is the combined usage with econometric forecasting approaches (cf. Beran et al., 2017).

¹⁸ A detailed discussion of this topic can be found in Pfenninger et al. (2017). They postulate more transparency in energy economic modelling and data.

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Appendix

A1 Generation technology classes and parameters

Technology (<i>pl</i>)	η_{min}	η_{max}	c_{pl}^{other}	Installed capacity at year end [GW]				
				2011	2012	2013	2014	2015
Biomass	1.00	1.00	0.00	5.47	5.70	5.86	6.36	6.80
CCG	0.40	0.6	1.20	14.97	18.74	19.52	19.25	19.68
Coal	0.30	0.46	2.50	25.72	27.28	26.76	26.21	26.48
Lignite	0.29	0.43	2.00	20.23	21.25	21.52	21.31	21.31
Miscellaneous 1	0.55	0.65	0.80	4.62	2.16	2.59	2.32	2.32
Miscellaneous 2	0.3	0.47	1.53	3.94	1.84	2.21	1.98	1.98
Nuclear	0.33	0.36	0.50	12.05	12.07	12.07	12.07	10.79
OCC	0.25	0.36	1.20	6.58	8.23	8.57	8.46	8.64
Oil	0.24	0.44	1.20	4.17	3.90	4.10	3.80	3.80
Pumped-storage	0.75	0.80	0.40	6.72	6.39	6.35	6.35	6.35
Run-of-river	1.00	1.00	0.00	3.56	4.40	4.60	4.30	4.30

A2 Shares of inflexible CHP power plants

Table 7: Share of inflexible CHP power plants

	coal	Lignite	oil	gas	biomass	misc.
Share of inflexible CHP plants ¹⁹	0.91	0.45	0.28	0.82	0.36	0.36

¹⁹ Own calculations based on Öko-Institut, 2014. We combine flexibility information by commercial sector with technology shares in these sectors to determine values stated in Table 7.

A2 German electricity balance 2011-2015

Table 8: German electricity Balance 2011-2015

	2011	2012	2013	2014	2015	Sources
Gross electricity generation	612.08	628.64	637.65	626.65	646.89	BMWi (2017)
of which Nuclear	107.97	99.46	97.29	97.13	91.79	BMWi (2017)
of which Fossil Fuels	355.75	361.20	362.92	341.20	340.44	
of which Coal	112.40	116.39	127.29	118.59	117.74	
of which Lignite	150.07	160.74	160.92	155.82	154.46	BMWi (2017)
of which Oil	7.16	7.63	7.20	5.66	6.21	
of which Gas	86.13	76.45	67.52	61.13	62.03	
of which Hydro	23.51	27.87	28.78	25.44	24.90	BMWi (2017)
of which Pumped-Storage	5.84	5.78	5.78	5.86	5.92	BMWi (2017)
of which Run-of-River & Seasonal Storage	17.67	22.09	23.00	19.59	18.98	
of which Other Renewables	100.34	115.22	122.80	135.62	162.49	BMWi (2017)
of which Wind	48.88	50.67	51.71	57.36	79.21	
of which Solar	19.60	26.38	31.01	36.06	38.73	BMWi (2017)
of which Biomass	31.85	38.17	40.08	42.20	44.55	
of which Miscellaneous (non-renewable)	24.50	24.89	25.86	27.26	27.28	BMWi (2017)
of which Waste	4.76	4.95	5.41	6.07	5.77	BMWi (2017)
of which Others	19.75	19.94	20.45	21.19	21.51	
-Own consumption	34.89	35.83	36.35	35.72	36.87	Own calculation based on AGEb (2017)
=Theoretical net electricity generation	577.19	592.81	601.31	590.93	610.01	
-Data gap	0.00	0.00	0.00	0.00	0.00	Own calculation
IEA data for net electricity generation	576.92	592.74	601.82	591.95	616.18	IEA (2017)
=Net electricity generation	577.19	592.81	601.31	590.93	610.02	ENTSO-E (2017)
of which Nuclear	102.20	94.18	92.15	91.80	86.77	ENTSO-E (2017)
of which Fossil Fuels	333.50	335.42	335.27	337.24	325.58	ENTSO-E (2017)
of which Coal	105.10	106.54	117.10	114.82	107.00	Own calculation based on ENTSO-E (2017)
of which without CHP	84.20	85.94	95.60	95.22	88.10	Own calculation
of which CHP	20.90	20.60	21.50	19.60	18.90	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MR CHP	19.06	20.31	19.29	16.70	16.69	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MO CHP	1.84	0.29	2.21	2.90	2.21	
of which Lignite	140.70	148.43	147.36	148.77	143.04	ENTSO-E (2017)
of which without CHP	135.30	142.73	141.46	143.67	137.74	Own calculation
of which CHP	5.40	5.70	5.90	5.10	5.30	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MR CHP	2.59	2.42	2.38	2.46	2.46	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MO CHP	2.81	3.28	3.52	2.64	2.84	
of which Oil	6.30	7.09	5.70	4.94	5.53	Own calculations based on ENTSO-E (2017), RWE (2017)
of which without CHP	4.50	4.99	3.60	3.04	3.53	Own calculation
of which CHP	1.80	2.10	2.10	1.90	2.00	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MR CHP	0.65	0.61	0.57	0.48	0.48	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MO CHP	1.15	1.49	1.53	1.42	1.52	
of which Gas	81.40	73.37	65.10	68.71	69.99	Own calculations based on ENTSO-E (2017), RWE (2017)
of which without CHP	29.04	21.24	14.34	19.21	17.40	Own calculation
of which CHP	52.36	52.13	50.77	49.50	52.59	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MR CHP	30.17	46.62	42.87	47.01	47.00	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MO CHP	22.19	5.51	7.89	2.49	5.59	
of which Hydro	23.51	27.87	28.78	25.44	24.90	BMWi (2017)
of which Pumped-Storage	5.84	5.78	5.78	5.86	5.92	BMWi (2017)
of which Run-of-River & Seasonal Storage	17.67	22.09	23.00	19.59	18.98	
of which Other Renewables	100.60	115.89	119.20	128.72	156.36	ENTSO-E (2017)
of which Wind	46.50	50.52	50.78	55.48	79.08	
of which Solar	19.00	26.38	31.02	34.96	35.21	ENTSO-E (2017)
of which Biomass	31.10	35.04	35.90	36.80	40.63	ENTSO-E (2017)
of which without CHP	18.36	19.47	17.56	15.80	19.22	Own calculation
of which CHP	12.74	15.57	18.33	21.00	21.40	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MR CHP	6.76	6.32	5.77	6.63	6.63	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MO CHP	5.98	9.25	12.57	14.37	14.78	
of which Other Renewables	4.00	3.95	1.51	1.48	1.44	ENTSO-E (2017)
of which Miscellaneous (not RES)	17.38	19.44	25.91	7.72	16.42	ENTSO-E (2017)
of which Waste	0.00	0.00	0.00	0.00	4.75	ENTSO-E (2017)
of which Others	17.38	19.44	25.91	7.72	11.67	Own calculation based on ENTSO-E (2017)
of which Others (raw) correction	18.20	17.64	25.91	14.99	7.98	ENTSO-E (2017)
of which without CHP	-0.82	1.80	0.00	-7.27	3.69	Own calculation
of which CHP	16.38	18.24	24.81	6.22	10.27	Own calculation
of which MR CHP	1.00	1.20	1.10	1.50	1.40	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MO CHP	0.76	0.36	0.42	0.37	0.37	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which	0.24	0.84	0.68	1.13	1.03	
of which CHP (overall)	94.20	97.30	99.70	98.60	101.60	Own calculation based on Öko-Institut (2015); AGEb (2017)
of which MR CHP	59.99	76.64	71.29	73.65	73.63	Own calculation
of which MO CHP	34.21	20.66	28.41	24.95	27.97	Own calculation
+ Imports (electricity flows from foreign countries)	49.70	44.20	38.40	38.90	33.60	AGEb (2017)
= Net Electricity Volume	626.89	637.01	639.71	629.83	643.62	
- Exports (electricity flows into foreign countries)	56.00	67.30	72.20	74.50	85.40	AGEb (2017)
= Net Domestic Electricity Volume	570.89	569.71	567.51	555.33	558.22	
- Pump Current Consumption	7.50	8.12	7.47	8.00	8.05	ENTSO-E (2017)
- Grid Losses and Unrecorded Factors	#NV	#NV	23.60	32.20	25.80	AGEb (2017)
= Net Electricity Consumption	#NV	#NV	536.44	515.12	524.36	

A3 MAE's for all hours of the day and all years

Table 9: MAE's for all hours of the day and all years

MAE	2011	2012	2013	2014	2015
1	4,19	4,56	3,87	3,39	4,19
2	4,58	4,95	4,45	3,83	4,18
3	5,29	5,46	4,96	4,23	4,60
4	5,89	6,09	5,03	4,73	4,83
5	5,65	5,59	5,03	4,44	4,76
6	4,71	4,96	4,43	3,68	4,04
7	4,87	6,11	6,89	5,24	4,76
8	5,46	6,35	7,75	6,66	6,03
9	5,15	5,92	7,54	6,11	6,51
10	4,48	5,47	7,67	5,18	5,48
11	4,42	6,44	7,97	4,78	4,74
12	4,75	7,34	8,74	4,85	4,62
13	4,76	8,02	8,47	4,81	4,94
14	4,55	8,37	8,55	4,96	5,41
15	4,96	8,99	9,04	5,00	6,01
16	5,45	8,47	8,45	4,82	6,27
17	5,17	7,96	8,40	4,50	6,22
18	4,63	6,78	8,42	4,57	6,02
19	5,72	6,86	8,43	5,60	5,55
20	5,96	7,13	8,20	6,45	5,24
21	5,01	5,72	6,68	5,04	4,62
22	4,54	4,63	6,60	4,61	4,46
23	4,38	5,09	7,07	4,40	4,15
24	4,01	4,22	4,10	3,41	4,02

A4 Histogram of day-ahead prices in the validation case and the counterfactual case

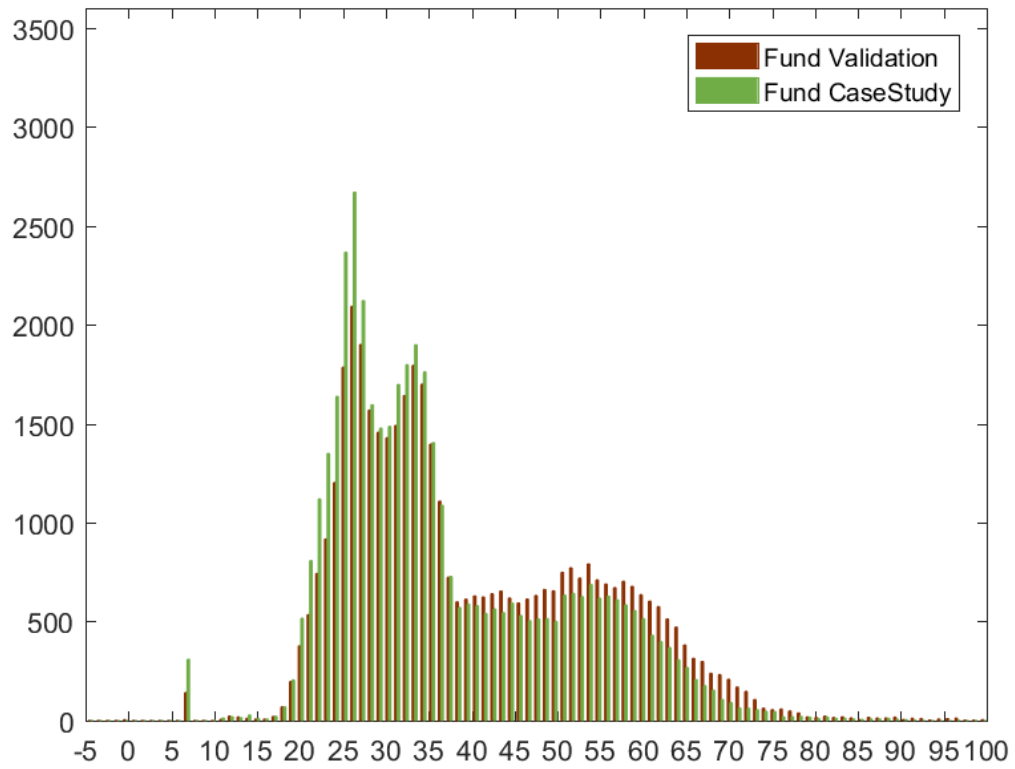


Figure 10: Histogram of day-ahead prices in the validation case and the counterfactual case

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