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An analysis of the decline of electricity spot prices in Europe: Who is to blame?

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ABSTRACT

The European electricity markets are going through a phase of agitating transition, which is shaped by different key factors, such as the expansion of renewable energies, the changes in the EU carbon trading scheme and the European market integration. In addition, markets are affected by the volatile prices of primary energy carriers, e.g. gas and coal. The development of these different factors led to a decline of German wholesale electricity prices of almost 40% — from about 51 €/MWh in 2011 to 31 €/MWh in 2015.

The goal of this study is to analyze the contribution of different price drivers to this decline. Thus, an agent-based modeling and a regression approach are applied to investigate the effect of price drivers and to verify model results by comparing both approaches. Our results show that, against the public perception, the impact of carbon and coal prices on German electricity prices has been twice as high as the renewable expansion between 2011 and 2015. Furthermore, if carbon and coal prices do not recover to at least the level of 2011, electricity prices will remain on the current low level complicating the economic operation of gas power plants.

1. Introduction

European electricity markets are currently going through a phase of transition, which is shaped by three key factors: The expansion of renewable energies, especially wind power and photovoltaics, the phase-out of nuclear energy and the European market integration.

Different promotion schemes were installed in European countries to support the expansion of renewable energies. Germany as a leading country in the promotion of renewable energy already introduced its first renewable energy law ("Stromeinspeisegesetz", (Bundesregierung, 1990)) in 1991. This law is regarded as the first feed-in law worldwide and marked the start of a tremendous rise of renewable energies. In 2000, technology-specific feed-in tariffs were established, as most renewable energies have not been able to undercut the costs of conventional fossil-fueled power plants. These tariffs guaranteed a fixed price for all electricity generated in a predetermined period that is paid by the transmission system operators who pass on the costs to the end consumers (German Renewable Energy Sources Act, (Bundesregierung, 2000)). In 2015, renewable energies contributed with 195.9 TWh (about 30%) to electricity generation, which compared to 2005 corresponds to an increase of 213% (Federal Ministry for Economic Affairs and Energy, 2016). Among the different renewable energy sources, wind is currently the most important source of energy production with a share of 44.9% followed by biomass (22.6%) and photovoltaic (19.6%). However, considering entire Europe, hydropower still has the largest share with 45.4% mainly due to the electricity production in the Alpine and Scandinavian countries (European Commission, 2015).

A major advance for the integration of the European electricity markets represents the market coupling in Central Western Europe (Benelux, France and Germany) at the European power exchange (EPEX SPOT), which started on November 9, 2010 (European Power Exchange, 2016). About three years later, market coupling was extended to also include North-Western Europe (NWE). Through market coupling, generation capacities can be used more efficiently across borders and market participants profit from welfare gains (Weber et al., 2010). As long as sufficient interconnecting capacities between neighboring countries are available, wholesale prices in coupled markets converge, leading for instance to identical day-ahead market prices in Germany and France in about 27% of the time in 2015.

In the last years, the transition of the German electricity market was accompanied by a substantial price decline in the base as well as peak wholesale prices (see Fig. 1). In 2011, the yearly base price corresponded equal to 51.12 €/MWh but dropped to 31.63 €/MWh in 2015, a decrease of roughly 38%. Electricity generators have been profoundly affected by these developments, even more so as no capacity remuneration market is currently implemented in Germany. Many power

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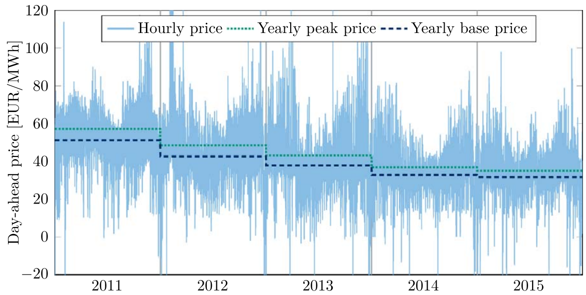

Fig. 1. The day-ahead market prices for the German/Austrian market zone.
Source: Own illustration based on data from European Power Exchange (2016).

plants are facing diminishing return. Currently, the decommissioning of 9 GW of thermal capacities within the next years is expected (Federal Network Agency, 2016a), stirring up concerns about generation adequacy.[1] In order to safeguard the transition phase of the electricity market and to guarantee the security of supply, the German government decided to implement a capacity reserve that will be procured in December 2016 (Federal Ministry for Economic Affairs and Energy, 2015). Investment decisions in a changing market with major uncertainties are challenging and certainly not all market participants expected the ongoing price decline. E.ON SE, for example, decided in 2008 to build a state-of-art gas-fired power plant (Irsching 5) with an efficiency of 59.7% and in 2010, Irsching 5 was commissioned. However, on 1 April 2016, the power plant was scheduled to be decommissioned due to economic reasons (Uniper, 2016).[2]

In the public perception and many political discussions, the blame for the current price slide and the related developments is shifted to the expansion of renewable energies, which have been strongly fostered by financial subsidies. Additionally, in the recent academic discourse, there is a broad spectrum of research that focuses on the impact of the promotion of renewable energies, but only few studies have been undertaken to analyze the impact of other factors on wholesale electricity prices. Therefore, this paper contributes to the academic discussion by providing a quantitative analysis of the fundamental price drivers and their impact on the recent decline in the German wholesale electricity prices, which also can be observed in other European markets such as France, Italy or Spain. To understand also the future effect of these price drivers on electricity prices and power plant investments, different scenarios for the development of price drivers until 2020 are generated and applied. These scenarios allow on the one hand to understand, how strongly electricity prices can vary in 2020, and on the other hand to assess the economic feasibility of power plant investments, especially that of gas power plants. For this reason, in the final step, an economic evaluation is carried out based on a net present value (NPV) approach for a state of the art technology, a combined gas power plant (CCGT) like the Irsching plant.

The remainder of the paper is structured as follows. In Section 2, selected studies on price drivers in electricity markets are discussed. In the next section, our methodology is described, and three different models are presented. Section 4 then shows an analysis of the main price drivers in the German electricity market. Finally, in Section 5 we summarize the results and conclude.

2. Literature review

In this section, we present an overview of previous studies that analyze the influence of fundamental factors on electricity prices. In these studies, a wide range of models[3] is utilized. According to Aggarwal et al. (2009), electricity market models can be classified into game theory, simulation and time series models. Game theory models often focus on the strategies of the market players, simulation models create a detailed representation of the electricity system and time series models use historical data of the dependent variable. Since there does not exist a study in the subject scope of this study that utilizes a game theory model, in the following, we only distinguish between simulation and time series models.

In line with the rise of renewable energies, many of the recent studies focus on the effect of wind and photovoltaic on the electricity price, the so-called merit-order effect (Sensfuß et al., 2008), and do not discuss the impact of fuel price changes or changing import/export flows. Furthermore, as Würzburg et al. (2013) point out, it must be kept in mind that the comparability of studies regarding the merit-order effect is limited due to the heterogeneous approaches, e.g. different sets of included fundamental variables (e.g. fuel prices, market scarcity), alternate scope (inclusion of neighboring countries or emission trading systems) and varying scenarios (no changes or alternative capacity expansion paths). An overview on the selected literature can be found in Table 1.

2.1. Simulation models

One of the first studies of the merit-order effect is carried out by Sensfuß et al. (2008), who use an agent-based model of the German electricity market to analyze the effect of electricity production from wind power and photovoltaic on the day-ahead electricity price. They determine an average price reduction for the year 2001 of 1.70 €/MWh and for the years from 2004 to 2006 a reduction of 2.50–7.83 €/MWh. In another study, Sensfuß (2013) applies the same model and calculates a price reduction of 8.72 and 8.91 €/MWh for 2011 and 2012 respectively. In this analysis, the electricity production of biogas and biomass is considered as well as additional capacities of coal and gas-fired power plants in the scenario with no renewable production. Bode and Groscurth (2006) take a rather simplistic approach by calculating the intersection of the electricity demand and supply curve under the assumption of perfect competition and static daily demand profiles for each month. They show that the price reduction depends on the level of the installed renewable capacity and quantify the effect in the case of an elastic demand at 0.55 €/MWh per GW and in the case of a nearly inelastic demand at 0.61 €/MWh per GW.

Using a fundamental merit-order model of the German electricity system that separates between 34 different power plant types, Weber and Woll (2007) find that in 2006 the feed-in of wind leads to a short-term price reduction of 4.04 €/MWh when compared to a scenario with no wind feed-in. However, if the wind capacity is replaced by alternative hypothetical power plants, they expect a medium-term price effect of −0.4 €/MWh and long-term effect of −1.00 €/MWh.

In another study, Weigt (2009) carries out an analysis of the effects of wind energy by applying a model of the Germany electricity market that minimizes unit commitment, start-up and marginal costs without taking into account cross-border flows. While the results show that the installed capacity cannot significantly reduce fossil capacities, it, however, does reduce the average wholesale market price.

Based on the work of Traber and Kemfert (2009), Traber and Kemfert (2011) apply an optimization model (ESYMMETRY) to analyze the impact of wind energy in Germany. Compared to the prices of a counterfactual scenario with no wind feed-in, the historical wholesale electricity prices from winter 2007 to autumn 2008 are on average 3.7 €/MWh higher. In a subsequent study, Traber et al. (2011)

[1] As power plant owners are not obliged to explain the reasons for a decommissioning, it not clear to which extent the decisions are based on economical or technical reasons.

[2] Already in 2012, Irsching 5 achieved only half of the expected yearly operating hours (Reuters, 2013) and became part of a reserve for redispatch measurements until 2016. Afterward, the power plant was supposed to be decommissioned. However, this decision is currently facing a ban from the regional TSO due to security and reliability of supply concerns.

[3] A recent discussion and outlook on electricity price modeling can be found e.g. in Weron (2014).

Table 1
Studies on influence factors of the electricity price.

Study	Methodology	Regional scope	Time period	Focus	Key findings	Numerical Results (€/MWh)		Reference point
Bode and Groscurth (2006)	Simulation	Germany	2005	Impact of renewables	Price reduction depends on the level of the installed renewable capacity	Renewable (Elastic demand):	−0.55	Per GW inj.[a]
						Renewable (Inelastic demand):	−0.61	Per GW inj.[a]
Cludius et al. (2014)	Time series	Germany	2008–2016	Effect of wind and solar	Energy-intensive industry profits from low electricity price due to welfare transfers	2010–12 Wind:	−1.07	Per GW inj.[a]
						2010–12 PV:	−1.14	Per GW inj.[a]
						2016 Wind + PV:	−14 to −16	Scen. vs. None[e]
Dehler et al. (2016)	Time series	Switzerland	2011–2015	Price influence of neighboring countries	Even though no large gas-fired power plants are installed in Switzerland, gas price drives electricity price which is explained by the important role of gas in the Italian market	Gas coefficent Summer:	0.25	Per GW inj.[a]
						Gas coefficent Winter:	0.81	Per GW inj.[a]
Ederer (2015)	Simulation	Germany	2006–2014	Impact of offshore wind	Similar impact of on- and offshore wind on market prices, offshore wind imposes less variability on market price	Wind onshore short-term:	−0.56	Per TWh y. g.[b]
						Wind offshore short-term:	−0.75	Per TWh y. g.[b]
						Wind onshore long-term:	0.11	Per TWh y. g.[b]
						Wind offshore long-term:	−0.19	Per TWh y. g.[b]
Gelabert et al. (2011)	Time series	Spain	2005–2010	Impact of renewables	Decreasing trend in the estimated magnitude of merit-order effect	Renewables 2005:	−3.80	Per GW inj.[a]
						Renewables 2006:	−3.40	Per GW inj.[a]
						Renewables 2007:	−1.70	Per GW inj.[a]
						Renewables 2008:	−1.50	Per GW inj.[a]
						Renewables 2009:	−1.10	Per GW inj.[a]
						Renewables 2010:	−1.70	Per GW inj.[a]
Hirth (2016)	Simulation	Germany/ Sweden	2008–2015	Drop in spot prices	Most important drivers in Germany Sweden is the increase of renewable generation, followed by the carbon prices respectively the demand	Renewables (DE):	−15.8	2008 vs. 2015
						Carbon emission allowances (DE):	−12.5	2008 vs. 2015
						Renewables (SE):	−19.9	2010 vs. 2015
						Demand (SE):	−18.2	2010 vs. 2015
Kallabis et al. (2016)	Simulation	Germany	2007–2014	Decline of futures prices	Carbon emission allowances price most important driver of futures electricity prices	Carbon emission allowances:	−14.14	2007 vs. 2014
						Wind and Solar:	−6.28	2007 vs. 2014
O'Mahoney and Denny (2011)	Time series	Ireland	2009	Effect of wind	Savings from wind-generated electricity are greater than subsidy over regarded time period	Wind	−9.90	Per GW inj.[a]
O'Mahoney and Denny (2013)	Time series	Ireland	2009	Generator behavior	Electricity market seems to be efficient, Gas is price driver, coefficients of coal and oil price are not significant	Gas coefficent:	0.55	Per GW inj.[a]
Paraschiv et al. (2014)	Time series	Germany	2010–2013	Effect of wind and solar	Merit-order effect differs among hours of the day due to changing demand, coal price has a strong effect in hours with a typically higher demand (e.g. 12 and 18), the influence of the gas price is strongest in peak-demand hours	(Results in figures only)		–
Sensfuß et al. (2008)	Simulation	Germany	2001, 2004–2006	Impact of renewables	Merit-order effect exceeds the volume of the net support payments	Renewables 2001:	−1.70	Hist. vs. None[c]
						Renewables 2004:	−2.50	Hist. vs. None[c]
						Renewables 2005:	−4.25	Hist. vs. None[c]

(continued on next page)

Table 1 *(continued)*

Study	Methodology	Regional scope	Time period	Focus	Key findings	Numerical Results (€/MWh)		Reference point
						Renewables 2006:	−7.83	Hist. vs. None[c]
Sensfuß (2013)	Simulation	Germany	2011–2012	Impact of renewables	Energy-intensive industry profits from low prices due to lower levys	Renewables 2011: Renewables 2012:	−8.72 −8.91	Hist. vs. Scen.[d] Hist. vs. Scen.[d]
Thoenes (2014)	Time series	Germany	2011	Impact of nuclear moratorium	Future prices adjusted by 6 GW shut down, shortly afterward less	–	–	–
Traber and Kemfert (2011)	Simulation	Germany	2007–2008	Effect of wind	Wind reduces profitablity of gas-fired power plants	Wind:	−3.70	Hist. vs. None[c]
Traber et al. (2011)	Simulation	Germany	2020	Impact of renewables	Slight increase of EEG levy expected in 2020	Renewables:	−3.20	2010 vs. 2020 Scen.
Weber and Woll (2007)	Simulation	Germany	2006	Effect of wind	Merit-order effect depends on the regarded time horizon	Wind (short-term):	−4.04	Hist. vs. None[c]
						Wind (medium-term): Wind (long-term):	0.40 1.00	Hist. vs. Scen.[d] Hist. vs. Scen.[d]
Weigt (2009)	Simulation	Germany	2006–2008	Effect of wind	Wind capacity cannot significantly reduce required fossil capacities	Wind 2006: Wind 2007: Wind 2008:	−6.26 −10.47 −13.13	Hist. vs. None[c] Hist. vs. None[c] Hist. vs. None[c]
Würzburg et al. (2013)	Time series	Germany, Austria	2010–2012	Effect of wind and solar	German nuclear exit did not affect merit-order effect, price effect of wind and solar are similar	Wind and Solar:	−1.00	Per GW inj.[a]

[a] Per GW injection.
[b] Per TWh yearly generation.
[c] Historical generation versus no generation.
[d] Historical generation versus alternative scenario generation.
[e] Scenario generation versus no generation.

compare two scenarios for the German electricity market in 2020, one baseline scenario with an expansion of renewable capacities and one scenario with no further expansion of renewable capacities but increased coal power plant capacity. Here, the additional electricity production of renewable energies is expected to lead to a price reduction of 3.2 €/MWh. Ederer (2015) analyzes the historical and expected impact of offshore wind in Germany from 2007 to 2019. Instead of constructing a detailed fundamental model, they use original market data for ask and the supply bids. For scenarios with additional wind capacity, a short and a long-term effect are incorporated, i.e. additional electricity supply bids at low variable costs and the replacement of base-load capacity. The simulation suggests that on short-term decreasing prices are related to the excess of supply, but on long-term market average prices do not change due to additional wind generation since base-load power plants are replaced. However, due to the limited availability of wind compared with thermal capacities, the electricity price shows increased volatility.

Contrary to most studies that focus on the day-ahead market, Kallabis et al. (2016) introduce a parsimonious model for the electricity futures market and analyze the development of the German futures prices from 2007 to 2014. They obtain the result that the volatile carbon emission allowances price was by far the most important driver of electricity prices with an effect of 14.14 €/MWh – more than the combined impact of changes triggered by the demand, thermal capacities and renewables (12.81 €/MWh). Subsequently, according to their results, the overall contribution margin of the power plants was affected the most by the increasing electricity production from renewables followed by the regressing demand. Moreover, they find that the effect of the carbon price on the margins is twofold, while gas-fired and nuclear units face decreasing margins, the more carbon-intensive technologies such as coal and lignite-fueled power plants could increase their profits.

2.2. Time series models

In contrast to the previous studies that represent the electricity system by using bottom-up modeling approaches, the papers presented in following paragraphs rely on econometric concepts, especially regression models to analyze the drivers of wholesale electricity prices. O'Mahoney and Denny (2011) develop an hourly multiple linear regression model for the Irish electricity market. They find that in 2009 the electricity price is 12% lower due to electricity generation from wind and with additionally installed wind capacity the electricity price decreases by 9.9 €/MWh per GW. In a subsequent study, in order to analyze the generator behavior in the Irish electricity market, O'Mahoney and Denny (2013) construct a multiple linear regression model with a set of variables that includes the fuel/carbon prices, the marginal capacity and the net demand that is covered by the conventional supply. They apply the model to hourly data from 2009 and show that the Irish price mainly depends on the gas price, the net demand and the marginal capacity. The coefficients of coal and oil price are not significant which they explain by the fact that in Ireland about 60% of the conventional capacities consist of gas-fired power plants.

In another piece of research, Würzburg et al. (2013) analyze the effects of the electricity generation of photovoltaic and wind for the German–Austrian market area via a multiple linear regression model that amongst others includes the load, gas price and cross-border flows. With data from July 2010 to June 2012, they quantify the impact of the wind and photovoltaic feed-in at about 1 €/MWh per GWh, which they describe as counterintuitive since the photovoltaic feed-in frequently correlates with higher demand than wind. Cludius et al. (2014) analyze the distributional effects of the rising renewable generation for different types of electricity customers by developing a multivariate regression model of the electricity price similar to Gelabert et al. (2011). They find that the electricity generation by photovoltaic and wind has reduced the electricity price by 6 €/MWh in 2010 and 10 €/MWh in 2012, which energy-intensive industries benefit from since, in contrast to private households, the industries cover only a small share of the passed through charges. Additionally, they carry out a prognosis for 2016 and estimate the price reduction to be around 14–16 €/MWh, depending on the different regarded expansion paths of renewable energies.

In a recent analysis, Dehler et al. (2016) focus on the Swiss electricity market and its interdependencies with neighboring countries in the timeframe of 2011–2014. They apply a multiple linear regression model and show that during summer the electricity price and the feed-in from renewables in Germany affect the Swiss price while during winter, peak load situations in Italy and France are correlated with high prices on the Swiss market.

Evaluating the effects of the nuclear moratorium in Germany in March of 2011, Thoenes (2014) develops a semiparametric cointegration model that incorporates daily prices of carbon emission allowances, natural gas and electricity. The results indicate that the change of the gas and carbon emission allowances price is insufficient to explain the increase in the futures electricity prices. Immediately after the decision, futures electricity prices showed a capacity effect of 6 GW, but after several trading days, this effect decreased.[4]

Instead of applying a classical linear regression model, Paraschiv et al. (2014) take a different approach by developing a dynamic fundamental model, which is used to analyze the impact of fuel and carbon prices as well as wind and photovoltaic on the day-ahead electricity price in Germany. By using separate time-varying coefficients for each hour of the day, they show how the impact of the fundamental variables depends on the load profile. For example, the effect of wind is highly dynamic, in night hours with a low demand the impact of wind can lead to strong price changes and even negative prices might occur.

In summary, the literature review shows the wide range of different approaches that are used to analyze especially the price impact of renewable energy sources. Since the sharp price decline in wholesale prices from 2011 to 2015 is not sufficiently analyzed in the existing literature, our research enhances the literature by focusing on this extraordinary development of the German wholesale electricity prices in this study. However, as many other European electricity markets face the same price decline triggered more or less by the same drivers, the analysis can be transferred to other spot markets going through similar changes like the switch to renewable energies.

While other studies apply a single method, which has its specific limitations, we apply different modeling approaches to the same research question to derive robust results taking into account these limitations. Moreover, we try to provide robust results by comparing two different years, thus, the stochastic influences e.g. a stronger or weaker wind year should have less importance. Contrary to other approaches (e.g. Kallabis et al. (2016)), the agent-based model applied in this study is able to incorporate, for example, different market players, ramping costs and strategic behavior.

3. Modeling approach

In order to analyze the price development in the German electricity market, a threefold approach featuring a standard linear regression, a dynamic regression[5] and an agent-based simulation model is adopted and described in the following subsections (for an overview see Table 2). In this way, the results of the models applying the same data can directly be compared and the strength and weaknesses of each approach can be considered. A linear regression model, for example, relies on strict assumptions such as the homogeneity of variance or the absence of multicollinearity in the input data that cannot always be ensured (e.g. Berry and Feldman, 1985). Additionally, non-linear

[4] This might be attributed to adaption effects e.g. different exchange flows.

[5] A detailed description of this model is provided in the appendix of this article B.1.

Table 2
An overview of the applied models.

	Objective	Strength	Weakness
Linear regression model	Explain dependent variable (electricity price) through regressors (e.g. demand, wind)	Easy to implement, wide-spread method	Multi-correlations have to be ruled out (Belsley et al., 1980), non-linear dynamic effects cannot be captured (e.g. the shutdown of several nuclear power plants)
Dynamic fundamental model	Capturing the varying influence of fundamental parameters on dependent variable	Dynamic influences can be considered while keeping a closed mathematical structure	Estimation of coefficients is complex, the system of equations requires many parameters (Bai et al., 2013)
Agent-based model	Detailed bottom-up model of relevant system (e.g. power plants, market players)	Imperfect markets and private information can be included, scenarios	Time-consuming implementation, decision-making rules hard to validate

dynamic effects, for instance, the shutdown of several nuclear power plants in 2011 in Germany, are difficult to implement. In contrast to linear regression models, agent-based models can integrate these effects, but rely on detailed data that is not always publicly available — e.g. the efficiency of power plants or the local heat demand that companies often treat as trade secrets — and hence assumptions have to be made that are difficult if not impossible to verify.

3.1. Linear regression model

We use a multivariate regression model similar to O'Mahoney and Denny (2013), where the hourly day-ahead electricity price p_t is the dependent variable and the explanatory variables consist of the hourly load $load_t$, the hourly forecasted feed-in from photovoltaic $solarForecast_t$ and wind $windForecast_t$ and the lagged daily prices for natural gas $gasPrice_{t-24}$, hard coal $coalPrice_{t-24}$ and CO_2 emission allowances $carbonPrice_{t-24}$.[6] Seasonal dummies ds_t are introduced to reflect systematic changes in the demand and the planned non-availability of power plants, which usually is higher during the summer and, hence, affects the fuel mix. Instead of choosing dummies to capture the daily and weekly patterns in the electricity prices that are caused by the different typical demand curves, which e.g. are lower at night and on weekends, the regression was applied for each combination of the day type, either a working day or a non-working day $t \mapsto d \in \{WD, WE\}$, and the hour of the day $t \mapsto h \in \{1, 2, \ldots, 24\}$:

$$p_t = \beta_{h,d}^{0} + \beta_{h,d}^{load} Load_t + \beta_{h,d}^{wind} windForecast_t + \beta_{h,d}^{solar} solarForecast_t + \beta_{h,d}^{gas} gasPrice_{t-24} + \beta_{h,d}^{coal} coalPrice_{t-24} + \beta_{h,d}^{carbon} carbonPrice_{t-24} + \sum_{i=1}^{3} \beta_{h,d}^{i} ds_t + \epsilon_t \quad \text{if } d(t) = d \ \wedge \ h(t) = h \tag{1}$$

As the estimation of the β-factors can be affected negatively by multicollinearity, ideally, all exogenous variables should be uncorrelated. While for some of the exogenous variables no relationship is expected e.g. the emission allowances price and the wind feed-in, others might influence each other, for example, the fuel prices. In order to test for multicollinearity, a condition number test was carried out (Belsley et al., 1980). The test results do not indicate severe multicollinearity, but there is a strong relationship between the intercept and the load as well as a moderate dependency between the emission allowances, coal and gas price (see Table A.1).

Outlier

The electricity prices from 2011 to 2015 contain only few outliers (see Table 3). However, these outliers, the upper as well as the lower ones, can significantly affect the results of the regression. While outliers can contain valuable information and do not necessarily have an adverse effect on the reliability of the results (Belsley et al., 1980), we found that in our case the coefficient of determination R^2 improved considerably when the outliers were excluded from the calculation of the coefficients. In order to identify the outliers, we apply the iterative process[7] proposed by Trück et al. (2007).

Table 3
Statistical outliers in the day-ahead electricity prices. *Data:* European Power Exchange (2016).

	Prices < −25 €/MWh		**Prices > 100 €/MWh**	
	Occurrences	Percentage	Occurrences	Percentage
2011	3	0.03%	11	0.13%
2012	23	0.26%	60	0.68%
2013	15	0.17%	17	0.19%
2014	16	0.18%	0	0.00%
2015	8	0.09%	0	0.00%

3.2. Agent-based simulation model

In addition to the previously described regression models, an agent-based bottom-up model of the German electricity market is chosen. Agent-based models have already served as a tool to assess a wide range of research questions in the context of electricity markets (e.g. (Guerci et al., 2010; Weidlich and Veit, 2008; Ringler et al., 2016)). Depending on the scope, each model features a certain architecture (e.g. included market areas, timely resolution) and a different set of agents. These sets usually contain agents that represent the most relevant market participants who interact with other agents, who make their own decisions based on public and private information and learn from their past behavior (Tesfatsion, 2006). One major advantage of the agent-based approach is that imperfect markets such as oligopolies can be represented.

As reliable input data is essential for obtaining accurate results — especially for a bottom-up model that requires large amounts of information — data needs to be chosen with care. For the model, all power plants of capacity greater than 10 MW are included with their techno-economic characteristics (efficiency, net capacity, fuel, ...) based on an official list provided by the Federal Network Agency (2016b). As national grid restrictions do not influence the day-ahead price formation in Germany, the German market area is regarded as a "copper plate".

In this model, the day-ahead market is operated by a central agent who receives bids from the different demand and supply agents. The

[6] Similar to Würzburg et al. (2013), we find that the electricity exchange with neighboring countries was most often insignificant and alternated between having a positive or negative impact. This is probably related to the fact that the exchange flows strongly depend on the expected price differences with neighboring markets and as these differences are not included in the model, it is challenging to interpret the exchange flows in itself. Thus, we decide to exclude the exchange from the regression.

[7] In a first step, all outliers are determined as prices that are outside of the interval $I = [-3\sigma + \tilde{x}, \tilde{x} + 3\sigma]$ where σ denotes the variance and $\tilde{x}$ the median of the electricity prices. This step is then repeated until all prices lie within the interval I.

supply side is modeled with a high level of detail. In order to determine the bids for its plants, each electric supply agent follows a multistep process. First, the price of the next day is forecasted. Based on the forecasted prices as well as the techno-economical restrictions, such as the start-up time of the power plant, a possible operating schedule is determined. Then, the supply agents submit hourly bids that include the variable costs and, in case the power plant is not already running, linear distributed start-up costs. To avoid start-up costs, block bids with a price below the variable costs can be placed for a base-load power plant, e.g. in a situation with high wind feed-in where the unit is expected to be out of the market for several hours. Thus, negative prices can be simulated as well. Different renewable energy sources, e.g. photovoltaic, wind, biomass, running water, are incorporated in the model. Since the model focuses on the German electricity market, the exchange with other countries is represented by an exchange agent that trades the historical exchange volumes.

After all agents have submitted their bids, the market operator determines the market-clearing price and the accepted volume for all bids. The electric supply agents then determine the dispatch off their power plants for the next day and learn from their profits.

A more thorough description of the model, as well as validation of the model's results, is provided by Bublitz et al. (2014).

4. Data and model validation

In this section, we provide an overview of the different data sources and a descriptive analysis of the price drivers in the regarded period from 2011 to 2015. Afterward, we use this information to validate the different selected models.

4.1. Data sources

As the day-ahead market price can be seen as an hourly reference price for the German electricity market, the German/Austrian day-ahead market price at EPEX SPOT was chosen for the analysis in the next section. While the intraday market could have been chosen as well, in comparison the total trading volumes on the day-ahead market are several times higher. In order to adequately model the day-ahead price, all other data should represent the day-ahead level of information as more recent information was not available to the market participants when submitting their bids to EPEX SPOT.

The hourly German electricity load $Load_t^*$ is published by the European Network of Transmission System Operators for Electricity (ENTSO-E, 2016). Since the total monthly load values do not cover the total monthly consumption, e.g. 95% for 2014 and 97% for 2015,[8] a constant for each month and year $c_{y,m}$ is added to the hourly load values so that 100% of the consumption is represented.[9]

$$Load_t = Load_t^* + c_{m,y} \tag{2}$$

Due to the stochastic nature of the electricity generation from solar and wind, market participants do not have knowledge of the exact next-day electricity feed-in from solar and wind when participating in the day-ahead market and need to rely on forecasted values. While each market participant uses undisclosed forecasts methods, there exists a publicly available forecast from each transmission system operators for their network area which we use.[10] As the forecasted feed-in differs from the total yearly feed-in published by the Federal Ministry for Economic Affairs and Energy (2016), the forecast is scaled by a parameter c_y:

$$Wind_t = c_y \cdot Wind_t^* \tag{3}$$

Due to the time-consuming transport of coal, coal is not traded on the spot but futures market at the EEX. For the analysis in the next section, the monthly futures of the coal reference index API2 at the ARA inland ports (API2-CIF-ARA-Coal-Month-Future) are used.

Since October 2011, there are two market areas for the trading of natural gas in Germany, GASPOOL that spans from North to East Germany and NetConnect Germany (NCG) from South to West Germany. For both market areas, a daily reference price is published at the EEX. The arithmetical average of these reference prices is then used for the case study.

For the carbon price, the settlement price of the EU-Emission Allowances (EUA) of the relevant trading phase (II or III) at the EEX is applied.[11]

4.2. Descriptive analysis of the price drivers

An overview over the yearly averages, the standard deviation, the minimum and maximum for each of the selected fundamental variables is provided in Table 4. Several conflicting trends can be identified: From 2011–2015 the load and the coal prices are decreasing, while the feed-in from photovoltaic and wind is increasing. The gas price shows a more volatile development, first the price rises until 2013 and afterward drops to a lower level than in 2011. By contrast, the CO_2 price falls until 2013 and then increases but stays behind the average value of 2011. The yearly standard deviation, as well as the range of the emission allowances, hard coal and natural gas price, are relatively low in comparison to the load and the feed-in from wind and photovoltaic.

As OTC transactions only account for a minor volume of the short-term electricity trades, the day-ahead price for the German-Austrian market area can be regarded as a reference price. Electricity producers offer their conventional capacities based on their variable costs that mainly consists of fuel, emission allowances and operation and maintenance costs. Fig. 2 shows these capacities sorted ascending by their variable costs (merit order curve) for the years 2011 and 2015. Base-load power plants, i.e. nuclear and lignite-fired power plants have the lowest variable costs, followed by coal and gas-fired power plants and peak load oil-fired units. The shut-down of roughly 11 GW of nuclear capacities in 2011 shifted the whole curve to the left, which alters the electricity price in most hours, as the minimum load from 2011 to 2015 is roughly 35 GW (see Table 4). This effect is partially compensated by the growing feed-in from wind and photovoltaic that increased from 2011 to 2015 on average by 6.6 GW. Moreover, the low carbon and coal price lead to an increased competitiveness of coal-fired power plants. As the gas price has only slightly decreased and gas-fired fuel plants are not as strongly affected by the lower carbon price, gas-fired power plants – even those with a high efficiency – cannot compete with coal-fired power plants in 2015.

Fig. 6 shows the relationship between the residual load[12] and electricity prices. It can be observed that an increase of the load usually results in a higher market price. If the residual load falls below a certain level and base-load power plants for some hours are forced to be turned off, negative prices can occur due to slow ramping rates, start-up costs and the obligation to provide system services such as the provision of primary reserve capacity. Negative prices strongly depend on the number of operational base-load plants and mostly occur at night, when a low demand coincides with a high feed-in from wind.

[8] This difference is mainly caused by the decentralized electricity generation and consumption in the grids of larger municipal utilities or industrial companies (BMWi, 2013).

[9] While a linear scaling factor could also be applied, in some cases this results in unreasonably high load values, thus, adding a monthly constant is the better option.

[10] Even though the data is usually published around 6p.m. on the previous day and thus usually not available to the market participants when submitting their bids to the day-ahead auction, which takes place at 12 a.m, it is assumed that this forecast is a reliable approximation of the different forecasts of market participants.

[11] Since no price exists for a weekend day or holiday, in this case, the last available price is extrapolated.

[12] Here the residual load is defined as the load subtracted by the electricity generation from wind and photovoltaic.

Table 4
Overview of the main input data. *Data:* (ENTSO-E, 2016; European Energy Exchange, 2016).

	Load [GW]	PV [GW]	Wind [GW]	Gas price [€/MWh]	Coal price [€/MWh]	Carbon price [€/EUA]
2011 Mean	**62.13**	**2.24**	**5.56**	**22.78**	**12.48**	**12.97**
SD	11.15	3.31	4.67	1.42	0.42	2.88
Min	35.96	0.00	0.29	15.27	11.67	6.50
Max	88.48	13.94	24.50	26.18	14.24	16.84
2012 Mean	**61.46**	**3.00**	**5.75**	**25.16**	**10.46**	**7.37**
SD	11.12	4.53	4.57	2.07	0.62	0.71
Min	35.98	0.00	0.25	20.24	9.41	5.71
Max	87.03	20.64	24.46	40.25	12.34	9.31
2013 Mean	**60.57**	**3.54**	**5.89**	**27.16**	**8.84**	**4.48**
SD	10.16	5.54	5.01	1.79	0.48	0.67
Min	36.95	0.00	0.30	25.20	7.97	2.68
Max	82.32	24.59	27.67	39.48	9.84	6.53
2014 Mean	**60.43**	**3.99**	**6.37**	**21.13**	**8.09**	**5.95**
SD	10.67	6.03	5.55	3.01	0.30	0.70
Min	36.00	0.00	0.30	15.36	7.53	4.35
Max	83.03	25.61	29.72	28.28	8.93	7.24
2015 Mean	**59.50**	**4.39**	**10.01**	**19.88**	**7.21**	**7.67**
SD	10.74	6.68	8.31	2.04	0.57	0.58
Min	35.26	0.00	0.55	13.40	6.00	6.42
Max	81.57	27.84	43.45	24.24	8.23	8.65

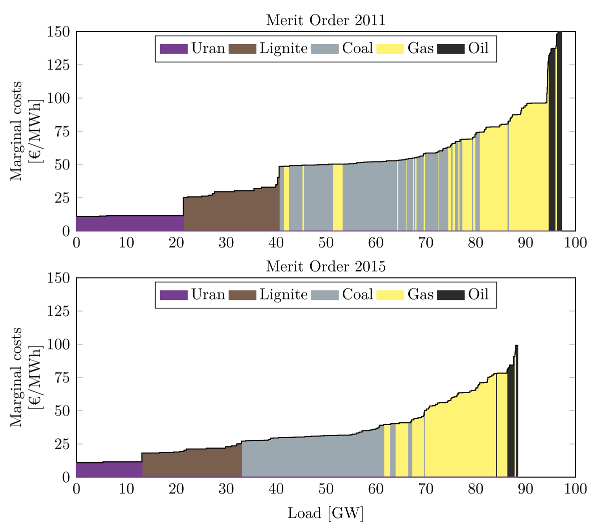

Fig. 2. The merit order of the conventional capacities in Germany at the beginning of the year 2011 and 2015. *Source:* Own illustration based on data from European Energy Exchange (2016); Federal Network Agency (2016b).

4.3. Model validation

In the following, we give a brief overview of the adequacy of the selected models for the price analysis described in the next section. While the linear regression model and the agent-based model yield valid results, the results of the dynamic fundamental model are only of limited informative value and, thus, are not regarded in the following analysis.[13]

The linear regression model has a high explanatory power with R^2 ranging from 0.69 to 0.83 (see Table A.2). Almost all coefficients of the selected fundamental variables are highly significant, except the coefficients of the gas price for several hours on weekends and the coal price in some night hours on weekends. As the load is typically lower on weekends and during the night, gas-fired power plants usually do not run on weekends and thus, is it not surprising that the gas price is not affecting the electricity price. The same holds true for the coal price since during very low load situations only base-load plants are operating.

As shown in Bublitz et al. (2014, 2015a, 2015b); Keles et al. (2016), the agent-based simulation model is well capable of representing electricity market dynamics. Seasonal, weekly and daily patterns are adequately represented, which results in significant statistical figures e.g. a R^2 above 0.75 or a mean average error (MAE) below 4.

5. Analysis of the price decline

In this section, we carry out an analysis of the decline of the German wholesale electricity prices based on historical data. First, we apply the models from Section 3, calculate the price effect of the different fundamental factors and compare the effect with existing studies. Then, we show how the development of the electricity price is affected by the selected fundamental factors in two scenarios.

5.1. Impact of each price driver

Based on the data mentioned above and the different modeling approaches introduced in Section 3, we will analyze the main drivers for the electricity price development at the EPEX SPOT market, especially the price reduction between 2011 and 2015. Therefore, we will determine the price reduction effect itself weighted with the hourly load in the analyzed year. The relative price effect will be calculated with the help of the regression model as well as with the agent-based simulation model. In the case of the regression model, the coefficients of the analyzed fundamental drivers will be used to determine the effect:

$$pe(x, T) = \frac{\sum_{t\in T} \beta^{x}_{d(t),h(t)} \cdot x_t \cdot Load_t}{\sum_{t\in T} Load_t} \tag{4}$$

In the case of the simulation model, two different runs are carried out. The first run is done by using the historical numbers for the analyzed fundamental parameter, e.g. carbon prices, and year (2014 or 2015), the second run is carried out by fixing the value of the analyzed parameter at the level of 2011, while the others remain the same as in the first run. The difference of electricity prices from both runs represents then the price (reduction) effect *pe* of the analyzed parameter:

$$pe(x, T) = \frac{\sum_{t\in T} (p^{x}_t - p^{ref}_t) \cdot Load_t}{\sum_{t\in T} Load_t} \tag{5}$$

Based on the models' results and the defined measures for the price reduction effect, the impact of main price drivers is analyzed in the following. Surprisingly, the price impact of the strong expansion of PV (from 2011 to 2015) in the last four years is not as strong as mentioned in recent public discussions (in total 2.10 €/MWh calculated with the ABS model between 2011 and 2015 and 2.40 €/MWh with the regression model respectively). The impact of wind power, however, seems to be stronger, especially if the year 2015 is examined. The sharp increase in German wind installations (on- and offshore) in 2015 combined with a windy year leads to a more significant wind merit-order effect. The price reduction resulting from wind power feed-in increased from rather low values below 1.00 €/MWh in 2014 to 3.30 €/MWh in 2015 determined with the agent-based model or 4.40 €/MWh with the regression model respectively. Both models determined a significant wind effect, which is, however, still below the price reduction effect of carbon or coal prices.

As illustrated in Fig. 3, the decrease of coal and carbon prices has by far contributed the strongest to the price reduction between 2011 and 2014 or 2015. The regression model calculates a stronger price impact

[13] A detailed discussion of the underlying causes can be found in the appendix of this article.

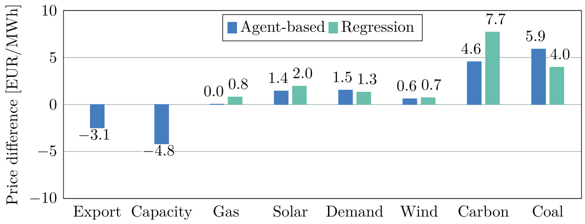

Fig. 3. Price effect 2014. *Source:* Own illustration.

for the coal price than the agent-based simulation, whereas for carbon prices it is vice versa. However, both models determine these two parameters as the main price reducers with a total price reduction effect of almost 11 €/MWh.

The results of the agent-based model show also that the price reduction between 2011 and 2015 would be even stronger if there was the same amount of capacities in the market as in 2011. The decrease of power plant capacities in the German electricity market (especially due to the nuclear phase out) and the growing net electricity exports lead to a recovery of prices by about 4.30 €/MWh and 4.60 €/MWh respectively.

However, there are some differences in the height of the impact of especially coal and carbon prices determined by the two different models (agent-based and linear regression model). Compared to the linear regression model, a lower price reduction effect of carbon prices is determined by applying the fundamental agent-based approach. This may result from the fact that mainly lignite-fueled power plants, as the most carbon-intensive technology, show a corresponding change in variable costs, but as base-load power plants, they are rarely price setting. Additionally, the increase in the electricity price induced by the carbon price is lowered when a fuel switch e.g. from coal to gas occurs. These effects are better captured by a fundamental agent-based model than by a statistical approach, so that price impact is much lower than the one in the case of the linear regression model. Another explanation of the high effect of the regression model might be that it does not include other explanatory variables, e.g. the electricity flows with neighboring countries or the German plant fleet, which can lead to an overestimation of the betas of the included variables.

The price effect of coal prices determined with the agent-based is about 2 €/MWh higher than the one calculated with the regression model. Since the agent-based model incorporates each power plant with its technical characteristics, it has the strength to adequately represent changes in the merit-order and hence, can provide a good estimation of the induced price effect. The agent-based model, therefore, can also deal with non-linear relationships between coal and electricity prices, while the linear regression model cannot capture these non-linearities and may underestimate the price reduction effects caused by significant changes in coal prices.

Overall, it can be stated that both models determine the development of the coal and carbon emission certificate prices as the main source for the reduction of wholesale electricity prices the German electricity market faces since 2011, while the impact of the fluctuating renewables is considerably lower. However, the differences in the renewables effects between 2014 and 2015 show that this effect is growing with the ongoing expansion of especially wind capacity.

5.2. Scenarios for the price effect and economic feasibility of gas power plants in 2020

In the following, the agent-based and the regression model are used to forecast the electricity prices in 2020 applying two scenarios for the fuel prices and a scenario for renewable power production extracted from ÜNB (2015). For the "low" fuel and carbon price scenario, the fuel prices are assumed to remain at the current level, while the 2011 prices are assumed as a "high" price scenario for 2020.

Table 5
Volume weighted day-ahead market price, hours with a positive clean spark spread (CSS) and annual return under different fuel scenarios of an exemplary CCGT power plant (efficiency 55%).

Year [-]	Scenario [-]	Price [€/MWh]	Annual return of a CCGT [k€/MW]	# hours with positive CSS [h]
2011	Historical	51.96	39.68	5338
2014	Historical	34.35	−6.31	2076
2015	Historical	33.05	−3.65	1947
2020	Low Regression	28.26	−8.07	1380
2020	Low ABSM	30.02	−4.18	1547
2020	High Regression	40.29	1.58	2382
2020	High ABSM	40.07	2.77	2782

The results indicate that the volume weighted average prices in 2020 will fall to or even below 30 €/MWh if the fuel and carbon prices stay on today's level. The additional reduction is expected to originate from the renewable power expansion until 2020, as all the other parameters remain on the same level as in 2015. An even stronger decrease would be expected if there was not be some already known decommissioning of power plant capacity, which is considered in the agent-based model. This may also be the reason why the model predicts a smaller price reduction.

In contrast to the "low" price scenario, a strong increase in electricity prices is determined by both models in the "high" fuel and carbon price scenario, in which the electricity prices are expected to reach the 40 €/MWh level again. In this scenario, the fuel and carbon price increase to the level of 2011 would strongly overbalance the price reduction effect of the additional RES expansion in the electricity sector.

Based on the electricity price development described above, Table 5 shows also the number of hours with a positive spread between the electricity prices and the variable costs of a combined cycle gas turbine (CCGT). It is obvious that the number of hours with a positive spread is further reduced in the "low" fuel and carbon price scenario, while there is a significant increase in the "high" price scenario. The numbers of a positive spread increase again to more than 2300 and even to 2782 determined by the agent-based model for the high price scenario. The increase in time with positive spread leads to a positive annual return for an exemplary CCGT power plant with 55% efficiency rate, an emission factor of 0.202 t/MWh_{th}, other variable costs of 2 €/MWh and operational fixed costs of 19 k€/MW (Blesl et al., 2012). However, the annual return is only slightly positive, so that it can be stated that without reaching the level of 2011 for coal and carbon prices or without further decommissioning of coal and lignite capacities, it will be difficult for even very efficient CCGT plants to operate economically feasible. Hence, if carbon and fuel prices remain at the low level of 2015, another market mechanism will be required to keep this efficient and flexible gas capacity in the market, especially if it should serve as backup capacity for fluctuant renewables.

5.3. Comparison of the results with existing studies

To embed our results into the discussion about electricity price drivers, we compare our results to those in the literature. As most of the existing studies focus only on the merit order effect of renewables, we carry out the comparison based on this criterion. We extend this then to the comparison of other price drivers analyzing the relative effect of these parameters, as there is hardly any study analyzing exactly price decline between 2011 and 2015. That is why the relative effect is calculated also from the absolute values described in other studies about price drivers (Fig. 4).

However, at first, the regression model is applied to determine the total effect of fluctuant renewable energy sources. The price reduction of renewables, i.e. the merit order effect, is equal to 8 €/MWh in total

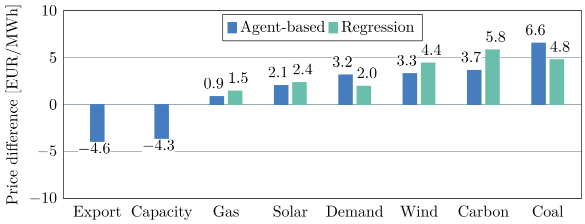

Fig. 4. Price effect 2015. *Source:* Own illustration.

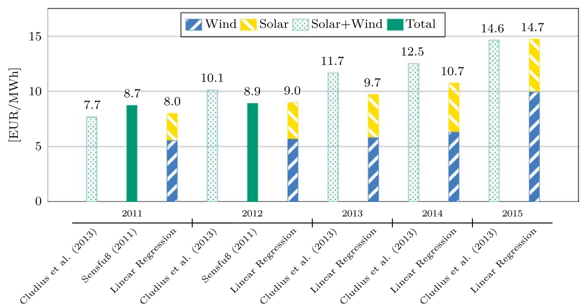

Fig. 5. Merit order effect in Germany from 2011 to 2015. The results from Cludius et al. (2014) for the period from 2013 to 2015 are taken the scenarios "reference" (2013/2014) and "high wind" (2015) and thus deviate from the historical feed-in values. *Source:* Own illustration.

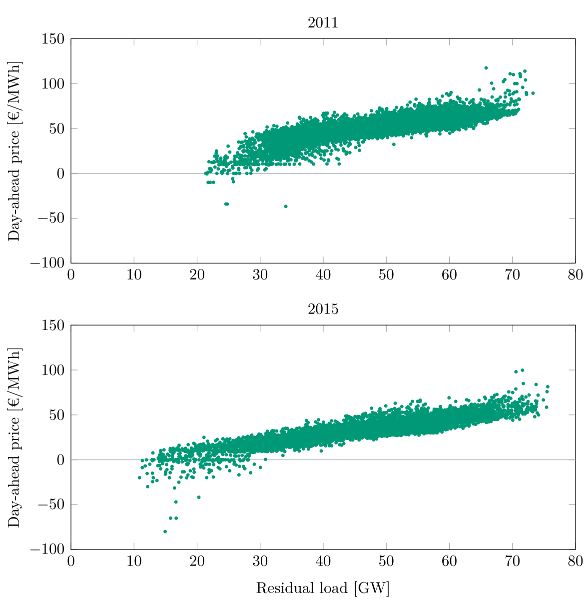

Fig. 6. The hourly day-ahead market prices as a function of the residual load. *Source:* Own illustration based on data from European Power Exchange (2016); European Energy Exchange (2016); ENTSO-E (2016).

for 2011 and 9 €/MWh for 2012, which is in the range of the merit order effect determined by Sensfuß (2011), who applies an agent-based model of the German electricity market (see Fig. 5).

In 2015, the merit order effect of the renewables available in total corresponds to 14.70 €/MWh. Cludius et al. (2014) determine a similar effect, whereby they use estimated values for the electricity prices in 2015. This shows that the hourly linear regression model introduced in Section 3.1 produces similar results for renewable effect compared to other models.

Comparing the results with Kallabis et al. (2016), who carry out a study for the decrease of German electricity future prices from 2007 until 2014, a similar relative price impact[14] can be observed for CO_2 prices. Kallabis et al. (2016) calculate an electricity price reduction of 0.71 €/MWh per €/EUA price reduction.[15] We determine a relative price effect of 0.70–1.09 €/MWh per €/EUA. This also applies to the effect of renewables, which corresponds to a reduction of 0.13 €/MWh per TWh power feed-in from RES and is close to the range of our calculated effect of 0.08–0.12 €/MWh per TWh.[16] However, there are interdependent effects between the price of carbon emission allowances and the level of renewable generation. While the effects are still investigated (Hintermann et al., 2016), in the long-term, a demand reduction induced by an expansion of renewable energies should lower the carbon price. Nonetheless, for the regarded time period, renewables explain only a small part of the carbon price variations (e.g. (Koch et al., 2014; Rickels et al., 2015)). Also taking into account that the expansion of renewable energies in Germany has only a limited impact on the European level, the interdependent effects should be negligible for the results of this study.

Regarding the effect of coal and gas prices, the relative effect calculated from the absolute values of Kallabis et al. (2016) is not indicative due to the small total change of the price drivers within the analyzed time period. However, within the time period of this study the fuel prices possess a significant development. Thus, we could determine a strong price reduction effect for especially coal prices 0.91–1.12 €/MWh_{el} per €/MWh_{th}). That is why we determine the coal price beside the carbon price as the strongest price driver between 2011 and 2015, while they only see the carbon price as the main driver of future electricity prices between 2007 and 2014.

5.4. Critical reflection of the modeling approach and results

Although the models described in Section 3 perform quite well to determine electricity price drivers, which becomes evident from the comparison of the results with other studies, the applied approaches have still room for improvement. To analyze the price impact of each influencing parameter between 2011 and 2015, we run two fundamentally different models, a linear multiple regression model based on historical time-series of the prices and their drivers as well as a fundamental agent-based approach that considers all important system elements of the electricity market. Thereby, it has to be mentioned that especially the linear regression model is not able to capture the non-linearities in the price relation. However, as we calibrate different regression models for each of hour of the day and make a further differentiation for workdays and non-workdays, the models are usually applied to relatively similar situations where the non-linearity should not distort the results.

The applied agent-based model simulates the German electricity system with its main fundamental elements. However, static import and export flows are used in the model to describe the electricity exchanges between Germany and its neighboring countries. This approach does not consider the reciprocal effect between prices and exports/imports and therefore possible changes in the price impact. In future research, this issue is to be addressed. However, we do not expect a significant change in the effect of each price driver, as wholesale prices in the neighboring countries show a similar development in the last years as the German electricity price and hence the cross-border flows are expected to be stable after varying a price parameter.

Additionally, the static approach we use for the determination of

[14] Here, a relative effect means that the absolute effect is broken down to the marginal change of a price driver.

[15] As Kallabis et al. (2016) show only the absolute effect in their study, we calculate the relative effect based on their absolute values for the base electricity futures with delivery in 2014 that traded in Q4 2007 and Q4 2013.

[16] In a working version of the paper (Kallabis et al., 2015), a value of 0.09€/MWh was presented, thus, closely matching the range in our results.

the price effect needs to be addressed as well. More detailed, we keep all other parameters fixed at the level of 2015 and change the analyzed parameter between the values of 2011 and 2015. We do not consider effects that a parameter would have on the other influencing parameters, if it really stayed at the level of 2011, e.g. the lower availability of wind power would influence the exports. As we consider a smaller period of four to five years, in which no larger differences in investments in power plants can be expected and the structure of the energy system may not strongly change, the model error without considering the interdependencies is assumed to be rather low. Therefore, the calculated price reductions of each parameter are still meaningful. However, the analysis could be extended allowing more cross-dependencies in future with applying e.g. vector autoregressive models.

6. Conclusions and policy implications

In this study, the main price drivers for the electricity prices at EPEX SPOT are analyzed focusing on their contribution to the price fall between 2011 and 2015 (decline of about 20 €/MWh). While recent studies have mainly focused on the price effect of renewable energies, especially photovoltaics and wind, and determined the so-called merit order effect, in this paper, the focus is set on the most important fundamental price drivers that lead to the price reduction in recent years. Our results demonstrate that fuel and carbon prices still have a dominating impact on wholesale electricity prices and that the drop in coal and carbon emission allowance prices was the main reason for the decline of electricity spot prices. Contrary to ongoing discussions, the strong expansion of photovoltaics in Germany was not the main price driver, and the related merit-order effect was not primarily responsible for the strong decline in wholesale electricity prices. The additional price effect of photovoltaics between 2011 and 2015 was relatively low compared to the effect of coal and carbon prices. Hence, the widespread opinion that the merit order effect of renewables is the main reason for the low prices we face today at wholesale markets has to be at least partly rejected. The total price effect of renewables since their market introduction makes up 14–15 €/MWh in Germany and is indeed a strong effect. However, the additional price effect between 2011 and 2015 is contributing only partly (5.40 €/MWh determined with the agent-based model, 6.80 €/MWh with the regression model) to the price decrease of almost 20 €/MWh in this period.

Using different types of models for our analysis proved to be helpful to gain a thorough understanding of the price impact of the regarded fundamental factors and to quantify the related uncertainty. As all models have their specific shortcomings, the application of several models helps to derive robust results. As the linear regression model can be implemented with relatively little effort it seems to be a suitable way to identify the main trends. However, caution has to be paid for large input changes that might result in non-linear effects. In this case, the agent-based bottom-up model yielded more plausible results. Nevertheless, the implementation and application of this type of models is time-consuming, which might have contributed to the fact that many recent studies apply regression models. The results of the time-varying regression model are of limited benefit for our analysis as in contrast to the volatile feed-in of wind and photovoltaic, the price effect of the gradually changing fuel and carbon prices is not adequately captured. The linear regression and the agent-based model, however, can also be used to analyze price effects in other countries and electricity markets, which faced a strong price decrease in the last years, too.

Furthermore, the price models are used to analyze the income situation and the annual return of gas power plants, which will still be required in the future energy system to balance fluctuating renewables. The scenario analysis for 2020 shows that if the coal and carbon prices recover to the level of 2011, a modern CCGT power plant can generate enough income to meet the variable and operational fixed costs. In this situation, the prices are high enough to achieve a slightly positive annual return. This may be sufficient to keep existing gas-based capacity in the market, but would not incentivize new investments. However, the development of other parameters, such as surplus capacities in the electricity market, plays also an important role for the recovery of electricity prices and hence for the profitability of gas-fired power plants.

In this context, the decision of the European Commission to establish a market stability reserve from 2019 on and to take emission certificates out of the carbon market is a step towards the right direction. However, it may not be sufficient to completely remove the oversupply with certificates and thus, to achieve a recovery of certificate prices. Regarding the development of the current surplus volume in the next years, additional measures might be necessary to trigger an increase in carbon prices in order to make the operation of more environment-friendly gas power plants favorable compared to coal power plants. However, policy measures regarding carbon policy have to be installed at European level and should even be harmonized worldwide, as more restrictive national measures without harmonization can lead to “carbon leakage” or a new surplus of certificates in the EU ETS.

If carbon and coal prices remain at the current low level, an economic operation of gas power plants will be hardly possible and it will be difficult for energy suppliers to keep them in the market. In this case, other market mechanisms, such as a capacity remuneration mechanism, will be required to operate these flexible power plants profitably and thus, to keep them in the electricity market. However, implementing new market regulations has to be done with care, as it can disturb the market operation resulting in new uncertainties for investors.

Continuing low prices will keep the market value of electricity generated from RES at a low level as well, which in turn makes higher funding volumes for renewables necessary. Also in this respect, the recovery of coal and carbon certificate prices is essential.

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Appendix A. Appendix

Table A.1 and Table A.2

Table A.1
Test for multicollinearity for hour 12 on working days.

CondIdx	Intercept	Load	Wind	pv	Gas	Coal	Carbon	Dummy1	Dummy2	Dummy3
1.000	0.000	0.000	0.005	0.002	0.000	0.000	0.001	0.002	0.002	0.002
2.522	0.000	0.000	0.013	0.007	0.000	0.000	0.000	0.208	0.044	0.052
2.631	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.171	0.146
3.833	0.000	0.000	0.632	0.011	0.000	0.000	0.000	0.137	0.008	0.002
5.123	0.000	0.000	0.136	0.104	0.001	0.005	0.049	0.242	0.052	0.063
6.850	0.001	0.001	0.032	0.111	0.007	0.000	0.066	0.243	0.387	0.390
9.304	0.000	0.001	0.018	0.365	0.022	0.003	0.254	0.026	0.239	0.215
22.975	0.024	0.046	0.121	0.233	0.066	0.389	0.038	0.002	0.079	0.062
32.169	0.007	0.018	0.000	0.014	0.880	0.601	0.590	0.005	0.008	0.029
83.451	0.968	0.934	0.041	0.154	0.024	0.001	0.002	0.134	0.011	0.039

Table A.2
Goodness of fit for the linear regression model.

	R^2		R^2 adj		RMSE	
Hour	WD	WE	WD	WE	WD	WE
0	0.767	0.745	0.766	0.741	4.502	5.915
1	0.740	0.744	0.739	0.740	4.683	5.753
2	0.726	0.723	0.724	0.719	4.960	5.981
3	0.711	0.716	0.710	0.712	5.078	5.991
4	0.724	0.699	0.722	0.694	4.743	6.237
5	0.770	0.703	0.769	0.698	4.916	6.444
6	0.695	0.712	0.693	0.708	6.010	6.811
7	0.712	0.746	0.710	0.742	6.054	6.479
8	0.739	0.772	0.738	0.768	6.192	6.326
9	0.784	0.788	0.783	0.785	6.080	6.197
10	0.793	0.801	0.791	0.798	6.129	6.163
11	0.817	0.798	0.816	0.794	5.838	6.296
12	0.829	0.798	0.828	0.795	5.570	6.119
13	0.838	0.785	0.837	0.782	5.314	6.063
14	0.834	0.764	0.832	0.760	5.005	5.965
15	0.815	0.755	0.814	0.751	4.941	5.852
16	0.788	0.758	0.787	0.754	5.125	5.851
17	0.770	0.767	0.768	0.763	5.611	5.914
18	0.714	0.771	0.712	0.767	7.074	6.145
19	0.690	0.763	0.688	0.759	6.962	5.977
20	0.741	0.794	0.739	0.791	5.306	5.025
21	0.741	0.822	0.739	0.819	4.860	4.657
22	0.791	0.790	0.789	0.787	4.349	4.923
23	0.800	0.751	0.799	0.747	4.152	5.643

Appendix B. Dynamic fundamental model

B.1. Model description

Similar to Paraschiv et al. (2014) and Karakatsani and Bunn (2008), we develop a state space model with time-varying regression coefficients for the day-ahead electricity prices. Applying an approach with time-varying coefficients is based on the assumption that the price formation is continuously adapting to the changing fundamental factors, e.g. sudden decommission of nuclear capacities, European market integration, new regulatory policies (e.g. market stability reserve) or new market rules (e.g. negative prices or block bids). Using a time-varying model has already proven to be effective in the studies of e.g. Mount et al. (2006) or Karakatsani and Bunn (2010).

Similar to the linear regression model, the dynamic fundamental model is implemented for each hour of the day, so daily patterns e.g. hours with high or low demand can be analyzed separately, yet in contrast, for this model only working days are included. This is related to the fact that coal, gas or carbon emission allowances are only traded on working days and thus for weekends/holidays no separate values exist which, however, are required for an adequate calibration.[17]

The incorporated variables differ slightly from the linear regression model with constant parameters. In order to deal with autocorrelation and include price signals, we use the lagged hourly electricity price from the previous day. The lagged price should have a positive reinforcing influence on the current price, as extreme electricity prices tend to occur within a short time frame (Huisman and Mahieu, 2003). The model is then formulated as follows:

$$y_{i,t} = X_{i,t}\, b_{i,t} + \epsilon_{i,t} \tag{B.1}$$

$$b_{i,t} = b_{i,t-1} + \eta_{i,t} \tag{B.2}$$

[17] For the linear regression model, the fuel price on weekends/holidays equals the last available traded price as the model does not take into account the price difference from the previous day. However, this approach is not applicable for the time-varying regression model that relies on the changes between time steps.

where for $i \in \{1, \ldots, 24\}$

$$b_{i,t} = (b_{i,t}^{0}, b_{i,t}^{load}, b_{i,t}^{wind}, b_{i,t}^{solar}, b_{i,t}^{gas}, b_{i,t}^{coal}, b_{i,t}^{carbon}, b_{i,t}^{exchange}, b_{i,t}^{meanlag-1})'$$
$$X_{i,t} = (x_{i,t}^{0}, x_{i,t}^{load}, x_{i,t}^{wind}, x_{i,t}^{solar}, x_{i,t}^{gas}, x_{i,t}^{coal}, x_{i,t}^{carbon}, x_{i,t}^{exchange}, x_{i,t}^{meanlag-1})$$
$$\eta_{i,t} \sim \mathcal{N}(0, Q_i)$$
$$\epsilon_{i,t} \sim \mathcal{N}(0, R_i)$$
$$E(\epsilon_{i,t}\eta_{i,t}) = 0$$
$$Q_i = \mathrm{diag}(\sigma_{i,0}^2, \ldots, \sigma_{i,meanlag-1}^2)$$

Eq. (B.2) is called the transition equation and describes the change of the regression coefficients over time. Eq. (B.1) represents the measurement equation, which relates the vector of the exogenous variables $X_{i,t}$ to the electricity price $y_{i,t}$. For the calibration of the model, first, the covariance matrices Q_i and R_i, which are assumed to be constant over time, are calculated with the maximum likelihood estimation. Afterward, the coefficients $b_{i,t-1}$ of the different fundamental factors are estimated with the Kalman Filter. This is done for each step t taking into account only the information that is already available at that time. Afterward, for each hour of the day, the dynamic influence of the regarded factors can be analyzed.

B.2. Model validation

As stated before, the results of the dynamic fundamental model are of limited benefit for our analysis, even though the statistical figures show that the model possesses a high explanatory power (see Table B.1). While highly volatile factors such as the wind feed-in or load are adequately captured within the model, the coefficients of less volatile price drivers are insignificant most of the time or if significant, possess values that are non-plausible from a fundamental economic perspective. In contrast to the other obtained results, the dynamic model states that e.g. an increasing coal price lowers the electricity price in peak hours by a factor of about 2. This is related to the fact that the calibration of the model is based on daily changes. However, a gradual development, e.g. the decline of the coal price that extends over several years, has an almost negligible short-term effect in comparison with the changes of the wind or photovoltaic feed-in. Strong daily changes or price shocks which could improve the results, only occur once in the regarded period, when the gas price increases from about 24–40 €/MWh within a few days. Besides this single significant change, there are no remarkable changes in the fuel prices in the short-term. Therefore, the dynamic model cannot determine plausible beta coefficients for the long-term developing fuel prices. This approach can determine short-term effects quite well but indeed fails for the analysis of the mid- and long-term effect, which is in the focus of this study.

Table B.1
Result of the linear regression and the dynamic fundamental model.

Hour	3		12		18	
Model	Dynamic	Linear	Dynamic	Linear	Dynamic[a]	Linear
Observations	1247	1250	1247	1258	1222	1227
R^2	0.771	0.711	0.876	0.829	0.794	0.714
Adjusted R^2	0.770	0.710	0.875	0.828	0.793	0.712
MAE	3.172	3.752	3.629	4.383	5.300	5.493
MAPE	0.907	1.048	0.087	0.107	0.093	0.102
MAPE*[b]	0.173	0.180	0.087	0.107	0.093	0.102
RMSE	5.186	5.078	4.824	5.570	7.625	7.074
prob $b_{i,t}^{carbon}$	0.106	0.000	0.194	0.000	0.449	0.000
prob $b_{i,t}^{coal}$	0.153	0.044	0.733	0.000	0.005	0.000
prob $b_{i,t}^{gas}$	0.466	0.000	0.916	0.000	0.928	0.000
avg $b_{i,t}^{carbon}$	−0.139	1.162	0.767	1.106	0.779	0.838
avg $b_{i,t}^{coal}$	−0.778	0.254	0.196	0.933	−2.366	0.944
avg $b_{i,t}^{gas}$	0.134	0.219	0.588	0.624	1.016	1.077

[a] The first 25 values are not included for the calibration with the dynamic model as they contain a price jump, which strongly distorts the statistical figures e.g. a RMSE of almost 100.
[b] Due to the large impact of prices close to zero on the MAPE, all historical prices in the interval [−1, 1] are filtered for the calculation of the MAPE*.

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