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Drivers of electricity price dynamics: Comparative analysis of spot and futures markets

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ABSTRACT

Against the backdrop of numerous evidence that variable renewable generation decreases electricity prices and increases price volatility, this paper assesses the drivers of electricity prices in spot and futures markets, focusing on the German electricity markets. We take into account nonlinearities in electricity prices by means of structural breaks and threshold regressions. We find that short-run and medium/long-run price drivers differ and, more importantly, that they vary over time. In the case of the spot market, the determinants of prices are renewable infeed and electricity demand, while in the futures market the main drivers are natural gas, coal and carbon prices. Our results give relevant insights for market participants who seek to optimize procurement/selling strategies in the spot market, and use the futures market to hedge against spot price volatility, which has increased due to a higher renewable generation.

1. Introduction

In order to mitigate the negative impacts of fossil fuels on the environment, many countries have embraced the renewable energy agenda. Germany has one of the most ambitious targets to increase renewables penetration. In 2000, the German share of renewables was only 6%, while in 2016 it reached 32%. The increasing share of renewables has been accompanied by decreasing day-ahead electricity prices. The prices dropped from 51 €/MWh in 2011–29 €/MWh in 2016. The decrease in German electricity prices is mainly attributed to the merit-order effect of renewables. Moreover, given the high dependence of wind and solar power generation on weather factors, their intermittency tend to increase electricity spot price volatility in the absence of viable electricity storage (see e.g., Benhmad and Percebois, 2016; Ketterer, 2014; Kyritsis et al., 2017; Rintamäki et al., 2017).

Market participants have access to the electricity futures market in order to hedge risk derived from spot price volatility. And, if it is the case that this volatility is higher due to the impact of renewables on day-ahead electricity prices, the need for trading these contracts may increase. Accordingly, we propose to not only analyze the impact of renewables on spot prices, but also to determine the drivers of electricity futures prices, and to assess the differences across markets, which to our knowledge is a novelty in the literature. We use factors such as wind power and PV infeed forecast, load, and conventional generation input variables like natural gas, coal, and carbon prices. We use a new time span that ranges from January 2010 to September 2017, which enables us to take into account not only the decline in prices until 2016, but also the price increases–despite continuous growth in renewables infeed–in the subsequent period.

Given the nonlinearity of electricity prices dynamics, we use nonlinear econometric techniques to quantify the impact of our selected variables on the different electricity markets. Moreover, we argue that the merit-order effect (MOE) of renewables could be time-varying. Unlike the current literature, we assess the existence of structural breaks in a multivariate linear regression framework, and we estimate the MOE using rolling windows to quantify the dynamics over time of renewables penetration in German's electricity spot market. We also evaluate if the effect of renewables on electricity prices varies with the level of wind power or photovoltaic (PV) generation.

The extant literature evaluating the impact of renewable energy production on electricity day-ahead prices has largely focused on the German market. For example, in recent works like Cludius et al. (2014) and Zipp (2017), following a multivariate linear regression approach, the authors estimate the MOE induced by renewable energy, finding that during 2011–2013 wind and solar electricity generation reduced spot prices between 7 €/MWh and 14 €/MWh. Analyzing the prices from 2010 to 2013, Paraschiv et al. (2014) also found that renewable energies decrease market spot prices, but the prices for final consumers

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increased because they were charged in addition the feed-in tariffs for the promotion of renewable energy in Germany. Using quantile regressions, Hagfors et al. (2016) show that renewables have a mild effect decreasing prices, and that negative prices, often attributed to renewable generation, are rare events that occur during periods of low demand, like at night time. Mosquera-López et al. (2017) also use quantile regressions to assess the impact of weather factors on electricity prices; the authors find that wind speed and temperature are the main drivers, especially in the tails of the price distribution. Paschen (2016) analyzes the effect of structural shocks in wind and solar power on spot prices, finding that wind power shocks have a more prolonged effect decreasing prices than solar power shocks. Bublitz et al. (2017) using agent-based modeling and a regression approach find that during 2011–2015 the impact of carbon prices on decreasing German electricity day-ahead prices was higher than the impact of renewables.

The negative impact of renewables on electricity spot prices has also been found for other countries like Spain (see Azofra et al., 2014; Ballester and Furió, 2015; Gelabert et al., 2011), Italy (see Clò et al., 2015; Gullì and Balbo, 2015), the United States (see Brancucci Martinez-Anido et al., 2016; Kaufmann and Vaid, 2016; Woo et al., 2016), and Australia (see Bell et al., 2017; Forrest and MacGill, 2013), among others. However, the impact of renewables on futures markets has been scarcely studied (see Kallabis et al., 2016). We aim to fill this gap in the literature by assessing the effect of renewables–among other factors–on both electricity spot and futures prices.

Regarding the nonlinearities that electricity prices exhibit, few studies have taken them into account. For example, Hagfors et al. (2016) use quantile regressions for estimating the effect of renewables on different parts of the distribution of electricity prices, and Paraschiv et al. (2014) and Bublitz et al. (2017) follow a time-varying coefficients approach. We also contribute to the literature by allowing price drivers to have distinct time-varying effects on electricity spot and futures markets' price dynamics. Finally, unlike previous studies that measure the MOE (see e.g., Cludius et al., 2014; Zipp, 2017) by years, we estimate a MOE for each day in the data, following a rolling windows approach.

We find that short-run (spot market) and medium/long-run (futures market) price drivers are different, and more importantly that they vary over time. In the case of the spot market, the determinants of prices are renewable infeed and demand, and we find five time- regimes during 2010–2017. Also, by means of a threshold regression we find that PV is the variable that has a different effect on prices once it crosses a certain value. In the futures market the main drivers are natural gas, coal and carbon prices, and different regimes are found depending on the delivery period (week, month, quarter or year). Concerning the MOE, we find the MOE of wind power is higher than solar power, but PV has gained considerable importance in time, from not reducing the prices at all in 2010 to reducing them on average approximately by 4 €/MWh per additional GWh in 2017.

The observation of different period-regimes is suggestive of continuously changing dynamics in electricity markets as variable renewables are incrementally added to the electricity generation mix. As an example, we find for the first time, a trend reversal in spot prices that is likely indicative of a transition to a new regime. Our finding that futures markets are not influenced by renewables point to the need for novel instruments, such as Wind Power Futures and Purchasing Power Agreements (PPAs), to hedge the price-volatility risks induced by high renewables penetration.

The remainder of this document is organized as follows. Section 2 contains the methodology proposed to determine the impact of different factors on electricity spot and futures prices. In Section 3, the data used is described, distinguishing between dependent and explanatory variables. In Section 4, the main results are discussed. Finally, in Section 5, conclusions and policy implications of our study are presented.

2. Methodology

Following a multivariate regression approach, we model the linear effect of potential price drivers on electricity day-ahead and futures prices. Afterwards, we assess if the statistically significant variables have nonlinear effects on prices: first, we use ordinary least squares (OLS) with breaks to determine the existence of any structural breaks during the time span analyzed that may produce period-regimes; second, we fit a threshold regression to evaluate the existence of different regimes in the model due to observed variables crossing unknown threshold values. Lastly, we measure the MOE using rolling windows to estimate the dynamics of the MOE of renewables over time.

2.1. Linear regressions

Eq. (1) shows the model built for daily average electricity spot prices:

$$\begin{aligned} Spot_t \;=\;& \beta_0 + \beta_1 Wind_t + \beta_2 PV_t + \beta_3 Load_{t-1} + \beta_4 EGIX_{t-1} \\ &+ \beta_5 API2_{t-1} + \beta_6 EUA_{t-1} + \epsilon_t, \end{aligned} \tag{1}$$

where *Wind* and *PV* are the wind and solar power infeed day-ahead forecast, respectively. *Load*[1] is the electricity consumption, *EGIX* is the EEX European natural gas price index, *API2* is the benchmark price reference for coal imported into northwest Europe, and *EU A* refers to the European Emissions Allowances, which is the benchmark of carbon prices in Europe. Since the decisions that form today's price are made by market participants the day before, all the explanatory variables are lagged one day or are a day-ahead forecast.

For futures prices we use the following model:

$$\begin{aligned} Futures_t \;=\;& \beta_0 + \beta_1 Wind_t + \beta_2 PV_t + \beta_3 Load_t + \beta_4 EGIX_t \\ &+ \beta_5 API2_t + \beta_6 EUA_t + \epsilon_t. \end{aligned} \tag{2}$$

In this case, we do not use lagged variables because bidding decisions at time t for futures contracts are based on all information available at time t. The dependent variable *Futures* stands for an index constructed with the settlement price and the volume traded of Phelix-Base-Futures contracts for different delivery periods (week, month, quarter and year). Each index was calculated building successive nearest contracts series given the maturity dates, and computing the volume-weighted average of each series.[2]

2.2. Nonlinear regressions

2.2.1. OLS with breaks

Following Bai (1997), Bai and Perron (1998), and Bai and Perron (2003), we consider a multiple linear regression with m breaks ($m + 1$ regimes)[3]:

[1] We do not include thermal generation, which is also a significant source of electricity in Germany, since it is a large component of the residual load, which is equal to the load minus wind and solar power generation. Therefore, the inclusion of this variable would translate into a high multicollinearity in the model.

[2] The results presented here, with our model setup for spot and futures market, are robust to the inclusion of a variable that measures exports and imports flows between the Germany and its commercial partners. Following Zipp (2017), we constructed this variable as $trade_t = \sum_{j=1}^{N} exports_j - \sum_{j=1}^{N} imports_j$, where $exports_j$ is the total amount of electricity exports from Germany to the country j, $imports_j$ is the total amount of electricity imports of Germany from the country j, and N are the total number of countries Germany trades with. Indeed, this variable does not improve the goodness of fit of the linear models nor the nonlinear ones, and in many cases it lacks any explanatory power on the prices.

[3] By using OLS with breaks we endogenously capture different period-regimes in electricity prices that could be likely related to changes in the power plant availability in Germany. Moreover, this approach enables us also to capture

$$y_t = x_t'\beta + z_t'\delta_j + \epsilon_t, \tag{3}$$

where $t = T_{j-1}+1, ..., T_j$ for $j = 1, ..., m + 1$, and where $T_0 = 0$ and $T_{m+1} = T$. y_t corresponds to the spot or futures prices, x_t are the explanatory variables whose coefficients (β) do not vary across regimes, z_t are the variables that have regime-specific coefficients (δ_j), and ϵ_t is the disturbance term.

If Eq. (3) is expressed in matrix form, the multiple linear regression system is equal to:

$$Y = X\mathrm{B} + \bar{Z}\delta + \mathcal{E}, \tag{4}$$

where $Y = (y_1, ..., y_T)'$, $X = (x_1, ..., x_T)'$, $\mathcal{E} = (\epsilon_1, ..., \epsilon_T)'$, $\delta = (\delta_1', ..., \delta_{m+1}')$, and $\bar{Z}$ is the matrix which diagonally partitions z at (T_1, …, T_m), which are the break points.

Following the least-squares principle, the estimates of β and δ_j are obtained by minimizing the sum of the squared residuals:

$$(Y - X\mathrm{B} + \bar{Z}\delta)'(Y - X\mathrm{B} + \bar{Z}\delta) = \sum_{j=1}^{m+1} \sum_{t=T_{i-1}+1}^{T_i} [y_t - x_t'\beta + z_t'\delta_j]^2. \tag{5}$$

According to Bai and Perron (1998), the estimation of the breaks can be done simultaneously, in which case the break points are global minimizers of the objective function (Eq. (5)), or sequentially, where each break is estimated one at a time. Bai (1997) demonstrated that it is possible to consistently estimate all break points in a sequential manner, so that each break point is a local minimizer of the objective function. With the sequential approach, the selection of each break point is done using the information of each partition only, and not with the information of the whole sample. This means, for instance, that whether a break point today is selected or not is independent on whether that there is a break point tomorrow (as it is done with the simultaneous approach). Hence, we follow the more intuitive sequential approach to estimate the break points in our models.

2.2.2. Threshold regression

A threshold regression model combines a linear specification with a regime switching structure to describe a nonlinear relationship between the variables (see Hansen, 2011, 1999; Potter, 1999). The change in the regime occurs when an observed variable crosses unknown threshold values. In other words, the correlation between the explanatory and the explained variables is allowed to differ before and after a certain threshold is crossed in the data. In our model the statistically significant variables from Eq. (1) are selected as possible threshold variables.

Consider a multiple linear regression model with T observations and m potential thresholds, which gives $m + 1$ potential regimes:

$$y_t = x_t'\beta + z_t'\delta_j + \epsilon_t, \tag{6}$$

where j denotes a regime, and $j = 0, …, m$. Just as in the case of the OLS with breaks, the x_t variables are those whose parameters do not vary across regimes, while the z_t variables have coefficients that are regime-specific.

If q_t is an observable threshold variable, the thresholds allowed by the model are $\gamma_1 < \gamma_2 ... < \gamma_m$, so that the model is in regime j if $\gamma_j \le q_t \le \gamma_{j+1}$.

In a two regime model where q_t has a single threshold value, γ_1, the model is given by:

$$y_t = \begin{cases} x_t'\beta + z_t'\delta_1 + \epsilon_t, & -\infty < q_t < \gamma_1 \\ x_t'\beta + z_t'\delta_2 + \epsilon_t, & \gamma_1 \le q_t < \infty \end{cases} \tag{7}$$

In the general case of $m + 1$ regimes, we have:

$$y_t = x_t'\beta + \sum_{j=0}^{m} 1_j(q_t, \gamma) \bullet q_t \delta_j + \epsilon_t, \tag{8}$$

where $1_j(q_t, \gamma)$ is an indicator function equal to $1_j(\gamma_j \le q_t < \gamma_{j+1})$.

2.3. Merit-order Effect (MOE) estimation

Lastly, we use rolling windows of size k to estimate the dynamics of the MOE of renewables over time. The MOE is the average reduction in electricity day-ahead prices per additional gigawatt hour of electricity produced by wind power or PV in a given hour. Since the MOE is a short-term phenomenon, for its calculation we use hourly day-ahead electricity prices, and we estimate the following model for each subsample[4]:

$$Spot_t = \beta_0 + \beta_1 Wind_t + \beta_2 PV_t + \beta_3 Load_t + \epsilon_t. \tag{9}$$

Following Cludius et al. (2014), we calculate the absolute wind power and PV MOE as:

$$Total\ MOE_k = \beta_1 Wind_k^{mean} + \beta_2 PV_k^{mean}, \tag{10}$$

where k is the length of the rolling window, and the *mean* is the load-weighted average of wind power or PV generation during k.

3. Data

We selected Germany for our analysis since it is one the countries with the highest share of variable renewables worldwide. The German share of renewable electricity increased considerably from 6% in 2000 to about 32% in 2016. This increase is attributed mainly to the Energiewende, in particular, the Renewable Energy Act 2010 (and its following amendments), where priority dispatch for renewable power was established, and feed-in tariffs and auctions for renewables were stated. Besides renewables, Germany has a significant fleet of coal power plants and is phasing out nuclear power plants as part of the Energiewende. From 2011–2017 nine nuclear plants went out of operation, and the Energiewende has 2022 as the target year for the last nuclear plant to be shut down.

In 2016, the German generation mix was composed by 54% fossil fuels (coal - 37% and natural gas - 15%), 15% wind power, 7% solar power, and 11% nuclear power (See Fig. 1). During 2010–2016, the generation with fossil fuels has been stable, while the higher penetration of renewables have replaced nuclear generation. Regarding electricity prices, the day-ahead prices decreased from 51 €/MWh in 2011 to 29 €/MWh in 2016 (average per year).

Our dataset of dependent variables consists of the hourly and daily average day-ahead (spot) electricity prices for the German/Austrian zone, quoted in €/MWh, and the Phelix-Base-Futures (week, month, quarter, and year contracts), also quoted in €/MWh. The dataset of explanatory variables consists wind power infeed day-ahead forecast, photovoltaics infeed day-ahead forecast, load, and natural gas (EGIX), coal (API2) and carbon (EUA) prices. The frequency of the futures contracts prices and the explanatory variables is daily. The sample period starts on January 2010 and ends on September 2017. Table 1 presents a description of each of the time series, specifying data source, units, stationarity tested with the Augmented Dickey-Fuller Test, and the transformation performed to the data in order for it to become stationary.

(footnote continued)
significant changes in feed-in tariffs that otherwise would not be possible to detect on a daily price analysis.

[4] If the number of increments between successive rolling windows is one period (one hour), then the number of subsamples would be N = T – k + 1. The first rolling window contains observations for period 1 through k, the second rolling window contains observations for period 2 through k + 1, and so on.

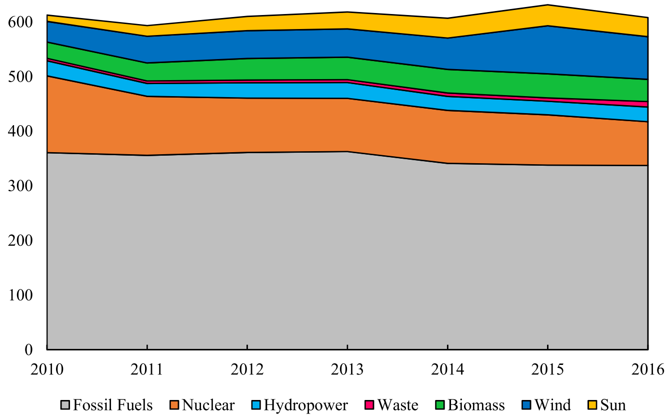

Fig. 1. Evolution of the generation matrix, TWh, 2010–2016.
Source: own elaboration with Data from the Federal Ministry for Economic Affairs and Energy and ENTSO-E.

Table 2
Descriptive statistics dependent variables.

	Hourly spot	Daily spot	Week-Base-Future	Month-Base-Future	Quarter-Base-Future	Year-Base-Future
Mean	38.10	38.10	38.50	39.29	40.32	39.96
Maximum	210.00	101.92	63.85	66.04	64.05	60.74
Minimum	−221.99	−56.87	14.45	21.53	21.97	20.62
Std. Dev.	16.30	12.44	9.51	9.56	9.91	10.66
Observations	67,919	2830	1874	1960	1960	1960

Table 1
Data description.

Variable	Source	Units	Stationarity	Transformation
		Dependent variables		
Hourly Spot Prices	EPEX SPOT SE	€/MWh	Stationary	None
Daily Average Spot Prices	EPEX SPOT SE	€/MWh	Stationary	None
Phelix-Week-Future Prices	EEX	€/MWh	Stationary	Growth rate
Phelix-Month-Future Prices	EEX	€/MWh	Stochastic trend	Growth rate
Phelix-Quarter-Future Prices	EEX	€/MWh	Stochastic trend	Growth rate
Phelix-Year-Future Prices	EEX	€/MWh	Stochastic trend	Growth rate
		Independent variables		
Wind Power Infeed Forecast	German grids: 50Hertz, Amprion, TenneT, and TransnetBW	GWh	Stationary	None
Photovoltaics Infeed Forecast	German grids: 50Hertz, Amprion, TenneT, and TransnetBW	GWh	Stationary	None
Load	ENTSO-E	GWh	Stationary	None
EGIX	Datastream	€/MWh	Stochastic trend	Growth rate
API2	Datastream	$/MT	Stochastic trend	Growth rate
EUA	Datastream	€/EUA	Stochastic trend	Growth rate

3.1. Dependent variables

The spot prices correspond to the electricity traded for delivery the following day in 24 h intervals on the German/Austrian TSOs zones. The futures prices correspond to delivery or acceptance of delivery of electricity with a constant output of 1 MW into the maximum-voltage level of the German/Austrian area (Phelix-Futures contracts), during the delivery time on the delivery period.[5] The delivery time refers to base-load if the electricity is to be delivered during all 24 h of the delivery period, or peak for delivery from 8:00–20:00, or off-peak that accounts to base-load minus peak. We use the prices of base-load contracts in order for them to be comparable to the average daily spot price. The delivery period specifies the period of time during which the electricity must be delivered, and it might be a week, a month, a quarter or a year, among others.[6]

The descriptive statistics of the spot and futures prices indices[7] are presented in Table 2. On average, futures prices are higher than spot prices, especially for the contracts with longer maturities. The daily average electricity prices are depicted in Fig. 2. The prices present spikes, seasonal patterns and volatility clustering, and they have been decreasing in time, at least until 2016. During our sample the prices decreased in average from 51 €/MWh in 2011 to 29 €/MWh in 2016. Fig. 3 plots the future prices indices and their returns. The prices present dynamics similar to standard financial futures: no strong seasonal patterns nor spikes (Aïd, 2015). Also, the longer the maturity, the less volatility the prices present, which is due to the seasonality effect of changing to contracts with shorter maturities once they become available. Until 2016 the futures prices also presented a continuous decrease.

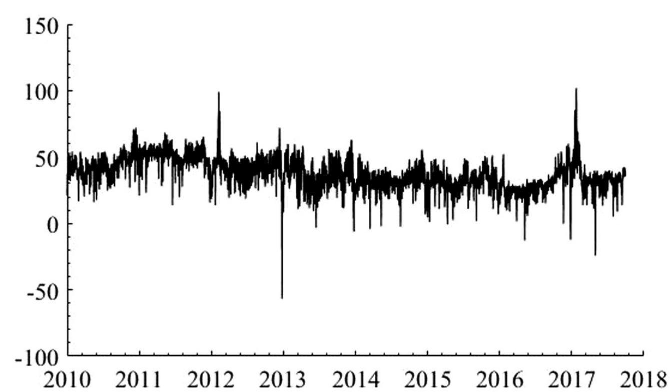

Fig. 2. Daily average electricity prices, January 2010 - September 2017, €/MWh.

3.2. Explanatory variables

We propose six variables as potential electricity drivers: wind power and PV infeed day-ahead forecast, consumption of electricity (load), natural gas prices, coal prices, and carbon prices. Following, we define each factor:

[5] All the power futures traded in EEX are only financially settled.

[6] EEX trades the following maturities: for the week contracts the current and the next four weeks; for the month contract the current and the next nine months; for the quarter contracts the next 11 full quarters; for the year contracts the next six years.

[7] Indices constructed as explained in Section 2.1 of the Methodology.

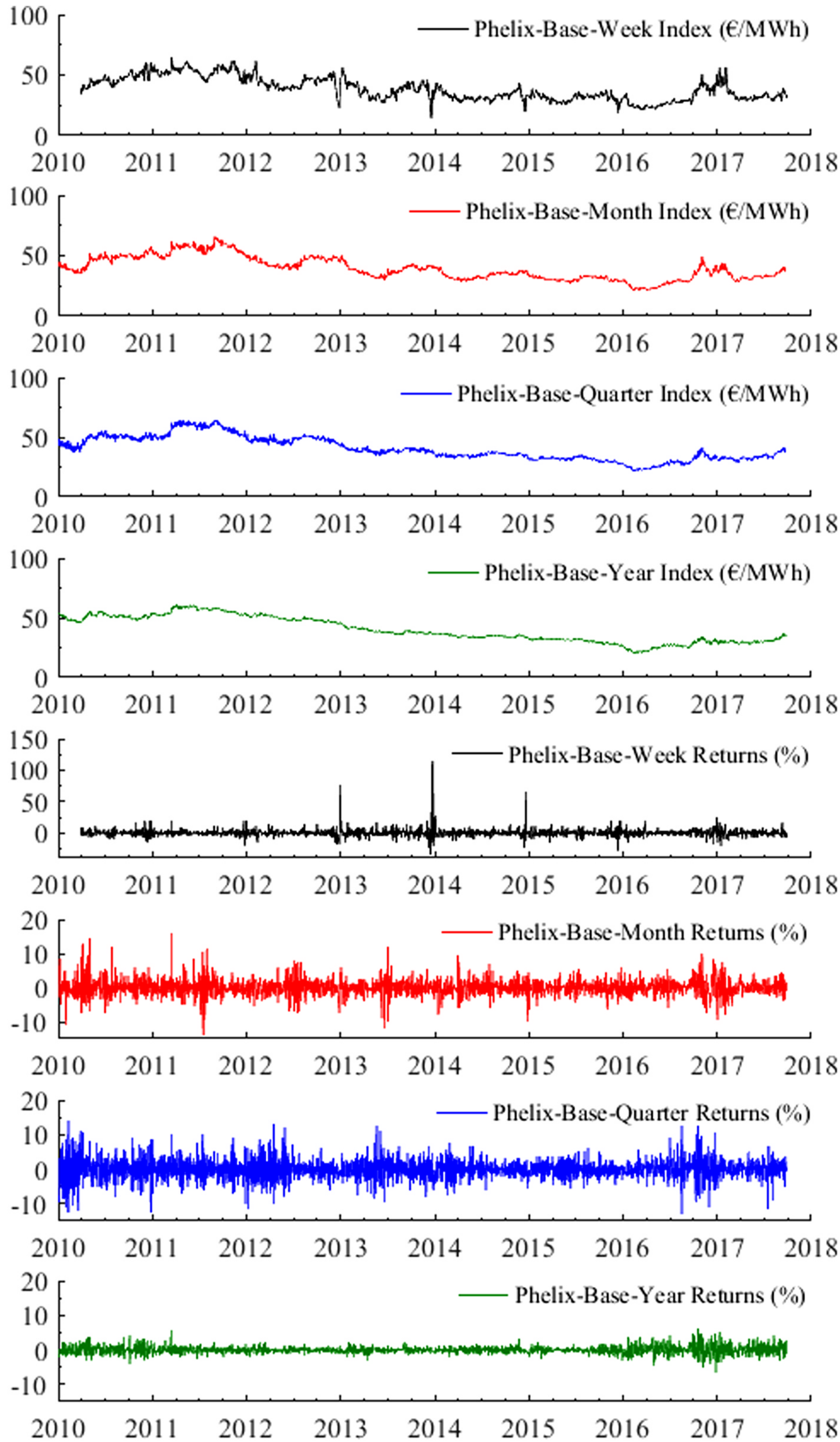

Fig. 3. Phelix-Base-Future price index, January 2010 - September 2017.

3.2.1. Wind power and PV infeed day-ahead forecast

Corresponds to the daily hourly average generation forecast for the next day published by German transmission grid operators.

3.2.2. Load

Following the definition from ENTSO-E, load is the consumption corresponding to the short-term average active power absorbed by all installations connected to the transmission grid or to the distribution grid, excluding the consumption for operating pumped-storage stations and the consumption of power plants auxiliaries, including network losses.

3.2.3. Natural gas

This factor is expected to affect the electricity price dynamics via

Table 3
Descriptive statistics explanatory variables.

	Wind infeed forecast	PV infeed forecast	Load	API2	EGIX	EUA
Mean	6.60	3.26	55.37	82.72	8.00	20.76
Maximum	33.20	9.77	71.04	131.40	16.84	29.06
Minimum	0.38	0.04	37.52	43.40	2.68	11.24
Std. Dev.	5.48	2.39	6.74	21.32	3.69	4.63
Observations	2830	2830	2830	2034	2034	2034

supply. We take European Gas Index (EGIX) as the reference for natural gas prices. EGIX is the daily index for the virtual German market area; the volume-weighted average price of the month con- tracts traded in the NCG and GASPOOL market areas.

3.2.4. Coal prices

As in the case of natural gas, this driver is expected to affect prices via supply. For coal prices we use the prices of the contract API2, which gives delivery or acceptance of delivery of steam coal with a calorific value of 6.000 kcal/kg net and maximum 1% of sulphur within 90 days, at the ARA (cif Amsterdam-Rotterdam-Antwerp) delivery point.

3.2.5. Carbon prices

It is also expected that carbon prices affect prices via supply due to the incentive scheme for reducing fossil-fuel electricity generation when the carbon price is high. We use the European Emission Allowances (EUA), which are the European benchmark for carbon prices. EUA prices correspond to the delivery or acceptance of delivery of General Allowances, which is the allowance to emit one tonne of carbon dioxide equivalent during a specified period.

Table 3 presents the descriptive statistics of the explanatory variables, which are shown in Fig. 4. PV infeed has increased steadily during the sample, and it presents clear seasonal patterns (higher generation during the summer and during the day). Wind power infeed has also increased, but not as pronounced as PV generation, and during winter time the generation tends to be higher than in other periods of the year. The level of consumption has been relatively stable during our period of analysis, and its maximum levels are around 70 GWh. From visual inspection, EGIX seems to have two regimes: an increasing- price regime from 2010 to 2014, and a low-price regime after mid-2014. In the case of API2 and EUA, both variables present a high-price regime until 2011, and a low-price regime thereafter. EUA had a steep drop in their prices: in 2011, the price per allowance reached 16 €, and in 2013–only two years later, the price reached levels below 3 €/EUA.

3.3. Preliminary analysis of the relation between dependent and explanatory variables

Table 4 presents the Pearson's correlation between the dependent variables (spot prices and Phelix-Base-Futures indices) and the six explanatory variables. For all the dependent variables, the correlation with wind and PV infeed forecasts is negative, as expected. However, the negative correlation is higher for the spot prices than for the futures indices, independently of the delivery period. In the case of input prices (EGIX, API2, EUA) the opposite holds: the correlation with the futures indices is higher than with the spot prices; although, as expected, the correlation is positive in both cases. Figs. 5 and 6 show scatterplots of spot prices against each explanatory variable, as well as the scatterplots for the futures week index. These plots indicate similar patterns: the higher the electricity generation with renewable sources, the lower the spot prices or futures indices. And the higher the prices of natural gas, coal or carbon, the higher the prices of electricity in spot and futures markets.

4. Results and discussion

Based on the estimation of the proposed models for electricity prices, we find that the determinants of spot prices are wind power and PV generation, and load (see Section 4.1), but their effects on prices change in time. In the case of futures prices, the drivers are natural gas, coal, and carbon prices, and their effects are also time-varying (see Section 4.2). We also estimated a threshold regression for the spot prices, and we find that PV is the selected threshold variable. Figs. 7 and 8 present the specific and absolute MOE, respectively.

4.1. Spot prices

Table 5 presents the estimation results of the OLS and OLS with breaks for the spot prices. From the linear regression we find that wind power and PV generation coefficient estimates are statistically significant and have the expected negative sign. From 2010–2017, one additional GWh of electricity generated by wind power decreased the spot price by 1.2 €/MWh, and in the case of solar generation, an additional GWh decreased prices by 2.1 €/MWh.[8] Load is also statistically significant in the linear setup, having an impact of increasing prices 0.3 €/MWh for each additional GWh of electricity demanded. The prices of inputs are not significant.

Although we find, as expected, that increments in renewable generation decrease spot prices, their effect on electricity prices is time-varying. We estimated an OLS regression with breaks, allowing all the explanatory variables to be breaking regressors. The resulting model has a better fit measured by the adjusted R^2 (79%) compared to the linear regression with an adjusted R^2 of (53%). During the sample period, the regression identifies five regimes, the first four of which capture the declining spot price dynamics. From January 2010 to August 2016 (end of the fourth regime), the price decreased from an average price of 47.6 €/MWh to 30.2 €/MWh. This decrease is mainly explained by the effect of renewables generation. Wind power and PV infeed have coefficient estimates statistically significant across all the five regimes. For wind power, its effect on prices is always negative but changes across regimes, ranging from decreasing the price by 0.7 €/MWh (first regime) to 1.5 €/MWh (third regime) from each additional GWh generated. PV also decreases prices across regimes, except in the first regime when the level of PV generation was still low. The initial price-increasing effect of PV may be attributed to the high cost of PV at the beginning of the period under study, but we did not explore this further.

Regarding the other factors included in our model, the load is also regime-sensitive with its effect ranging between 0 (third regime) and 1.1 (first regime). The electricity spot price increase in the last regime may be explained by a demand effect, where each additional GWh of electricity demanded increased the price by 1 €/MWh. For conventional generation input prices, EGIX is not statistically significant in any of the regimes, while API2 is significant in regimes one and three, with the expected positive impact. In the case of carbon prices, EUA is only significant during the second and third regimes, and in the second regime (December 2011 to March 2013) its effect on prices is negative. The decrease in prices due to carbon prices in this regime is explained by the steep decrease in EUA prices, where a decrease of 50% from regime one to regime two was recorded (result in line with Bublitz

[8] This result does not mean that the effect of PV is actually higher than the effect of wind power because these coefficients are not comparable due to differences in scale between the variables. In fact, after calcu- lating the standardized coefficients, it is found that wind power has a higher effect (a one sample standard deviation increase in wind power infeed leads to a decrease of 0.62 standard deviations in the prices) than PV (a one sample standard deviation increase in PV infeed leads to a decrease of 0.48 standard deviations in the prices) on prices.

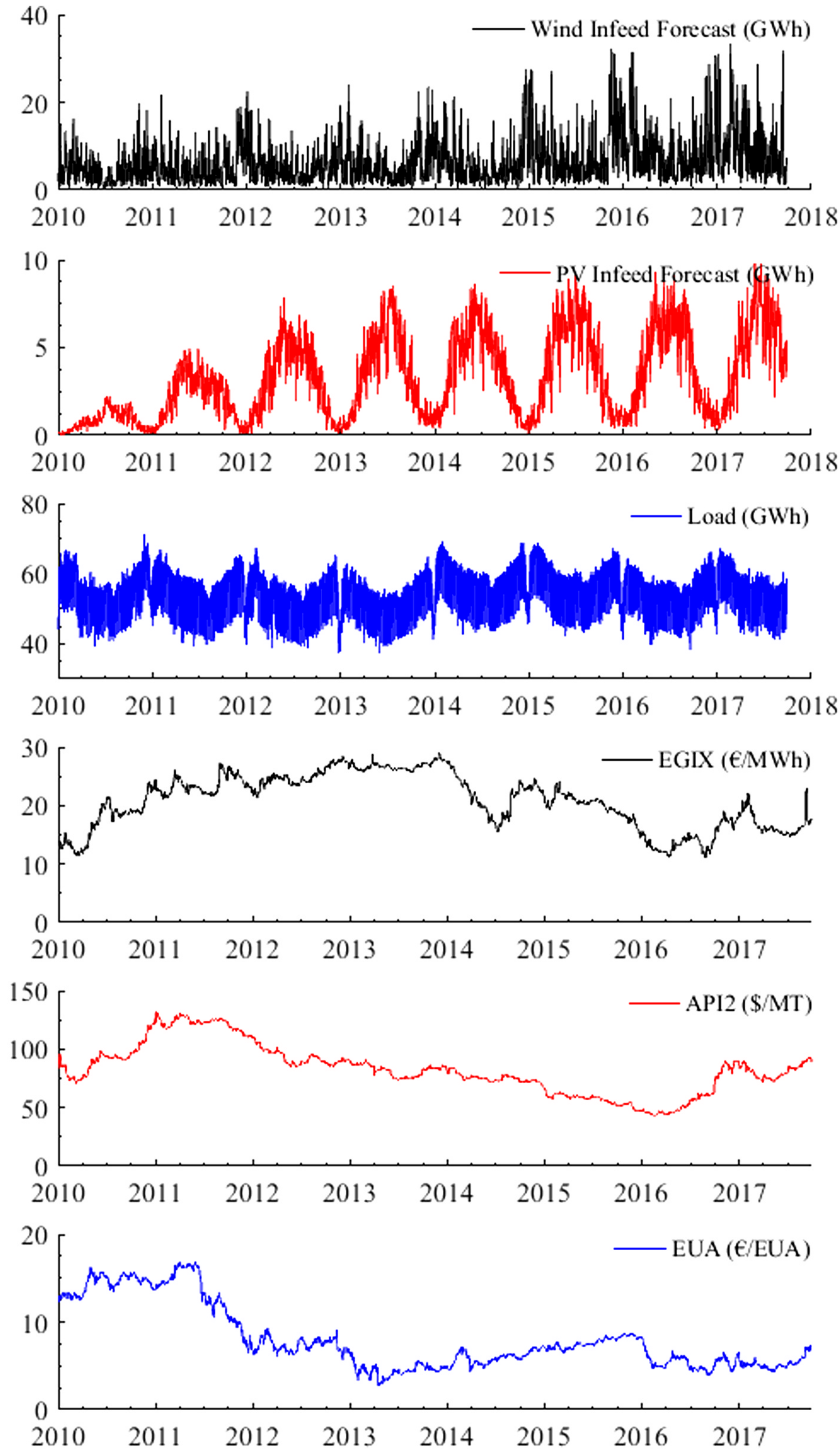

Fig. 4. Explanatory variables, January 2010 - September 2017.

et al., 2017, where the authors find that carbon prices are the main reason behind the decrease in German electricity prices during 2011–2015).

To assess whether the effect of renewables on electricity prices varies with the level of wind power or PV generation, we estimated a threshold regression for the spot prices (Table 6). The model selected PV as the variable that has a different effect on prices once it crosses a certain value. When the hourly average of PV generation is above 3.8 GWh, the impact on prices increases by 122%, compared to when the generation is below this threshold. This result is explained by the fact than once PV reaches an hourly average generation of more than four gigawatt hour, it is able to displace even higher fuel-cost marginal generation than when its value is lower.

After assessing the impact of different factors on electricity prices,

Table 4
Correlation coefficients between dependent and explanatory variables.

	Wind infeed	PV infeed	Load	EGIX	API2	EUA
Spot	−0.52	−0.41	0.21	0.43	0.69	0.50
Futures week	−0.17	−0.50	0.07	0.50	0.86	0.66
Futures month	−0.21	−0.45	−0.05	0.49	0.92	0.68
Futures quarter	−0.28	−0.33	−0.15	0.48	0.91	0.71
Futures year	−0.28	−0.39	−0.11	0.46	0.87	0.73

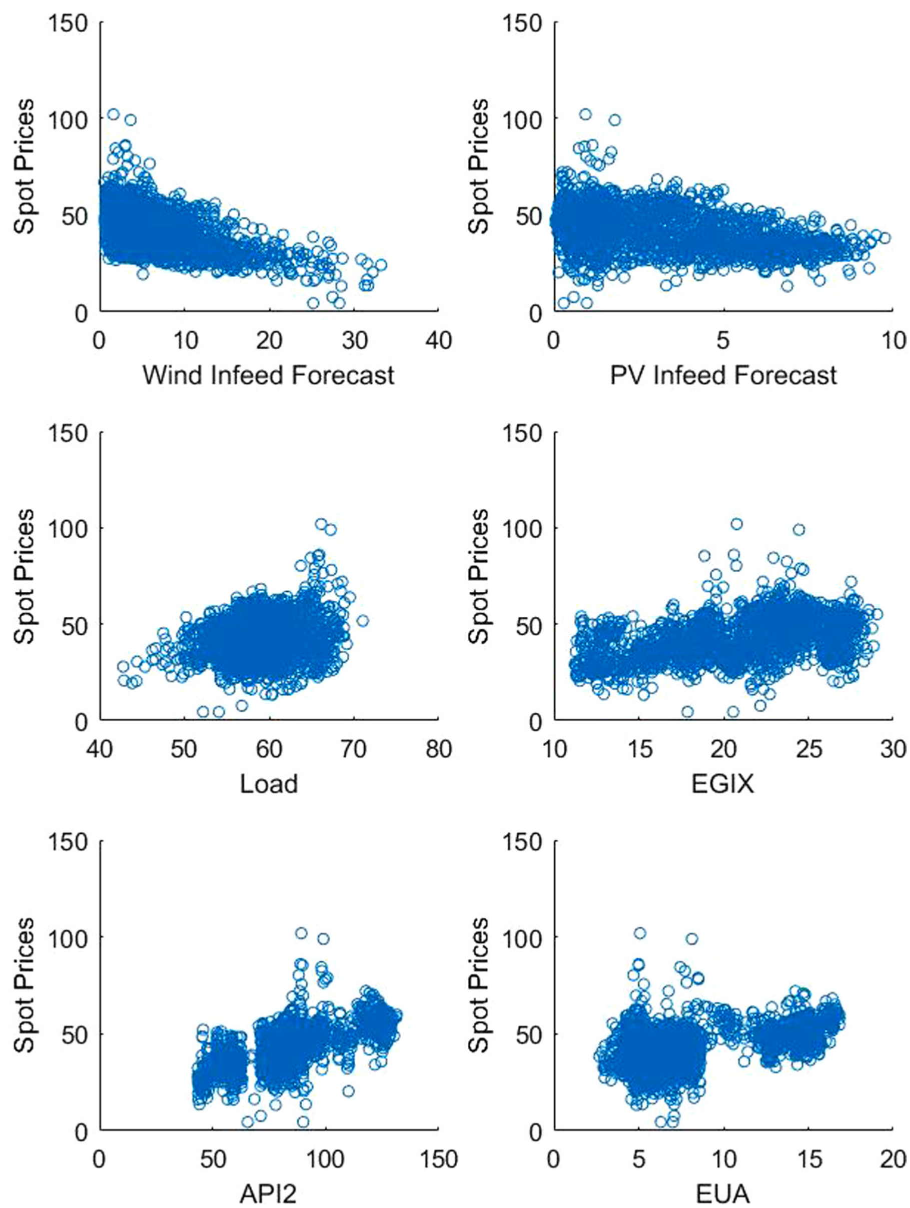

Fig. 5. Scatterplot spot prices and explanatory variables.

we estimated the specific and absolute MOE of renewables using a rolling window of two years (17,520 h).[9] We estimated the model using means of a rolling window with increments of one hour, so that we can determine the dynamics of the MOE of wind power and PV infeeds during each point of our sample period, and not dividing the estimation by years as previous studies have done (e.g., Cludius et al., 2014; Zipp, 2017).

The specific MOE of wind power and PV (i.e., the estimated coefficients in the OLS regression) are depicted in Fig. 7. Wind power specific MOE is always negative and from the beginning of our sample until 2014 this negative effect became larger, however after 2014 this marginal effect reverted to almost its initial values (around 1 €/MWh decrease in prices per each additional GWh of wind power generation). The specific effect of PV generation became negative around the first quarter of 2012, and thereafter the PV coefficient estimates decreased until reaching values around 1. Nevertheless, the estimates of wind power and PV coefficients are not comparable due to scale and magnitude differences, nor do they tell us by how much–on average–an additional GWh of renewable generation decreased the price at each point. To solve these issues we estimated the absolute MOE, which is a measure that takes into account the load-weighted generation average with each renewable source.

[9] We also estimated the MOE with rolling windows with sizes of one month (720 h), one quarter (2190 h), six months (4380 h), and one year (8760 h). However, we only present the results regarding the estimation with two years, since–as expected–the shorter the length of the rolling window the more volatile the estimates are. The results for the other sizes are available upon request.

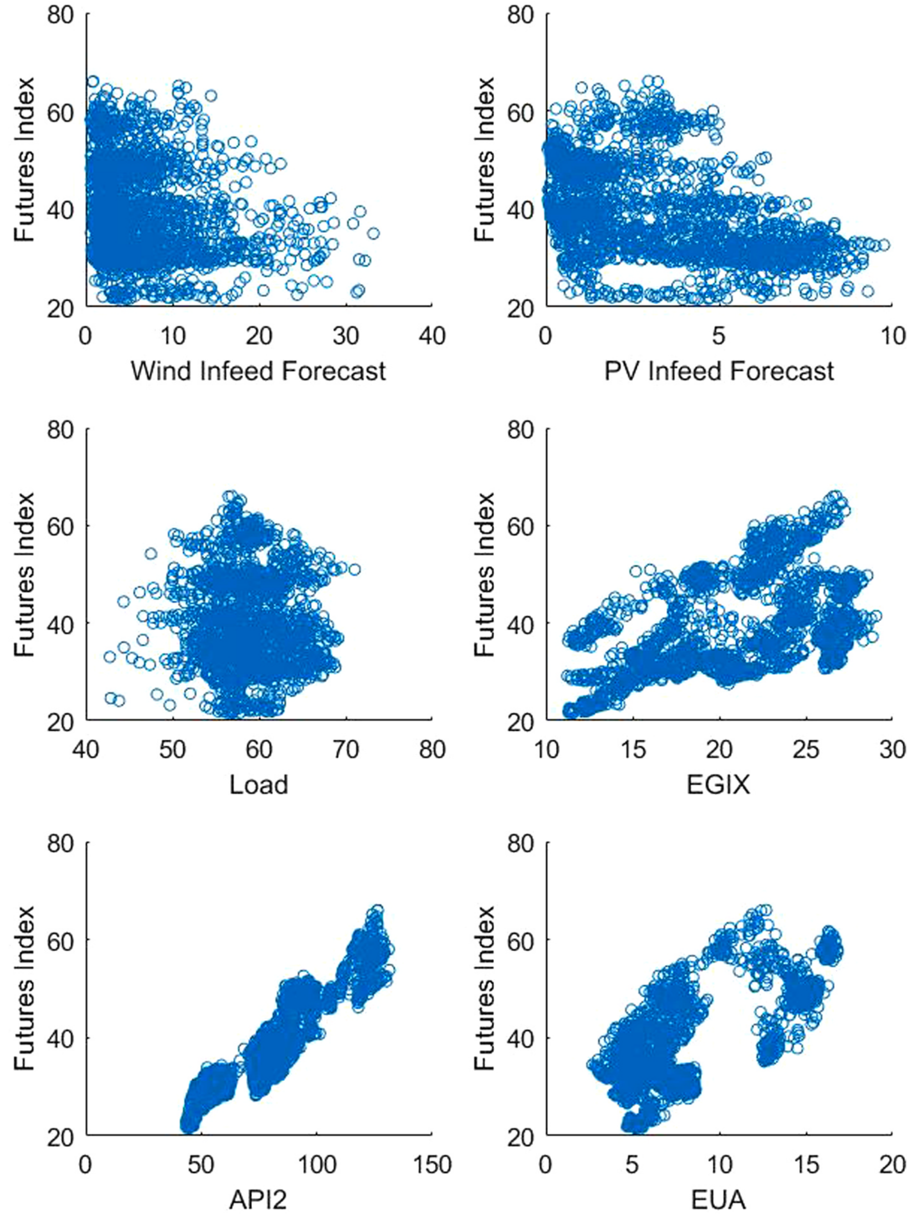

Fig. 6. Scatterplot phelix-base-week index and explanatory variables.

Fig. 8 plots the wind power, PV, and total absolute MOE on the left Y-axis, and the hourly day-ahead electricity price on the right Y-axis. The MOE estimations are presented in absolute values so the interpretation is more straightforward; for example, in 2017 the average reduction in German electricity prices per additional GWh of electricity produced with renewable sources was around 12 and 14 €/MWh. Comparison of the impact of wind power and PV shows that wind's MOE is always higher than PV's MOE, but PV has gained considerable importance in time, from not reducing the prices at all to reducing them on average approximately by 4 €/MWh per additional GWh. In general, we find that high levels of MOE coincide with low prices, and increments in this effect translate most of the times to reductions in price. Nevertheless, part of the MOE may be driven by the fact that renewables are primarily replacing nuclear generation, and that fossil fuels account for about 50% of the production throughout the period analyzed.

4.2. Phelix-futures index prices

We present in Table 7 the results of OLS estimation for Phelix-future index prices for weekly, monthly, quarterly and yearly contracts. Unlike the spot prices, the drivers of futures prices are natural gas, coal, and carbon prices, while renewables and load have non-significant coefficient estimates or its values are approximately zero. EGIX, API2 and EUA coefficient estimates present the expected positive sign; increases in the returns of these factors raises futures prices. Moreover, in general, the impact of each of these prices is similar across different delivery periods.

Applying the same approach followed with the spot price, we also assess if the regression presented in Table 7 presents structural breaks. The only index that does not present breaks in the regression is the one corresponding to contracts that have a quarterly delivery period. The regression results for the other indices are presented in Table 8. In this case the variables that vary across regimes are only the statistically significant variables from the linear regression.

Table 5
OLS and OLS with breaks estimation results for day-ahead electricity spot prices.

	OLS	OLS with breaks				
		Breaks: 26/10/2011, 12/04/2013, 27/06/2014, 08/08/2016				
		06/01/2010 25/10/2011 459 obs	26/10/2011 11/04/2013 368 obs	12/04/2013 26/06/2014 302 obs	27/06/2014 05/08/2016 535 obs	08/08/2016 27/09/2017 294 obs
Constant	41.423***	-18.377**	-2.030	57.235***	-1.610	-4.672
	(6.140)	(8.644)	(13.786)	(6.737)	(7.037)	(15.322)
$Wind_t$	-1.217***	-0.678***	-1.262***	-1.529***	-0.889***	-1.046***
	(0.053)	(0.098)	(0.070)	(0.110)	(0.049)	(0.132)
PV_t	-2.136***	3.248***	-0.711***	-2.152***	-0.704***	-1.863***
	(0.133)	(0.360)	(0.237)	(0.236)	(0.196)	(0.336)
$Load_{t-1}$	0.259**	1.140***	1.022***	-0.010	0.744***	1.023***
	(0.106)	(0.148)	0.240	(0.106)	(0.106)	(0.276)
$EGIX_{t-1}$	4.913	9.880	-0.418	20.985	4.393	2.511
	(8.209)	(12.651)	(18.215)	(22.099)	(8.908)	(8.340)
$API2_{t-1}$	-9.253	46.719*	-64.713	90.758**	-15.358	-17.207
	(15.608)	(24.178)	(39.409)	(36.907)	(17.591)	(17.470)
EUA_{t-1}	-4.990	-11.673	-11.579**	8.078*	5.409	-4.647
	(4.035)	(13.628)	(5.651)	(4.200)	(7.649)	(7.861)
Observations	1958			1958		
Adjusted R^2	0.534			0.788		

Note: *, ** and *** indicate significance at a 90%, 95%, and 99% confidence level, respectively. Robust standard errors are presented in parentheses. The standard errors are robust to heteroscedasticity and auto- correlation according to Newey and West (1994).

Table 6
Threshold regression estimation results for day-ahead electricity spot prices.

	Threshold regression	
	PV < 3.780 1187 obs	3.780 ≤ PV 771 obs
$Wind_t$	−1.262***	−1.073***
	(0.060)	(0.061)
PV_t	−0.953**	−2.118***
	(0.415)	(0.152)
	Non-threshold variables	
Constant	38.520***	
	(6.201)	
$Load_{t-1}$	0.286***	
	(0.107)	
$EGIX_{t-1}$	2.764	
	(8.341)	
$API2_{t-1}$	− 9.855	
	(16.048)	
EUA_{t-1}	− 4.665	
	(3.979)	
Observations	1958	
Adjusted R^2	0.544	

Note: *, ** and *** indicate significance at a 90%, 95%, and 99% confidence level, respec-tively. Robust standard errors are presented in parentheses. The standard errors are robust to heteroscedasticity and autocorrelation according to Newey and West (1994).

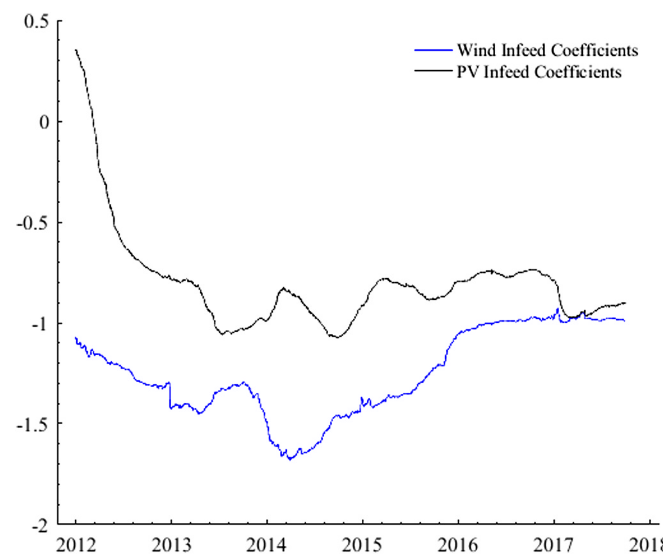

Fig. 7. Wind and photovoltaics infeeds coefficient estimates, 2010–2017.

For contracts with a delivery period of one week the model estimates one break point in August 2015. In the first regime EGIX and EUA are statistically significant, while in the second regime, which corresponds to the period after 2015 when the prices stopped decreasing, only EUA is significant. In the case of monthly and yearly contracts, two break points are found, resulting in three price regimes. For both contracts all regime-specific variables are statistically significant. When comparing the changes in the variables' coefficients, we find that when the effect of EGIX increases from one regime to the other, the effect of API2 and EUA decreases, and vice versa.

5. Conclusion and policy implications

We assess the impact of potential price drivers on German's electricity day-ahead and futures prices. Unlike previous research, we extend the analysis beyond 2015, allowing us to capture not only the decreasing price (until 2016), but also the trend reversal in 2017. By analyzing both the spot and the futures market, we find that the price drivers of each market are different and time-varying. For the spot market we find that the determinants of prices are renewable infeed and demand, while in the case of the futures market the main drivers are natural gas, coal and carbon prices, and their effects on the prices is quite similar across different delivery periods.

On the one hand, during the period analyzed we find that the spot prices regression model presents four break-points, yielding five temporal-regimes during which all the factors taken into account present regime-specific coefficients. Across all regimes, wind power and PV have statistically significantly coefficients with the expected negative sign, except for the first regime where PV has a positive effect on prices. During the studied period– 2010–2017, renewables infeed in the German electricity grid grew steadily, especially in the case of solar power generation. However, the negative impact of wind power and PV

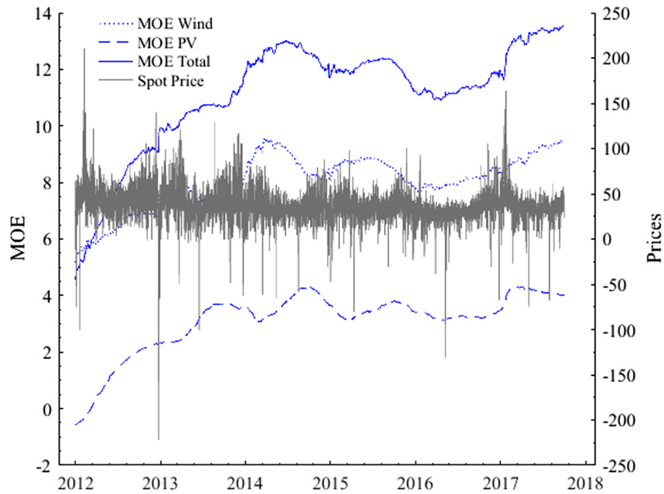

Fig. 8. Hourly spot prices and absolute Merit-order Effect (MOE): Total, wind power and photovoltaics.

Table 7
OLS estimation results for phelix-base-future contracts.

	Week	Month	Quarter	Year
Constant	0.116*** (0.040)	0.004 (0.007)	−0.004 (0.007)	0.001 (0.003)
$Wind_t$	0.001*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
PV_t	−0.001 (0.001)	0.000* (0.000)	0.000** (0.000)	0.000 (0.000)
$Load_t$	−0.002*** (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
$EGIX_t$	0.150* (0.083)	0.189*** (0.042)	0.156*** (0.037)	0.086*** (0.020)
$API2_t$	0.191* (0.101)	0.255*** (0.060)	0.254*** (0.070)	0.222*** (0.036)
EUA_t	0.153*** (0.043)	0.143*** (0.022)	0.119*** (0.021)	0.117*** (0.010)
Observations	1873	1959	1959	1959
Adjusted R^2	0.030	0.088	0.041	0.217

Note: *, ** and *** indicate significance at a 90%, 95%, and 99% confidence level, respectively. Robust standard errors are presented in parentheses. The standard errors are robust to heteroscedasticity and autocorrelation according to Newey and West (1994).

Table 8
OLS with breaks estimation results for phelix-base-future contracts.

	Week *Break: 10/08/15*	**Month** *Breaks: 01/11/11, 01/04/14*	**Year** *Breaks: 24/06/11, 31/07/15*
	30/03/10–07/08/15 1327 obs	05/01/10–31/10/11 464 obs	05/01/10–23/06/11 373 obs
$EGIX_t$	0.434*** (0.101)	0.286*** (0.064)	0.163*** (0.035)
$API2_t$	0.180 (0.138)	0.270* (0.154)	0.131** (0.053)
EUA_t	0.089** (0.040)	0.347*** (0.103)	0.270*** (0.039)
	10/08/15–27/09/17 546 obs	01/11/2011–31/03/14 607 obs	24/06/2011–30/07/15 1032 obs
$EGIX_t$	-0.107 (0.074)	0.646*** (0.083)	0.105*** (0.020)
$API2_t$	0.061 (0.158)	0.176** (0.090)	0.158*** (0.027)
EUA_t	0.321*** (0.108)	0.069*** (0.020)	0.074*** (0.006)
		01/04/14–27/09/17 888 obs	31/07/15–27/09/17 554 obs
$EGIX_t$		0.072** (0.037)	0.038 (0.029)
$API2_t$		0.202*** (0.068)	0.247*** (0.077)
EUA_t		0.208*** (0.039)	0.205*** (0.027)
		Non-breaking variables	
Constant	0.115*** (0.040)	0.002 (0.007)	0.000 (0.003)
$Wind_t$	0.001*** (0.000)	0.000 (0.000)	0.000 (0.000)
PV_t	-0.001 (0.001)	0.000** (0.000)	0.000 (0.000)
$Load_t$	-0.002*** (0.001)	0.000 (0.000)	0.000 (0.000)
Observations	1873	1959	1959
Adjusted R^2	0.039	0.117	0.260

Note: *, ** and *** indicate significance at a 90%, 95%, and 99% confidence level, respectively. Robust standard errors are presented in parentheses. The standard errors are robust to heteroscedasticity and autocorrelation according to Newey and West (1994).

does not always increase across regimes. Load always has the expected positive effect on prices, whereas the conventional generation inputs prices are only significant in some regimes, yet they have the expected positive impact on prices. Only for carbon prices in the second regime, December 2011 to March 2013, the effect on prices is negative.

On the other hand, for futures prices we show that the only variables that have regime-specific coefficients are natural gas, coal and carbon prices. For the monthly and yearly futures contracts, the model selects two break-points, while for the weekly contracts it selects only one, and none for the quarterly contracts. For the futures contracts that do present structural breaks the substitution effect between natural gas and coal is clearly depicted, since we find that when the effect of natural gas prices increases from one regime to the other, the effect of coal and carbon prices decreases, and vice versa. Renewable infeed and load have no explanatory power on futures prices.

We broaden the analysis of the impact of renewable infeed on spot prices, assessing–by means of a threshold regression–if the relation between wind power or PV with the prices shifts once the variables cross a certain value. We determine that the relation changes only for PV, and that once solar infeed is above 3.8 GWh, its impact on prices increases. Additionally, we estimate the absolute MOE induced by wind power and PV using rolling windows, in order to evaluate the dynamics of the MOE during each point in our sample. We show that although the impact of wind power is always higher than that of PV, the price-dampening effect of PV increased during the period analyzed.

Our results provide relevant insights for market participants, who seek to optimize procurement/selling strategies on the spot markets, and who aim to participate in futures market by using risk-hedging strategies based on the generation mix and spot-price volatility. Moreover, our results can also help policy makers shed light over the challenges in energy transition.

For instance, our findings suggest that the MOE growth will not necessary persist with higher penetration of renewables, since this effect depends on the complex configuration of electricity markets, as indicated by multiple period-regimes and threshold effects in our analysis. Evidence of a trend-reversal in electricity prices further reinforces our conjecture of time-varying electricity dynamics as a function of the technological costs—and by corollary installed capacity—and policy incentives such as feed-in tariffs and subsidies. Future work should delineate the different price drivers at play in the different regimes.

We note further, that there is currently only limited storage capacity in the German power system. Viable storage may provide a stabilizing effect for the prices, countering price volatility. In light of the recent policy incentives for and the growth of “PV + storage” systems along with the slow emergence of utility-scale storage (Tenne T, 2017), future work should account for installed storage capacity and its effect on the MOE dynamics. Such data-driven evidence will allow policy makers to proactively adapt the incentives schemes for energy storage to improve the functioning of electricity markets with increasing shares of variable renewables and maximize the welfare gains from the *Energiewende*.

Additionally, we highlight the importance of electricity futures for hedging against spot price volatility derived from higher renewables infeed. Considering that renewables do not influence futures prices in our analysis, we conclude that traditional hedge mechanisms are of limited use against renewables-induced price uncertainty. Policy makers should promote the use of other derivatives, such as wind power futures, which are currently not being traded in the market.

A Purchasing Power Agreement (PPA) is another instrument that can provide reasonable medium-term (three to five years) price-risk hedge. PPAs are particularly relevant for Germany since the first cohort of wind power plants will be dropping out the 20-year support system. Policy makers along with practitioners should work together to identify the barriers to the uptake of PPAs and ensure that the terms and structure of the PPA contracts are not an impediment to broader electricity market reforms at national and EU-level.

Relatedly and lastly, since Germany is a net exporter of electricity in the European interconnected grid, it would be of interest to further analyze the spillovers of the MOE from Germany to other countries, as well as the policy implications of cross-border constraints and market integration in a context of high renewable energy penetration.

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