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Assessing the impact of renewable energy sources on the electricity price level and variability – a Quantile Regression approach

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Abstract

The literature on renewable energy sources indicates that an increase of the intermittent wind and solar generation affects significantly the distribution of electricity prices. In this article, the influence of two types of renewable energy sources (wind and solar photo voltaic) on the level and variability of German electricity spot prices is analyzed. The quantile regression models are built to estimate the merit order effect for different quantiles of electricity prices. The results indicate that both types of renewable generations have a similar, negative impact on the price level, approximated by the price median. When the price volatility, measured by the inter-quantile range (IQR), is considered, the outcomes show that wind and solar influence prices differently. Conditional on the level of the total demand, the wind generation would either increase (when the demand is low) or decrease (when the demand is high) the IQR. Meanwhile, the increase of solar power stabilizes the price variance for moderate demand level. Thus, policy supporting the development and integration of RES should search for a balance between the wind and solar power.

Keywords: electricity prices, quantile regression, merit order effect, price variability

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1. Introduction

Over the last decades, many countries have experienced a dynamic change of their electricity markets. First, a model of centrally managed generation has been abandoned and replaced by organized and competitive market structures. Electricity is soled on power exchanges such as Nord Pool or EEX in Europe, IEE in India, PJM or NYISO in US, where dominate the day-ahead contracts. The day-ahead prices, often called 'spot prices', are set in the early afternoon on the day preceding the delivery. The day-ahead markets are complemented by intra-day and balancing markets, which aim at adjusting the variable generation to the market demand. Second, the technological development and new regulations have created a favorable environment for introduction of renewable energy sources (RES), among which wind and solar photo voltaic play a central role. According to the Climate Package, the EU countries are obligated to increase their RES share in the energy consumption to 20% by the year 2020. A more recent Winter Package set a new, UE-wide target of 27% by the year 2030. Increasing input of RES results in the reduction the CO_2 emission and the fall of the energy costs. Unfortunately, adding more renewable energy capacity creates new challenges. Electricity generated by wind and solar is intermittent and difficult to forecast, as it depends strongly on weather conditions. In some countries, such as Germany, RES are granted priority during the dispatch and generators receive a fixed feed-in tariff. As the result, it becomes more and more difficult to balance the market and electricity prices suffer from spikes or negative values.

The impact of RES is one of the most appealing topics in the literature on electricity markets. It has been shown that an increase of RES generation leads to a fall of prices (see Ketterer, 2014; Paraschiv et al., 2014; Galanert et al., 2011; Cló et al., 2015; Woo et al., 2016; Frauendorfer et al., 2018). This phenomena is called a merit-order effect. It fallows from the fact that RES marginal costs are closed to zero and hence an increase of RES generation shifts the supply curve to the right. Since the demand for electricity is inelastic, it results in a fall of electricity prices. Although the price-dampening effect has been confirmed by the data, it is still not clear how RES influences the whole distribution of prices. Some recent articles Ketterer (2014), Rintamäki et al. (2017), Woo et al. (2011), Cló et al. (2015) show that rise of RES generation could result in the increase of the price variance. Ketterer (2014) uses the ARX-GARCH approach to model and test the wind influence on price variability in Germany. The results imply that an increase of the wind to load ratio leads to an rise of the expected variance. Woo et al. (2011) analyze the impact of wind generation on the price variance in Texas using simulation techniques. They results indicate that a 10% increase of the installed capacity of wind is followed by a 1-5% rise of the variance. A sightly different approach is adopted by Rintamäki et al. (2017). They model a within-day price volatility and relate its changes to two types of RES: wind and solar. They show that wind and solar generation may have different impacts on the price variances. For example, in Denmark, an increase of solar leads to the fall of the price variability, whereas the rise of wind results in its increase.

In this article, a semi-parametric approach of modeling the distribution of electricity prices is adopted. The distribution is approximated by quantiles of electricity prices, $P_t(\tau)$, where $\tau = 0.1, 0.2, ..., 0.9$. Each quantile is described by a regression including exogenous variables together with lagged observation of prices. This approach allows to evaluate the impact of RES not only on the price level but also on the shape of the distribution. Finally, it can be used to model the price variability, approximated by the inter quantile range ($IQR_t = P_t(0.9) - P_t(0.1)$). When the distribution of electricity prices is normal or t-Student, then the IQR is a linear transformation of the price variance. Moreover, IQR allows to model conditional heteroscedasticity, as the IQR_t may be govern by a set of explanatory variables.

The quantile regression (QR) is a well establish econometric approach, which has been successfully used in macro and micro economics (see Koenker and Hallock, 2001). There are a few papers which apply QR for modeling electricity markets in areas such as electricity load (Li et al., 2017), CO_2 emission allowance prices (Hammoudeh et al., 2014) and electricity prices (Hagfors et al., 2016b; Bunn et al., 2016; Nowotarski and Weron, 2015; Maciejowska et al., 2016). In the paper of Hagfors et al. (2016b), the UK electricity market is modeled and the dependence of electricity prices on fuel prices and reserve margin is examined. Hagfors et al. (2016c) apply the QR to describe the influence of RES on electricity prices in Germany. They analyze hourly data and present the estimates of the wind and solar impact on the electricity prices for a set o quantiles. They do not conduct neither formal comparison of RES types nor asses the impact of RES on the price variability. Finally Bunn et al. (2016) apply QR to forecast the Value-at-Risk and show its superiority to benchmarks such as GARCH or CAViAR.

An alternative approach for modeling the distribution of electricity prices was adopted by Gianfreda and Bunn (2018). In their comprehensive study, the effects of fundamental variables on the first four moments of German spot prices are analyzed. The results indicate a significant merit order effect of wind and solar generation. Moreover, they suggest a mixed impact on higher moments, such as standard deviation, skewness and kurtosis.

This article extends the previous research in various directions. Fist, it formally compares impact of wind and solar on the distribution of electricity prices. It is examined, which type of generation has a stronger price-dampening effect both on the median and on tails of the distribution. Second, a non-linear respond of prices to changes in fundamental variables is allowed. In the proposed model, the impact of RES is conditioned on the level of total demand. This assumption, although recognized in the literature (see Chen and Bunn, 2010), has not been explored in previous analysis. Finally, it is showed that the price variability could be successfully modeled via IQR.

The remainder of the paper is structured as follows. Section 2 presents the data describing the German electricity market. In Section 3, the quantile regression model used in the analysis is introduced. Section 4 shows the results and Section 5 concludes.

2. Data

The data used in this research spans from January 1, 2015 to 29 January 2018 and describes the German electricity market. In this article, the relation between spot (day-ahead) prices and market fundamentals is examined. The prices, denoted by P_{ht}, where h is an hour and t is a day index, are obtained from EPEX (epexspot.com). The fundamental variables are: the forecasted total load (L_{ht}), the forecasted wind generation (W_{ht}) and the forecasted solar generation (S_{ht}) published by TSO's https://transparency.entsoe.eu/. In this research, the weakly seasonality is describes by a (5×1) vector D_t of deterministic variables. The vector consists of a constant and dummy variables for Mondays, Saturdays, Sundays and Holidays. The Holidays dummy includes

Table 1: Data source

Data	Notation	Units	Source
Spot prices	P	EUR/MWh	EPEX SPOT, http://www.epexspot.com
Forecasted load	L	GW	https://transparency.entsoe.eu
Forecasted wind generation	W	GW	https://transparency.entsoe.eu
Forecasted solar generation	S	GW	https://transparency.entsoe.eu

the calendar holidays and associating them unofficial holidays (for example, when a holiday takes place on Thursday, then Friday is typically characterized by a reduced electricity demand although it is not an official day-off). Data sources and units are summarized in Table

The time series are next transformed form hourly observations into daily, peak and off-peak indexes. The indexes are computed as an arithmetic mean of corresponding variables across all hours, peak hours (9:00-20:00) and off-peak hours (0:00-8:00 and 21:00-23:00), respectively. Additionally, the peak indexes, which represent periods of the highest electricity demand, are restricted to working days.

Descriptive statistics of electricity prices together with predicted load and RES (wind and solar) are presented in Table 1. The results indicate that all the variables are non-normal. Electricity prices are characterized by fat tails (kurtosis is much above 3) and take both positive and negative values. At the same time, RES variables are positively skewed. These observations are confirmed by Jarque-Bera (J-B) normality tests presented in Table 3. Finally stationarity of the data is tested with the Augmented Dickey-Fuller (ADF) test. Table 3 reports the test statistics and corresponding p-values for the test with seven lags and a drift under the alternative. All of the p-values, apart from solar off-peak index, are below 5%, which confirm stationarity of examined variables.

The time plots of daily, peak/off-peak indexes are presented in Figure 1 and Figure 2, respectively. Analysis of daily data indicate that fundamental variables exhibit a strong yearly seasonality. The load and the wind generation are the highest during winter time, whereas the solar generation peaks in a summer. The behavior of fundamentals affects electricity prices, which also follow a yearly pattern. Moreover prices are exposed to extreme fluctuations with both: positive and negative spikes, see Hagfors et al. (2016b) for more discussion.

Peak and off-peak indexes are presented on Figure 2. The comparison of variables in different hours indicate that both load and electricity prices are the highest during the peak hours. Moreover, the peak prices exhibit relatively more positive spikes, whereas the off-peak prices are characterized by more frequent negative values. When the RES generation is considered, it could be noticed that wind generation does not change within the day, whereas solar depends strongly on analyzed hours. During the off-peak hours, the solar radiation is weak and therefore the off-peak production accounts only for a small friction of the peak generation. This observation is also revealed by statistics presented in Table 2, which show that the average off-peak solar generation is only 13.7% of its mean peak value.

Finally, the relationship between daily prices and the total load is illustrated by Figure 3. The scatter plots shows that the dependence is close to linear, when the load takes intermediate values. However, the sensitivity of prices to load changes becomes much stronger in tails of load

Table 2: Descriptive statistics

	Mean	Median	Min	Max	St.dev.	Skewness	Kurtosis
	Daily index						
Prices	31.6	31.61	-47.46	101.82	11.27	-0.026	9.345
Load	218.22	222.34	139.53	265.6	23.94	-0.54	2.668
Wind	39.68	31.74	3.87	136.69	29.01	1.142	3.656
Solar	16.2	15.76	0.95	39.65	10.39	0.225	1.794
	Peak index						
Prices	34.99	34.29	-36.76	126.5	13.73	0.83	10.02
Load	243.3	250.4	167.6	306.3	29.99	-0.51	2.3
Wind	38.98	29.92	1.92	152.5	31.2	1.16	3.74
Solar	28.1	28	1.66	67.41	17.25	0.2	1.84
	Off-peak index						
Prices	28.2	29	-58.17	77.11	9.76	-1.49	12.55
Load	198.4	202.2	142.5	245.6	21.86	-0.41	2.41
Wind	38.95	30.87	3.24	131.86	27.31	1.14	3.64
Solar	3.85	3.04	0.01	13.11	3.6	0.57	2.07

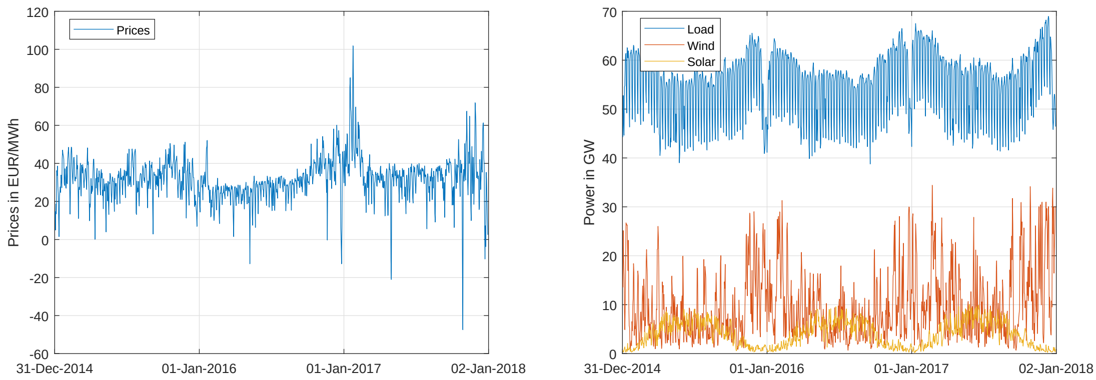
Table 3: Statistical properties: normality (J-B tests) and non-stationarity (ADF) tests

	J-B test				ADF test			
	Prices	Load	Wind	Solar	Prices	Load	Wind	Solar
	Daily index							
test	1838.8	58.21	258.0	75.68	1838.8	58.21	258.0	75.68
p-value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
	Peak index							
test	2379.3	68.78	272.1	68.79	-2.864	-4.581	-8.203	-3.331
p-value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	0.014
	Off-peak index							
test	4577.7	47.35	256.5	98.89	-8.107	-4.961	-7.382	-2.336
p-value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	0.161

Note: the normality hypothesis is rejected, when the p-value is not larger than the assumed significance level; the ADF test with seven lags and a drift under the alternative.

distribution, where the extreme high or low values of prices occur.

Figure 1: Time paths of daily indexes



(a) Prices

(b) Fundamental variables

3. Quantile regression model

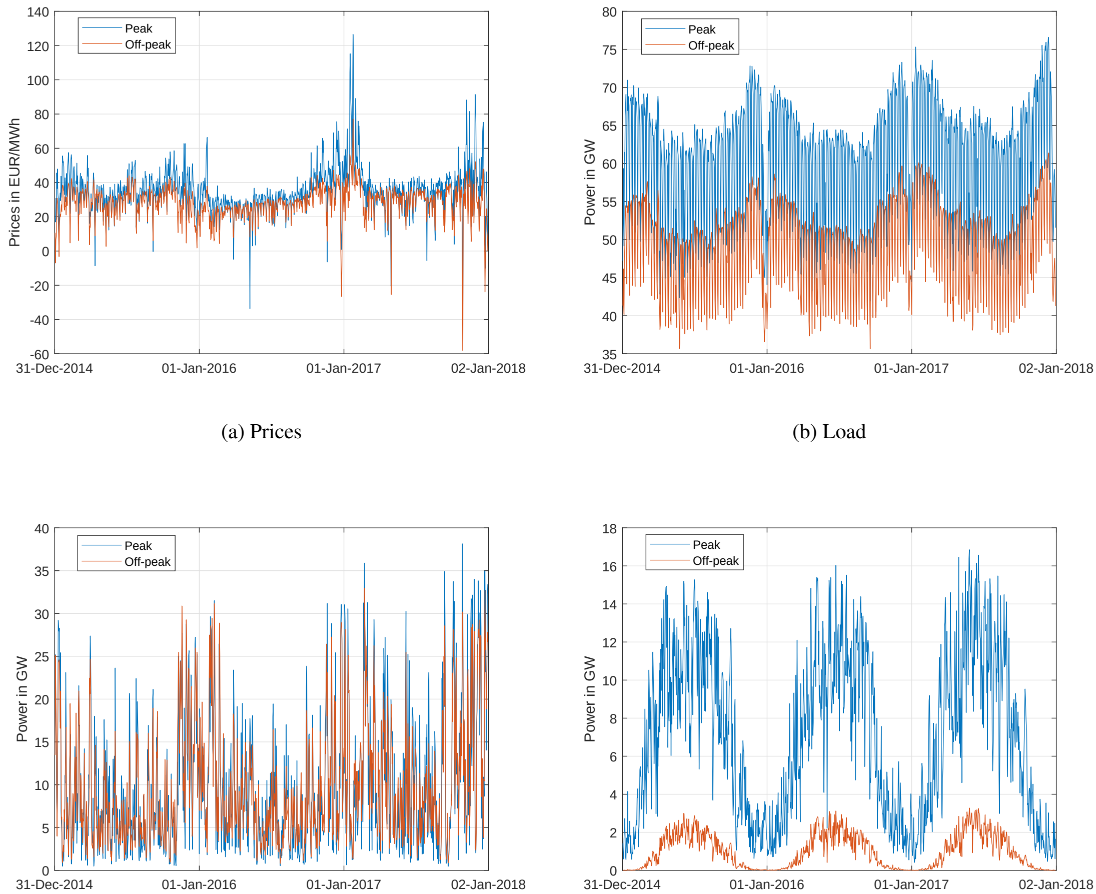
First, a simple linear quantile regression model is considered, which links the quantile τ of the electricity price, $P_t(\tau)$, with the level of fundamentals. In order to account for a time dependency between spot prices, their lagged values are added to the regression. The model takes the following form:

$$P_t(\tau) = \alpha_{0,\tau} D_t + \beta^L_\tau L_t + \beta^W_\tau W_t + \beta^S_\tau S_t + \sum_{i=1}^{p} \theta_{i,\tau} P_{t-i}, \tag{1}$$

where β^L_τ, β^S_τ and β^W_τ describe the influence of corresponding fundamentals: L_t, S_t and W_t on the τ quantile and the parameters $\theta_{i,\tau}$ are the autoregressive parameters, which link the current quantile of P_t, with lagged values of spot prices P_{t-i}. It should be mentioned that the lag order, p, is chosen to capture the weekly seasonality. Hence, for daily and off-peak prices, it is set $p = 7$, whereas for peak indexes $p = 5$. The model specifications differ also in terms of the deterministic component. In the peak price model, the vector D_t includes only a constant. At the same time, for daily and off-peak prices, D_t consists of a constant and dummy variables defining Mondays, Saturdays, Sundays and Holidays.

In order to account for nonlinearities in the relationship between electricity prices and the generation structure, the influence of corresponding variables on quantiles of the spot price is conditioned on the level of the forecasted load, L_t. The daily, peak and off-peak indexes are analyzed separately. In this research, three levels of load are considered and described by the indicator variables: $I_{1,t} = 1_{L_t < L(\tau_L)}$, $I_{2,t} = 1_{L(\tau_L) \leq L_t \leq L(\tau_H)}$ and $I_{3,t} = 1_{L_t > L(\tau_H)}$, where $L(\tau)$ describes the τ unconditional quantile of L_t and thresholds are set $\tau_L = 0.1$ and $\tau_H = 0.9$. Then $I_{1,t} = 1$ implies that the load is below its 0.1 quantile, when $I_{2,t} = 1$ then it takes an intermediate value and stays between the 0.1 and the 0.9 quantile. Finally, $I_{3,t} = 1$ when the load is higher than the

Figure 2: Comparison of peak and off-peak indexes.



(a) Prices

(b) Load

(c) Wind generation

(d) Solar generation

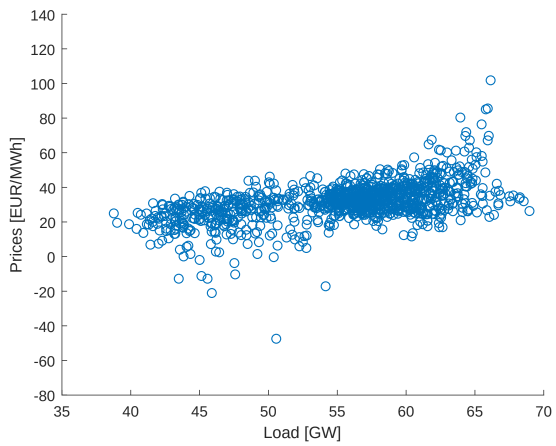
0.9 quantile. The thresholds $\tau_L = 0.1$ and $\tau_H = 0.9$ are chosen because, on one hand, they ensure the sufficient number of observation in each state and, on the other hand, allow to capture the price behavior in periods of very high and low load level. Other choices of thresholds was also examined: $\tau_L = 0.15$, $\tau_H = 0.85$ and $\tau_L = 0.2$, $\tau_H = 0.8$ confirming the robustness of the outcomes (see Tables ..., Appendix).

As the result, the model becomes

$$P_t(\tau) = \alpha_{0,\tau} D_t + \sum_{j=1}^{3} \beta^L_{j,\tau} L_{j,t} + \sum_{j=1}^{3} \beta^W_{j,\tau} W_{j,t} + \sum_{j=1}^{3} \beta^S_{j,\tau} S_{j,t} + \sum_{i=1}^{p} \theta_{i,\tau} P_{t-i}, \tag{2}$$

where $L_{j,t} = I_{j,t} L_t$, $S_{j,t} = I_{j,t} S_t$ and $W_{j,t} = I_{j,t} W_t$. Notice that the effect of a particular variable, for example the wind generation, W_t, on the $\tau-$quantile of the spot prices is now described be three parameters: $\beta^W_{1,\tau}$, $\beta^W_{2,\tau}$ and $\beta^W_{3,\tau}$ and depends on the level of load. If the effects are equal $\beta^*_{1,\tau} = \beta^*_{2,\tau} = \beta^*_{3,\tau}$, then model (2) could be reduced to (1). Finally, due to the price inelasticity of

Figure 3: Scatterplot of prices and load, daily indexes



demand and the need of permanent balance the market, the expected total load and demand are closely related. Hence, different values of $I_{i,t}$ corresponds also with low, intermediate and high level of demand.

The estimation algorithm for quantile autoregression models is described by Koenker and Xiao (2006) and is an autoregressive counterpart of the method presented by Koenker and Bassett (1978). The parameters are estimated by minimizing the pinball loss function

$$min_{\psi_\tau \in \Psi} \sum_t \rho_\tau(P_t - X_t\psi_\tau), \tag{3}$$

where $X_t^{(i)}$ is a combined vector of all explanatory variables and ψ_τ is a vector of corresponding parmeters. The function $\rho_\tau(P_t - X_t\psi_\tau)$ is defined as in Koenker and Bassett (1978) and takes a value

$$\rho_\tau(P_t - X_t\psi_\tau) = \begin{cases} \tau(P_t - X_t\psi_\tau) & \text{when } P_t > X_t\psi_\tau \\ (\tau - 1)(P_t - X_t\psi_\tau) & \text{when } P_t \leq X_t\psi_\tau. \end{cases}$$

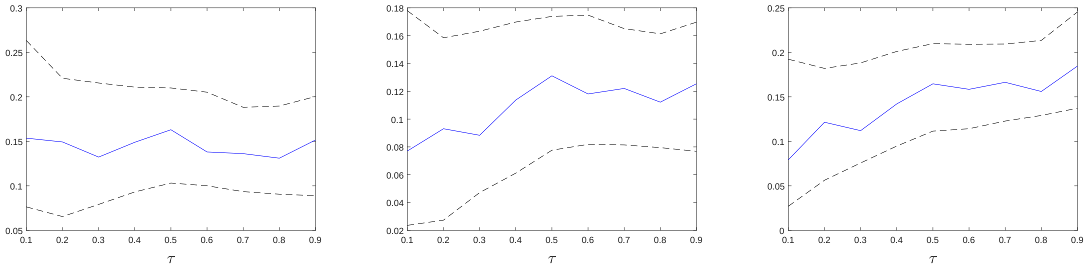
The confidence intervals and statistical tests are computed using the bootstrap method with 1000 replications. In order to account for the possible ARCH effect, a block bootstrap is used, as in Fitzenberger (1998). The block length is set to equal 10 for peak and 14 for off-peak hours and daily data, which corresponds to two weeks of observations.

4. Results

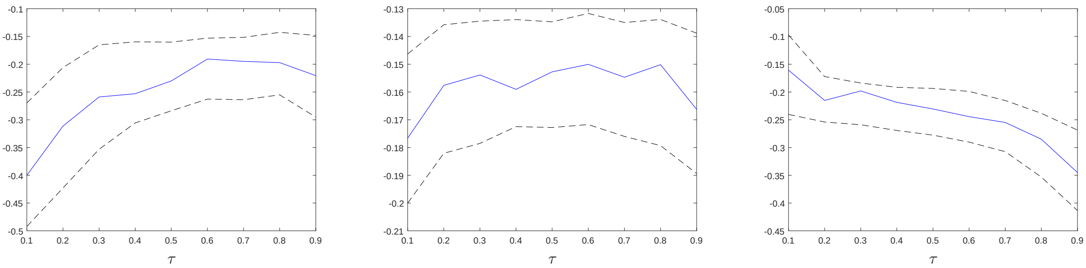
4.1. Merit-order effect

The merit-order effect is a shift of a supply curve due to an increase of a low cost renewable generation, which results in a fall of electricity prices. The phenomena is well described and widely discussed in the literature (see Ketterer, 2014; Cludius et al., 2014; Woo et al., 2016; Gürtler and Paulsen, 2018). Here, it is illustrated by the sample data on the Figure 5, which shows the electricity prices together with total load and the generation structures in the 46th week of the

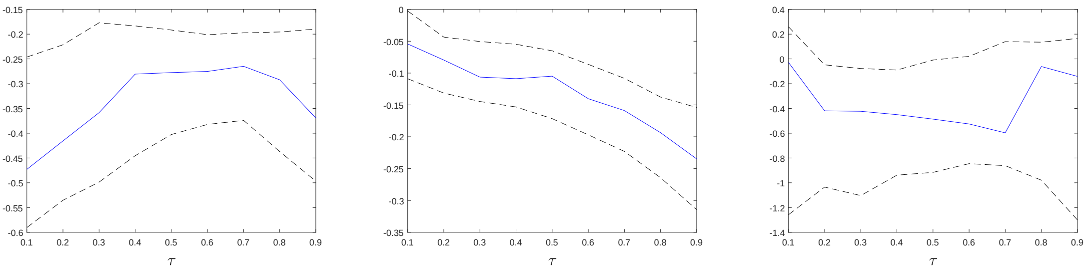
Figure 4: Estimates of model (2) coefficients, average daily prices, across different quantiles : $\tau = 0.1, 0.2, ..., 0.9$ (solid, blue lines) with 90% confidence intervals (dashed lines).



(a) Load: $\beta^L_{1,\tau}$ (b) Load: $\beta^L_{2,\tau}$ (c) Load: $\beta^L_{3,\tau}$



(d) Wind: $\beta^W_{1,\tau}$ (e) Wind: $\beta^W_{2,\tau}$ (f) Wind: $\beta^W_{3,\tau}$



(g) Solar: $\beta^S_{1,\tau}$ (h) Solar: $\beta^S_{2,\tau}$ (i) Solar: $\beta^S_{3,\tau}$

year 2017. It can be noticed that days with a high RES generation, such as 19*th* of November, are characterized by low conventional generation. At the same time, on days with a small RES generation, such as 15*th* of November, majority of generation comes from conventional power plants. Hence, an increase of RES, with marginal cost close to zero, pushes more expensive utilities out of the market. This results in a fall of the electricity prices, which can substantially decrease or even fall below zero.

In the proposed models, the merit order effect is reflected by negative values of parameters β^S_τ and β^W_τ. The parameter estimates for daily data, together with their 90% confidence intervals, are presented on Figure 4. In the plot, columns represent different levels of demand and rows are associated with fundamental variables: total load, wind and solar generation. The results confirm a price-dampening merit order effect of RES and indicate that an increase of wind and solar leads to a fall of all quantiles of electricity prices, whereas an increase of load rises the prices.

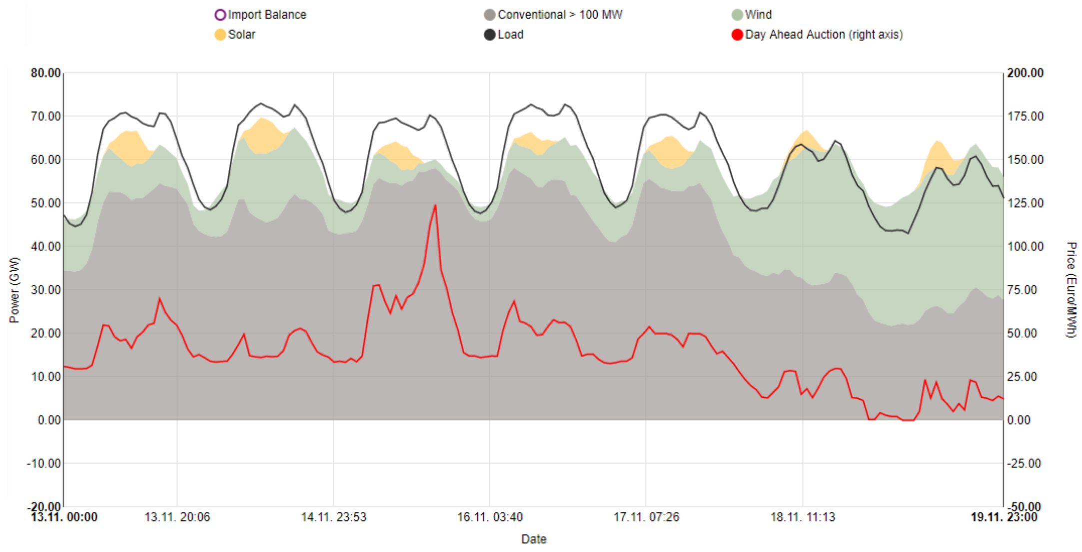


Figure 5: Main generation sources (conventional, wind, solar) and wholesale electricity prices (day-ahead, intraday) for the 46th week of 2017 in Germany.Source: https://www.energy-charts.de, Fraunhofer ISE.

A detailed description of the merit-order effect of RES is presented in Table 4, which shows the estimates of the parameters of the linear (1) and the non-linear (2) models for three types of indexes. First, it could be noticed that all of the coefficients representing the wind impact on the price quantiles are significantly lower than zero. Moreover, their magnitude depends on the time of the day and the level of load. It is the strongest for high demand/ peak prices and low demand/off-peak prices. Second, the hypothesis of the merit-order effect of RES is also supported by solar coefficients. Similar to wind, solar has the strongest influence on the peak prices, when the load is high and the off-peak prices, when the load is low. Unfortunately, some of these results are not statistically significant. The findings are mixed due to a strong yearly seasonality of solar generation. As demonstrated on Figure 1 and Figure 2 in winters a high load is associated with a weak solar radiation. This leads to very volatile estimates of $\beta^S_{3,\tau}$ and their statistical insignificance.

Although both types of RES have qualitatively similar effect on the supply curve, it is not clear, whether their influence on the price distribution is exactly the same. There are only a few articles, which include both energy sources, see Cludius et al. (2014), Paraschiv et al. (2014) and Hagfors et al. (2016b). They show a price dampening effect of both wind and solar but do not directly compare them. Based on previous results, it is expected that both types of RES influences the median, which approximates the level of prices, in the same way. The impact on tails of distribution may however differ, because each RES is associated with different uncertainty and risk (see Rintamäki et al. (2017)).

In this research, it is verified, whether wind and solar have the same merit-order effect on different quantiles of electricity prices. Conditional on the quantile and the level of load, changes

Table 4: The estimates of parameters β^W and β^S for linear (1) and the non-linear (2) models.

τ	Wind				Solar			
	β^W_{τ}	$\beta^W_{1,\tau}$	$\beta^W_{2,\tau}$	$\beta^W_{3,\tau}$	β^S_{τ}	$\beta^S_{1,\tau}$	$\beta^S_{2,\tau}$	$\beta^S_{3,\tau}$
Daily index								
0.1	-0.178***	-0.400***	-0.177***	-0.161***	-0.067***	-0.473***	-0.054**	-0.028
0.2	-0.166***	-0.311***	-0.158***	-0.215***	-0.107***	-0.416***	-0.080***	-0.419**
0.3	-0.164***	-0.259***	-0.154***	-0.198***	-0.118***	-0.359***	-0.106***	-0.423**
0.4	-0.168***	-0.253***	-0.159***	-0.219***	-0.140***	-0.281***	-0.109***	-0.450**
0.5	-0.166***	-0.230***	-0.153***	-0.231***	-0.136***	-0.278***	-0.105***	-0.486*
0.6	-0.160***	-0.191***	-0.150***	-0.244***	-0.170***	-0.275***	-0.140***	-0.525*
0.7	-0.170***	-0.195***	-0.155***	-0.255***	-0.196***	-0.265***	-0.159***	-0.597*
0.8	-0.172***	-0.197***	-0.150***	-0.285***	-0.231***	-0.292***	-0.194***	-0.061
0.9	-0.184***	-0.221***	-0.166***	-0.345***	-0.267***	-0.369***	-0.235***	-0.141
Peak index								
0.1	-0.158 ***	-0.182 **	-0.160 ***	-0.189 ***	-0.030 *	-0.114	-0.035 *	-0.073
0.2	-0.175 ***	-0.175 ***	-0.175 ***	-0.251 ***	-0.066 ***	-0.076	-0.065 **	-0.078
0.3	-0.172 ***	-0.122 ***	-0.170 ***	-0.266 ***	-0.087 ***	-0.101 *	-0.073 ***	-0.319 *
0.4	-0.177 ***	-0.129 ***	-0.172 ***	-0.301 ***	-0.096 ***	-0.144 **	-0.077 ***	-0.376 *
0.5	-0.181 ***	-0.130 ***	-0.172 ***	-0.303 ***	-0.102 ***	-0.132 ***	-0.092 ***	-0.513 *
0.6	-0.186 ***	-0.147 ***	-0.182 ***	-0.303 ***	-0.115 ***	-0.121 ***	-0.106 ***	-0.500 *
0.7	-0.189 ***	-0.148 ***	-0.186 ***	-0.290 ***	-0.147 ***	-0.122 ***	-0.145 ***	-0.379
0.8	-0.202 ***	-0.137 ***	-0.197 ***	-0.333 ***	-0.156 ***	-0.134 **	-0.158 ***	-0.131
0.9	-0.213 ***	-0.186 **	-0.189 ***	-0.484 ***	-0.211 ***	-0.104 **	-0.211 ***	-0.188
Off-peak index								
0.1	-0.169 ***	-0.211 ***	-0.172 ***	-0.149 ***	-0.013	-0.769 ***	0.012	0.816
0.2	-0.166 ***	-0.197 ***	-0.163 ***	-0.178 ***	-0.094 *	-0.630 ***	-0.054	-0.160
0.3	-0.161 ***	-0.209 ***	-0.150 ***	-0.163 ***	-0.155 **	-0.528 ***	-0.075	-0.454
0.4	-0.157 ***	-0.194 ***	-0.157 ***	-0.165 ***	-0.146 ***	-0.407 ***	-0.095	-1.022
0.5	-0.156 ***	-0.192 ***	-0.154 ***	-0.162 ***	-0.139 **	-0.508 ***	-0.089	-1.047
0.6	-0.152 ***	-0.213 ***	-0.147 ***	-0.164 ***	-0.136 **	-0.471 ***	-0.070	-2.039 *
0.7	-0.155 ***	-0.199 ***	-0.152 ***	-0.175 ***	-0.137 ***	-0.543 ***	-0.093 **	-2.520 *
0.8	-0.161 ***	-0.198 ***	-0.148 ***	-0.182 ***	-0.201 ***	-0.533 ***	-0.138 ***	-3.321 *
0.9	-0.178 ***	-0.230 ***	-0.159 ***	-0.214 ***	-0.313 ***	-0.431 **	-0.259 ***	-4.806

Note: the asterisks *, ** and *** the significance at the significance level 10%, 5% and 1%, respectively.

Table 5: The estimates of the differences between the merit-order effects of wind and solar generation for daily, peak and off-peak indexes.

τ	$\beta^W_\tau - \beta^S_\tau$	$\beta^W_{1,\tau} - \beta^S_{1,\tau}$	$\beta^W_{2,\tau} - \beta^S_{2,\tau}$	$\beta^W_{3,\tau} - \beta^S_{3,\tau}$
		Daily index		
0.1	-0.111***	0.073	-0.122***	-0.132
0.2	-0.059***	0.104	-0.078***	0.204
0.3	-0.045**	0.100	-0.047***	0.225
0.4	-0.027	0.027	-0.050**	0.231
0.5	-0.029	0.048	-0.048	0.255
0.6	0.010	0.085	-0.010	0.281
0.7	0.027	0.070**	0.004	0.342
0.8	0.058**	0.095**	0.043	-0.224
0.9	0.083*	0.149**	0.068	-0.204
		Peak index		
0.1	-0.127***	-0.069	-0.125***	-0.116
0.2	-0.109***	-0.098	-0.111***	-0.173
0.3	-0.085***	-0.022	-0.096***	0.053
0.4	-0.081***	0.015	-0.095***	0.075
0.5	-0.078***	0.002	-0.080***	0.210
0.6	-0.070***	-0.027	-0.075***	0.197
0.7	-0.042***	-0.025	-0.041***	0.090
0.8	-0.046**	-0.003	-0.038	-0.201
0.9	-0.002	-0.082	0.022	-0.297
		Off-peak index		
0.1	-0.156**	0.338**	-0.245***	-0.254
0.2	-0.073*	0.332**	-0.195***	0.620
0.3	-0.007	0.386**	-0.117*	0.685
0.4	-0.012	0.337**	-0.063*	2.161
0.5	-0.017	0.360***	-0.057	2.660
0.6	-0.016	0.352***	-0.031	2.796
0.7	-0.019	0.491**	-0.035	2.364*
0.8	0.040	0.341***	0.070	3.185*
0.9	0.135	0.386**	0.159***	5.166*

Note: the asterisks *, ** and *** indicate rejection of null $H_0 : \beta^W_\tau - \beta^S_\tau = 0$ at the significance levels 10%, 5% and 1%, respectively.

in price distribution could be associated more with one of the RES variables. The differences between coefficients β_τ^W and β_τ^S are presented in Table 5, in which columns represent estimates of the linear (1) and the non-linear (2) model, respectively. Since both $\beta_\tau^W < 0$ and $\beta_\tau^S < 0$ then $\beta_\tau^W - \beta_\tau^S \leq 0$ implies that the wind has a stronger price lowering effect than the solar. When $\beta_\tau^W - \beta_\tau^S > 0$ then an increase of solar leads to a stronger reduction of prices than a rise of wind.

4.1.1. Daily average prices

Lets first analyze the behavior of the average daily prices. The results of the linear model (1) show that the wind reduces more low quantiles of prices, wheres solar decreases more high quantiles. This indicate that solar is more successful in reducing the occurrence of positive price spikes and does not decrease the low quantiles of price distribution as strong as wind.

When the results of a non-linear model are analyzed, it could be noticed that the relationship between β_τ^w and β_τ^S depends on the level of demand. When the load is low, which is typical for summer time, the solar has a stronger price dampening effect than the wind, with the difference being statistically significant for quantiles $\tau \geq 0.7$. On the other hand, for the intermediate level of load, wind reduces more low quantiles , whereas solar decreases more high quantiles of prices. The dominance is significant only for $\tau \leq 0.4$. For the high level of load, the differences $\beta_\tau^w - \beta_\tau^S$, although big in the magnitude, are not statistically significant due to large variances of estimators.

Finally, both models (1) and (2) indicate that wind and solar have very similar effects on the median of prices. The differences between coefficients related to different energy sources are statistically insignificant. Therefore for the analysis of the average level of prices, the most important is the sum of wind and solar generation. The division between different types of energy sources is relevant when the tails or higher moments of price distribution are modeled.

4.1.2. Peak prices

The results of a linear model (1) suggest that wind generation has a stronger price reducing effect on the peak prices than solar, with the difference $\beta_\tau^W - \beta_\tau^S$ being significantly lower that zero for almost all quantiles. When different levels of load are considered, it seems that the dominant impact of wind is confirmed only for intermediate levels of load. For low and high load, the differences between wind and solar effects are not significantly different from zero.

When the median of peak prices is considered, the outcomes indicate that wind has a significantly stronger impact on the average peak price than the wind for intermediate level of load. In other cases, solar dominates but the effect is not statistically significant.

4.1.3. Off-peak prices

The results for the off-peak hours are similar to those of daily indexes. They show that wind has a stronger price reducing impact than solar for intermediate level of load and low price quantiles. When the level of load is either low or high, the solar seems to dominate the wind, particularly for high quantiles of electricity prices.

Finally, the linear model (1) does not find any significant differences between impacts of wind and solar on the median of electricity prices. The results of the non-linear model indicate that the solar has a statistically stronger effect on the median for low level of total load.

4.2. Variability effect

In this research, the variability of spot prices is described by the inter-quantile range. It provides information about the shape of the distribution of prices and is closely related to the price variance. The IQR_t could be directly derived from models (1) or (2) by subtracting $IQR_t = P_t(0.9) - P_t(0.1)$. If the assumed data generating process is linear (1) then the IQR_t becomes

$$IQR_t = \alpha_0 D_t + \beta^L L_t + \beta^W W_t + \beta^S S_t + \sum_{i=1}^{p} \theta_i P_{t-i}, \tag{4}$$

where $\alpha_0 = \alpha_{0,0.9} - \alpha_{0,0.1}$, $\beta^* = \beta^*_{0.9} - \beta^*_{0.1}$ and $\theta_p = \theta_{p,0.9} - \theta_{p,0.1}$. The coefficients β^* measure the effect of given variables on the price variability. When $\beta^* > 0$, which means that $\beta^*_{0.9} > \beta^*_{0.1}$, then an increase of the variable results in the rise of variability. On the contrary, when $\beta^* < 0$, which means that $\beta^*_{0.9} < \beta^*_{0.1}$, then the variable reduce the price uncertainty.

Under the assumption of nonlinear responses to fundamental variables, as in (2), the inter-quantile range could be computed as follows

$$IQR_t = \alpha_0 D_t + \sum_{j=1}^{3} \beta^L_j L_{j,t} + \sum_{j=1}^{3} \beta^W_j W_{j,t} + \sum_{j=1}^{3} \beta^S_j S_{j,t} + \sum_{i=1}^{p} \theta_i P_{t-i}, \tag{5}$$

where $\alpha_0 = \alpha_{0,0.9} - \alpha_{0,0.1}$, $\beta^*_i = \beta^*_{i,0.9} - \beta^*_{i,0.1}$ and $\theta_p = \theta_{p,0.9} - \theta_{p,0.1}$. Similar to the linear case, when $\beta^*_i > 0$ then a given variable increases the IQR_t, whereas when $\beta^*_i < 0$ it decreases the variability.

The estimates of the parameters of (4) and (5) are provided in Table 6. When a daily data is considered, then the estimates of the linear model (4) coefficients are: $\hat{\beta}^L = 0.081$, $\hat{\beta}^W = -0.006$ and $\hat{\beta}^L = -0.200$. This implies that a rise of forecasted load results in an increase of the IQR_t, whereas an increase of RES stabilizes the price variability. The statistical significance of the parameters is tested using the percentile bootstrap approach. The results indicate that only solar affect is statistically significant and β^S is negative at significance level 1%. The lack of statistical significance of wind and load coefficients could be an effect of assumed linearity. The results presented in Figure 4 suggest that the impact of fundamental variables on price quantiles depends strongly on the level of load.

The results of model (5) show that the impact on the daily price variability depends on the level of demand. As expected, the load increases the price variability in high demand periods and decreases the variability for low demand periods. At the same time, wind and solar have an opposite effect. First, they increase the IQR_t in case of a low demand. The results are intuitive and is in line with previous results of Paraschiv et al. (2014), which show that for low level of load, an increase of RES generation have a price-dampening effect and may lead to negative prices. The statistical tests indicate that only the wind effect is significantly different from zero. When an intermediate load level is considered, it is observed that wind has a weak, positive impact on IQR_t, whereas solar decreases significantly the IQR_t. Finally, for high demand, both RES variables reduce strongly the IQR_t, with wind having a statistically significant effect. Hence, as shown by Hagfors et al. (2016b) the rise of RES stabilize prices when load is high and reduces the probability of positive price spikes.

Table 6: The influence of fundamental variables on the inter-quantile range, IQR, non-linear models.

Variable	Coefficient	Index		
		Daily	Peak	Off-peak
Linear model (4)				
Load	β^L	0.081	0.102**	0.117***
Wind	β^W	-0.006	-0.055**	-0.009
Solar	β^S	-0.200***	-0.181***	-0.299***
Non-linear model (5)				
Load	β_1^L	-0.002	0.030	-0.012
	β_2^L	0.048	0.066*	0.020
	β_3^L	0.105*	0.162*	0.049*
Wind	β_1^W	0.179**	-0.004	0.104
	β_2^W	0.010	-0.029*	0.019*
	β_3^W	-0.184***	-0.295*	-0.058**
Solar	β_1^S	0.104	0.009	0.057
	β_2^S	-0.181***	-0.176***	-0.386***
	β_3^S	-0.113	-0.115	-5.478

Note: the asterisks *, ** and *** indicate rejection of null $H_0 : \beta = 0$ at the significance levels 10%, 5% and 1%, respectively.

When the peak and off-peak data is analyzed, the results indicate some differences in price behavior within the day. It could be noticed that in peak hours both RES significantly reduce the price variability, with an exception of a low load, when the impact of solar is insignificantly positive. On the contrary, the effect of fundamental variables on off-peak prices is more diversified. The wind has a mixed impact, increasing the variability for intermediate level of load and decreasing it for high load. At the same time, solar stabilizes the price variation for both intermediate and high level of load. Finally, an increase of both types of RES rises IQR_t of off-peak prices for low level of demand. Although the corresponding coefficients are quite large in magnitude, they are statistically insignificant.

4.3. Robustness analysis

The robustness of the results is verified in two directions: the choice of the level of thresholds τ_L and τ_H and the choice of explanatory variables. First, the parameters and the IQR of the non-linear models (2) and (5) are estimated for daily indexes. Since the specification of the models depends on the assumed threshold levels, two pairs of values (τ_L, τ_H) are examined: (0.15, 0.85) and (0.20, 0.80). The results are presented in the Appendix, Tables 7-6.

Second, the set of fundamental variables is expanded and the time series of daily gas prices, G_t (Henry Hub natural gas spot price, https://fred.stlouisfed.org/series/DHHNGSP, converted to EURO) are added to the models. The literature shows that fuel prices may impact the level and variability of electricity prices (see Gianfreda and Bunn, 2018), therefore it is examined if they alter the effect of RES. It should be mentioned that gas power plans operate mainly during peak hours, when the demand for electricity is the highest. Therefore in the non-linear model (2), their impact is conditioned on the level of total load, similar to load and RES. As the result, the models (1) and (2) become:

$$P_t(\tau) = \alpha_{0,\tau} D_t + \beta_\tau^G G_{t-1} + \beta_\tau^L L_t + \beta_\tau^W W_t + \beta_\tau^S S_t + \sum_{i=1}^{p} \theta_{i,\tau} P_{t-i}, \tag{6}$$

$$P_t(\tau) = \alpha_{0,\tau} D_t + \sum_{j=1}^{3} \beta_{j,\tau}^G G_{j,t-1} + \sum_{j=1}^{3} \beta_{j,\tau}^L L_{j,t} + \sum_{j=1}^{3} \beta_{j,\tau}^W W_{j,t} + \sum_{j=1}^{3} \beta_{j,\tau}^S S_{j,t} + \sum_{i=1}^{p} \theta_{i,\tau} P_{t-i}, \tag{7}$$

where parameters β_τ^G and $\beta_{j,\tau}^G$ describe the impact of lagged gas prices on the τ quantile of electricity prices P_t. The variables $G_{j,t-1}$ are defined as $G_{j,t-1} = I_{j,t} G_{t-1}$. The parameter estimates for daily, peak and off-peak indexed together with corresponding IQR are presented in the Appendix, Tables 9-10. Since the main concern is the impact of RES on the price distribution, only the results for wind and solar are presented.

The analysis indicates a robustness of results obtained in previous sections. Although one could notice some minor quantitative differences, the outcomes do not change the qualitative interpretation of the results and final conclusions.

5. Conclusions

In this research, a quantile regression is applied to analyze the effects of RES on the distribution of electricity prices. The analysis focuses on the merit-order effect, and the impact of RES on the price variability. In the proposed models, the nonlinear relationship between fundamental variables and the electricity prices is allowed. The impact of RES and load on spot prices is conditioned on the demand level. Three states of the demand are analyzed: low, intermediate and high, which correspond to chosen quantiles of the load level.

The results confirm the price-dampening impact of both wind and solar generation. It is shown that when the level of prices is considered, which is approximated by the median, there are no gains from distinguishing between different types of RES. However, when the relationship between the range of quantiles and RES is analyzed, it is found out that wind has a stronger reducing impact on lower tails, whereas solar on higher tails of the price distribution. This results complements the previous findings of Paraschiv et al. (2014), Hagfors et al. (2016a) and Gianfreda and Bunn (2018).

Finally, the impact of RES on price variability is evaluated and tested using the IQR. It could be noticed, that IQR is closely related to the price variance, particularly when the price distribution is Normal or t-Student. The outcomes indicate that solar and wind impact the price variability differently. Wind increases the variability in a case of a low level of demand and reduces it, when the demand is high. At the same time, solar stabilized the variation of prices for an intermediate level of demand. Hence, different types of RES are associated with various risk levels. These outcome is in line with results of Gianfreda and Bunn (2018), which show that the impacts of solar and wind are distinct and varies conditional of the hour of the day.

The outcomes of this research are relevant for practitioners and policy makers, because they demonstrate how the structure and level of RES affects both: the level and the variability of electricity prices. The results could be used in various ways. First, generators could utilize the information on price uncertainty during their decision process (for example, when choosing an optimal market, as in Maciejowska et al. (2019)) or construction of offer curves. Second, understanding the mechanisms governing the movements of the price distribution could help to develop policies, which will aim at finding a desired generation mix - leading to markets with both low level of prices and limited risk. Finally, as the share of RES is continuously growing, the results encourage further investigation of the field, which is believed to be relevant not only for the energy sector but also for the global economy.

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6. Appendix

Table 7: The estimates of parameters β^W and β^S of the non-linear (2) models under different threshold values: τ_L and τ_H.

τ	Wind			Solar		
	$\beta^W_{1,\tau}$	$\beta^W_{2,\tau}$	$\beta^W_{3,\tau}$	$\beta^S_{1,\tau}$	$\beta^S_{2,\tau}$	$\beta^S_{3,\tau}$
$\tau_L = 0.15$, $\tau_H = 0.85$						
0.1	-0.353 ***	-0.1602 ***	-0.1453 ***	-0.4477 ***	-0.0572 **	-0.0507
0.2	-0.3167 ***	-0.1484 ***	-0.1836 ***	-0.3419 ***	-0.0844 ***	-0.2106 **
0.3	-0.3093 ***	-0.1503 ***	-0.1831 ***	-0.2864 ***	-0.0999 ***	-0.2727 ***
0.4	-0.2608 ***	-0.1546 ***	-0.1888 ***	-0.2316 ***	-0.1068 ***	-0.283 ***
0.5	-0.2429 ***	-0.1473 ***	-0.1933 ***	-0.2419 ***	-0.1012 ***	-0.3111 ***
0.6	-0.2073 ***	-0.1415 ***	-0.1894 ***	-0.2581 ***	-0.1297 ***	-0.4179 **
0.7	-0.2017 ***	-0.145 ***	-0.2041 ***	-0.2434 ***	-0.1403 ***	-0.5628 **
0.8	-0.1871 ***	-0.1435 ***	-0.2309 ***	-0.2606 ***	-0.1761 ***	-0.5669 **
0.9	-0.2097 ***	-0.158 ***	-0.2679 ***	-0.3537 ***	-0.2347 ***	-0.368 ***
$\tau_L = 0.2$, $\tau_H = 0.8$						
0.1	-0.3329 ***	-0.1514 ***	-0.1194 ***	-0.3708 ***	-0.0585 **	-0.0816 *
0.2	-0.3041 ***	-0.1479 ***	-0.1577 ***	-0.2961 ***	-0.0894 ***	-0.3264 ***
0.3	-0.2512 ***	-0.1507 ***	-0.1636 ***	-0.2523 ***	-0.0901 ***	-0.3548 ***
0.4	-0.2429 ***	-0.1505 ***	-0.1762 ***	-0.2252 ***	-0.1102 ***	-0.4234 ***
0.5	-0.2366 ***	-0.148 ***	-0.18 ***	-0.1921 ***	-0.1178 ***	-0.4078 ***
0.6	-0.2178 ***	-0.1415 ***	-0.1731 ***	-0.2265 ***	-0.129 ***	-0.3923 ***
0.7	-0.1994 ***	-0.1457 ***	-0.1985 ***	-0.2371 ***	-0.145 ***	-0.57 ***
0.8	-0.1912 ***	-0.1466 ***	-0.2175 ***	-0.2264 ***	-0.1747 ***	-0.5636 ***
0.9	-0.2008 ***	-0.1584 ***	-0.2414 ***	-0.3099 ***	-0.2244 ***	-0.5776 ***

Note: the asterisks *, ** and *** the significance at the significance level 10%, 5% and 1%, respectively.

Table 8: The influence of fundamental variables on the inter-quantile range, IQR, under different threshold values: τ_L and τ_H.

Variable	Coefficient	IQR	
Thresholsd	τ_L	0.15	0.20
	τ_H	0.85	0.80
Load	β_1^L	0.016	0.034
	β_2^L	0.058	0.067
	β_3^L	0.099 **	0.109 *
Wind	β_1^W	0.143 ***	0.132 ***
	β_2^W	0.002	-0.007
	β_3^W	-0.123 **	-0.122 ***
Solar	β_1^S	0.094	0.061
	β_2^S	-0.177 ***	-0.166 ***
	β_3^S	-0.317 *	-0.496 **

Note: the asterisks *, ** and *** indicate rejection of null $H_0 : \beta = 0$ at the significance levels 10%, 5% and 1%, respectively.

Table 9: The estimates of parameters β^W and β^S for linear (1) and the non-linear (2) models - the set of fundamental variables includes lagged gas prices.

τ	Wind				Solar			
	β^W_τ	$\beta^W_{1,\tau}$	$\beta^W_{2,\tau}$	$\beta^W_{3,\tau}$	β^S_τ	$\beta^S_{1,\tau}$	$\beta^S_{2,\tau}$	$\beta^S_{3,\tau}$
Daily index								
0.1	-0.187 ***	-0.407 ***	-0.186 ***	-0.188 ***	-0.137 ***	-0.531 ***	-0.101 ***	-0.171
0.2	-0.171 ***	-0.317 ***	-0.164 ***	-0.207 ***	-0.152 ***	-0.456 ***	-0.130 ***	-0.428 **
0.3	-0.171 ***	-0.262 ***	-0.160 ***	-0.215 ***	-0.152 ***	-0.305 ***	-0.136 ***	-0.552 **
0.4	-0.166 ***	-0.224 ***	-0.158 ***	-0.217 ***	-0.176 ***	-0.310 ***	-0.145 ***	-0.382 **
0.5	-0.163 ***	-0.223 ***	-0.155 ***	-0.234 ***	-0.192 ***	-0.377 ***	-0.157 ***	-0.514 **
0.6	-0.159 ***	-0.204 ***	-0.149 ***	-0.256 ***	-0.199 ***	-0.359 ***	-0.173 ***	-0.532 **
0.7	-0.162 ***	-0.202 ***	-0.146 ***	-0.250 ***	-0.213 ***	-0.385 ***	-0.188 ***	-0.636 *
0.8	-0.178 ***	-0.214 ***	-0.153 ***	-0.300 ***	-0.263 ***	-0.393 ***	-0.235 ***	-0.071
0.9	-0.186 ***	-0.193 ***	-0.173 ***	-0.338 ***	-0.321 ***	-0.395 ***	-0.301 ***	-0.321
Peak index								
0.1	-0.175 ***	-0.162 ***	-0.177 ***	-0.227 ***	-0.125 ***	-0.115 *	-0.126 ***	-0.483
0.2	-0.171 ***	-0.146 ***	-0.169 ***	-0.253 ***	-0.132 ***	-0.111 **	-0.133 ***	-0.182 *
0.3	-0.179 ***	-0.126 ***	-0.179 ***	-0.286 ***	-0.136 ***	-0.084 **	-0.140 ***	-0.532 **
0.4	-0.177 ***	-0.118 ***	-0.175 ***	-0.299 ***	-0.135 ***	-0.112 ***	-0.136 ***	-0.399 *
0.5	-0.183 ***	-0.141 ***	-0.172 ***	-0.330 ***	-0.138 ***	-0.132 ***	-0.133 ***	-0.533 *
0.6	-0.196 ***	-0.150 ***	-0.179 ***	-0.291 ***	-0.150 ***	-0.109 ***	-0.149 ***	-0.455
0.7	-0.194 ***	-0.143 ***	-0.185 ***	-0.324 ***	-0.170 ***	-0.104 **	-0.165 ***	-0.139
0.8	-0.210 ***	-0.162 ***	-0.190 ***	-0.331 ***	-0.186 ***	-0.166 **	-0.198 ***	-0.186
0.9	-0.207 ***	-0.150 ***	-0.216 ***	-0.436 ***	-0.205 ***	-0.113 *	-0.245 ***	-0.095
Off-peak index								
0.1	-0.175 ***	-0.218 ***	-0.179 ***	-0.158 ***	-0.114 ***	-0.684	-0.072 ***	0.101
0.2	-0.169 ***	-0.204 ***	-0.170 ***	-0.181 ***	-0.161 ***	-0.681 **	-0.093 ***	-0.493
0.3	-0.161 ***	-0.198 ***	-0.165 ***	-0.164 ***	-0.202 ***	-0.565 ***	-0.141 ***	-0.354
0.4	-0.161 ***	-0.203 ***	-0.163 ***	-0.183 ***	-0.208 ***	-0.611 ***	-0.152 ***	-1.651
0.5	-0.157 ***	-0.188 ***	-0.154 ***	-0.171 ***	-0.226 ***	-0.621 ***	-0.173 ***	-2.733
0.6	-0.151 ***	-0.195 ***	-0.148 ***	-0.175 ***	-0.238 ***	-0.550 ***	-0.183 ***	-1.832 *
0.7	-0.151 ***	-0.206 ***	-0.143 ***	-0.178 ***	-0.246 ***	-0.547 ***	-0.233 ***	-2.867 *
0.8	-0.161 ***	-0.208 ***	-0.141 ***	-0.188 ***	-0.297 ***	-0.497 ***	-0.286 ***	-2.994 *
0.9	-0.172 ***	-0.218 ***	-0.167 ***	-0.219 ***	-0.396 ***	-0.440 ***	-0.379 ***	-1.697

Note: the asterisks *, ** and *** the significance at the significance level 10%, 5% and 1%, respectively.

Table 10: The influence of fundamental variables on the inter-quantile range, IQR, non-linear models - the set of fundamental variables includes lagged gas prices.

Variable	Coefficient	Index		
		Daily	Peak	Off-peak
		Linear model		
Load	β^L	-0.030	0.116 **	0.077 **
Wind	β^W	0.001	-0.032 **	0.003
Solar	β^S	-0.184 ***	-0.080 **	-0.282 ***
		Non-linear model		
Load	β_1^L	-0.175 *	0.038	0.079
	β_2^L	-0.041	0.095	0.070
	β_3^L	-0.034	0.032	0.079 *
Wind	β_1^L	0.214 **	0.012	0.001
	β_2^L	0.013	-0.039 *	0.012
	β_3^L	-0.150 ***	-0.209 **	-0.061 **
Solar	β_1^L	0.136	0.002	0.244
	β_2^L	-0.200 ***	-0.119 ***	-0.308 ***
	β_3^L	-0.150	0.388	-1.798

Note: the asterisks *, ** and *** indicate rejection of null $H_0 : \beta = 0$ at the significance levels 10%, 5% and 1%, respectively.

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