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The dependence of quantile power prices on supply from renewables

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ABSTRACT

Understanding power prices dynamics is crucial for valuing flexibility assets such as storage or flexible consumption facilities that accommodate fluctuations in power supply from variable renewables. Owners of such assets need to know how extreme power prices can become in order to optimally manage (dis)charging or adjusting consumption volumes. We examine how to predict those high and low prices, being the different quantiles of the power price probability distribution function, and question how supply from variable renewable sources affect different quantile prices.

The first contribution of our paper is that we apply quantile regressions in a panel data framework. This methodology acknowledges that day-ahead power markets' data is structured as cross-sectional data and, as opposed to previous quantile regression techniques introduced in power markets, allows for simultaneous predictions for all hours during a delivery day. Day-ahead power prices for all 24 h in the next day are determined at the same moment, one day before delivery. The hourly data is therefore not a time-series, but a cross section. The second contribution is that we examine the interaction between demand and supply from variable renewable sources, instead of linear dependencies only.

We find that lower and higher quantile prices are more heavily affected by variations in supply from variable renewable sources than centre quantile prices. This enables owners of flexibility assets to better manage their assets in anticipation of excess or scarce supply from renewable sources. By doing so, they increase the flexibility of power systems that face increasing installed capacity of variable renewable energy sources.

1. Introduction

The inclusion of supply from variable renewable sources, hereafter referred to as VRES, challenges power systems. The volume supplied by these sources is variable as it depends on weather conditions, which change over time. Even though owners of VRES facilities are balance responsible parties and are financially bound to keep their positions balanced at al times, VRES sources have limited capacity to adjust volumes as they can only curtail, not increase, production. This occurs because most installed VRES capacities do not have attached to them flexibility assets such as batteries. Besides, supply from VRES comes with a low marginal cost which sometimes is complemented by a subsidy per MWh of power produced. Because of this, curtailment is most of the times not profitable for owners of such renewable assets. Moreover, weather dependent supply from wind and solar does not match demand patterns. Hence, supply from VRES challenges the power system as their volume variability needs to be dealt with. Many current power systems are not flexible enough to deal with such an environment. This leads to frequent negative power prices due to an abundance of supply from VRES at times when there is no demand for it. As a consequence, investments are needed to increase the flexibility of power systems in matching supply and demand.

One can think of power storage and more flexible consumption (demand response as some call it)[1] as potential solutions. What these solutions have in common is that they are flexibility offering type of assets. A power storage facility provides the option to charge when supply from VRES is high and demand for it is low. The facility then has the option to discharge and deliver power when demand is high and supply from VRES is low. The same holds for flexible consumption. Having the option to scale up or down consumption in response to more or less supply from VRES makes the power system more flexible. Investments in such flexibility offering type of assets only take place when sufficient income can be generated from these assets. For storage facilities and demand response applications, income depends on the variation of power prices. When power prices are more volatile, the

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[1] Demand response applications can provide flexibility to the grid through peak clipping, demand shifting or valley filing concepts.

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owner of a power storage facility can charge at lower prices and discharge at higher prices and yield more income than when prices are less volatile. This view of just volatility driving income of flexibility offering assets comes from financial markets, but is too simplistic for power markets. There, frictions between supply and demand and often the lack of storage, make power prices behave more erratically than prices of financial assets. There is sufficient evidence for that claim put forward in the literature as it reveals that power prices tend to mean-revert and frequently jump to high and low (even negative) levels. Understanding these price dynamics is crucial for valuing storage and demand response assets in power markets, assets which represent an important source of flexibility and, thereby, enable the efficient inclusion of VRES.

To include supply from VRES efficiently, we need those flexibility offering assets to respond to (expected) fluctuations in supply from renewables. Following the logic of supply and demand, the market price of power depends on supply from VRES. There is a consensus view on how a change in supply from VRES affects power prices since a change in the (expected) supply from VRES shifts the supply curve (or merit order as it is called in the energy world). Würzburg et al. (2013) summarises 20 studies and all find that an increase in supply from VRES decreases the market price of power. This result is intuitive since, by having almost zero marginal cost, VRES are highly competitive and are generally included in that part of the supply curve that is dispatched.

Other studies focus on the relation between supply from VRES and the volatility of the market price of power. Ketterer (2014), Kyritsis et al. (2017), and Rintamäki et al. (2017) show that an increase in the supply from wind producers increases the volatility of power prices as it challenges the flexibility of power markets especially during off-peak hours when demand is low and only a few power plants can curtail production. For supply from solar producers, Kyritsis et al. (2017) show that an increase in supply decreases price volatility as solar typically supplies during demand peak hours. Rintamäki et al. (2017) go one step further as they distinguish between periods with high and low prices. They show that supply from VRES lowers the volatility of power prices during periods with high prices and increases volatility when prices are low.

Beyond the mean and the variance of power prices, some papers, using either extreme value theory or regime switching models, show that VRES output influences also the likelihood of extremely high and low power prices. Lindstrom and Regland (2012), in a study on 6 European power markets, find a positive link between the two. Paraschiv et al. (2014) touches marginally on this aspect proving a connection between extreme negative prices and higher wind power output on the German EEX market. Benhmad and Percebois (2018) and Martin de Lagarde and Lantz (2018) show that a steep decrease in power prices was associated with an increase in wind power in-feed. Huisman et al. (2022) argue that extreme high and low prices should be analysed separately as VRES output has a different impact on the left tail of the power price probability distribution (low prices) than on the right tail (high prices). For instance, an increase in supply from wind sources decreases the occurrence and magnitude of extremely high prices, while it increases the occurrence and magnitude of extremely low prices. A similar conclusion is also drawn by Hagfors et al. (2016b).

The summarising view is that an increase in supply from VRES decreases the day-ahead power price on average, changes the volatility of power prices and the frequency and magnitude of extremely high and low prices. Consequently, power prices will be low when supply from VRES is high and demand for power is low. Alternatively, one may expect power prices to be high when supply from VRES is low and demand for power is high. But, in order to maximise value, a power storage (flexibility offering asset) owner wants to make charging/discharging decisions based on expectations when market prices will be lowest/highest. She/he wants to profit from extreme prices, which occur when the flexibility of the power system is challenged most. The same, for someone who can adjust consumption volumes, she/he wants to reduce consumption when prices are highest and vice versa. The point is that owners of flexibility offering assets want to profit from extreme price movements, and by doing so they will offer their flexibility at times when its most needed. In order to deliver this, they need to understand what drives those extreme prices. In power markets volatility by itself is not a sufficient parameter as input for valuation models of flexibility offering assets. What we need is to understand how the interaction between supply from VRES and demand for power affects market prices.

Owners of flexibility offering assets have to take decisions anticipating on power prices in the near future. Power storage owners want to have high/low inventory when they expect high/low prices. Therefore, understanding the range within which power prices behave in the near future is crucial for these owners in order to maximise the value of their assets. One could derive such a price range by estimating a confidence interval using the average price, standard deviation (volatility), and tail information (extreme prices) blended into a probability distribution function. More sensible is to estimate the boundaries of the confidence interval directly using a quantile regression. This enables the owners of flexibility offering assets to predict what – for instance – the 1st and 99th quantiles of the power price probability distribution function are. This is what we do in this paper, with a focus on the impact of VRES on power prices. We use a novel methodology and model for power markets, later detailed in the paper, and we show that these power price boundaries depend on information about expected supply from VRES.

Bunn et al. (2016) summarise the benefits of the quantile regression technique (applied to power prices): it provides a semi-parametric formulation for predictive distributions, allows for inclusion of fundamental variables, permits for separating moments with differing patterns, and can offer an alternative to regime switching models (through the indirect incorporation of regimes at different quantile levels). Jónsson et al. (2014), Rodríguez et al. (2014), Hagfors et al. (2016a), Maciejowska et al. (2016), Chen and Lei (2018), Troster et al. (2018), Kyritsis and Andersson (2019) and Goodarzi et al. (2019) all use quantile regression models to study power prices, demonstrating that this research method is suited to study a wide range of research topics in power markets. More specific to wind and photovoltaic solar supply, Hagfors et al. (2016c) include supply from VRES in a quantile regression to predict power prices. They observe that during off-peak hours, where extreme low prices are more likely to occur, the effect of wind output on day-ahead prices is stronger than during peak hours. For solar, at higher price quantiles the effect on day-ahead prices appears to be stronger than for the centre quantiles. Sapio (2019) and Maciejowska (2020) use quantile regression to predict price quantiles conditional on the share of supply from VRES.

Predicting power price quantiles through quantile regression is not a new topic, but we contribute to the existing literature in two ways. First, we apply quantile regression in a panel framework for reasons that we point out below. Second, all papers specify linear quantile regression models, whereas we think that there is reason to believe that some interaction between variables might be expected. When power markets are not flexible enough to accommodate variation in supply from VRES, we would expect the impact of variation in supply from VRES to be different during periods with moderate demand or share of VRES than in periods with low (high) demand and high (low) share of VRES.

But why a panel framework? Huisman et al. (2007) argue that one should use a panel framework to study day-ahead power price data. The reason comes from the microstructure of most day-ahead markets that we know. In the day-ahead market one can trade contracts that involve the delivery of 1 MWh of power during a specific hour in the next day. For instance, one can trade a contract for delivery during hour 1 (starting at midnight) in the next day and/or for delivery during hour 18 (between 5pm and 6pm) in the next day. In fact, day-ahead contracts are futures contracts for delivery during a specific hour with maturity being the next day. The microstructure of such markets instructs traders to supply their bids and offers before a specific time (11am in the Netherlands for example) for all day-ahead contracts. The bids and offers for the hour 1 contract are submitted at the exact same time as the bids and offers for the hour 18 contract. After receiving those bids and offers, the market operator determines the market clearing price for all hour day-ahead contracts. This implies that the price of the hour 1 contract is determined at the exact same time as the price of the hour 18 contract. The information embedded in the price for the hour 1 contract is exactly the same information embedded in the price for hour 18 delivery. Therefore, those individual hourly prices are not formed based on information that evolves in a continuous time series manner. Identifying those contracts as hour 1 through hour 24 suggests a time-series but is misleading. This was observed by Huisman et al. (2007) and they therefore argue that day-ahead price data is in effect panel data; one should see day-ahead power prices as a time-series of a cross-section of 24 individual delivery hours. The papers that we mentioned above that use quantile regressions all use a time-series framework and not a panel framework. Off course, one can study the prices of hour 18 contracts in isolation, which is a time-series, or the average price during peak or off-peak hours. That is what the above studies did. But by doing so, they ignore (or do not need) the information embedded in the cross-section. Thus, when studying the prices of hour 1 and 18 in isolation, one does not observe the information that is embedded in both prices simultaneously as they were determined at the same market clearing time. Thinking about flexibility offering assets, we think that focusing on average prices or hourly prices in isolation is an important limitation. For instance, when we expect a high price during hour 10, for instance because of low supply from renewables, we had expect that the prices for the adjacent hours 9 and 11 could also be higher as solar radiation and wind supply does not have hourly boundaries. Huisman et al. (2007) show that such cross-sectional correlations are apparent. Correlations are close to one for adjacent hours and between all off-peak and peak hours. The correlations are lower between peak and off-peak hours.

Studying the time series of average prices or prices for one-hour contracts in isolation, in the way the papers cited above do, ignores this cross-sectional dependence among hourly prices and the information that is embedded in each hourly day-ahead price. This is fine if one is interested in the price dynamics of one hour or of the average price of a group of hours such as the daily average price or the average price during peak or off-peak hours. This is for instance what Maciejowska (2020) are interested in. If one is interested in the dynamics of different hours simultaneously, then using a time series approach ignores the cross-sectional dependence. For instance, when one wants to operate a power storage system, one needs to make charging and discharging decisions based on expected prices over adjacent hours. Then, the cross-sectional dependence is crucial as the price for one hour relates to adjacent hours. This is the contribution of this paper upon those previous studies: we use a panel quantile regression approach. This avoids this information loss and provides a more realistic framework that matches the market microstructure of day-ahead markets which is attractive for market participants. Managers of storage facilities or demand response applications can use panel quantile regression techniques to predict how low or high power prices are expected to be at each hour for the next delivery day. In this way, they can foresee the moments in time when power prices are likely to become extremely low or high. This technique would then also indicate for how many hours power prices are expected to remain extreme. Hence, operators of flexibility offering assets could use such techniques in optimising their bidding strategies. To our knowledge, this paper is the first one to apply a panel quantile regression approach to day-ahead power markets.

There are various ways in which panel quantile regression models can be built and used. This paper chooses to use them focusing on the impact that supply from VRES has on power prices. Getting back to day-ahead prices and their fundamentals, it makes sense that supply from VRES influences power prices much stronger at the higher and lower quantiles of the power price probability distribution function. To see this, keep the “hockey stick” shape of the supply curve in mind (see Borenstein, 2002). At high demand levels, when usually high prices occur, the supply curve is steeply upward curved, whereas it is almost flat at “normal” demand levels. This implies that the impact of a change in demand on prices is stronger at high demand levels than at normal demand levels. Supply from VRES, having zero marginal costs, will shift the supply curve to the right. At high demand levels, supply from VRES will have a sharp price reducing impact on power markets as the upward sloped part of the supply curve shifts to the right. At normal demand levels, when moderate prices are expected to occur, the supply curve is almost flat and this remains the case when supply from VRES moves the supply curve to the right. Consequently, during periods of high demand, the price impact of an increase in supply from VRES will be stronger than during periods with normal demand. In other words, when prices are high due to high demand, an increase in supply from VRES is expected to reduce that high price more than what the same level of supply from VRES increase will reduce the price at normal demand level. This predicts that an increase of supply from VRES will have a bigger impact on the right side of the price probability distribution function than on the centre part. We expect to observe the same effect also on the other side of the power price probability distribution function, on the very low prices, but for a different reason. In many countries, the cheaper non-VRES suppliers are relatively inflexible power producers (i.e. coal and nuclear). For those producers, ramping up/down production is costly. Therefore, for short periods, for such inflexible producers, maintaining a stable level of production, even when the power prices are falling below their marginal costs, can be less costly than temporarily ramping down production. Such a situation can lead to extreme low prices during periods with low demand and high supply from VRES. This predicts that an increase in supply from VRES during moments when prices are already very low, should decrease much more the power price than the same increase in supply from VRES would do during periods with moderate prices. These predictions suggest the following claim: An increase in supply from VRES reduces power prices more at extreme low and high quantiles than at the centre part of the power price probability distribution function.

We test this claim in this paper using quantile regressions in a panel framework. The knowledge that we can gain from this result may help market players to better predict power prices and especially the likelihood of occurrence and magnitude of extreme power prices. If the impact of wind and solar output on power prices has different magnitudes in different moments in time, this information adds value to participants in power markets. Consequently, market players should consider this information when constructing bidding strategies. More accurate price predictions can lead to less risky and hence more profitable strategies for storage facilities used in arbitraging in power markets. This can lead to an increase in investments in storage units and other flexibility offering assets in the power market and, thus, will then smoothen the path towards a more sustainable and flexible power market.

To test our claim, we chose to study day-ahead prices, being one day futures prices and not real-time imbalance prices. The reason for this choice comes from the fact that, in many countries, day-ahead markets are the platform on which most of the supply from VRES is traded. Especially in European markets, feed-in tariffs are linked to the day-ahead prices. This policy makes it rational for VRES suppliers to sell their power output on the day-ahead markets. An alternative would have been to study intraday or imbalance markets, where, because of their weather dependency, supply from VRES plays a big role. However, these markets are less liquid than day-ahead markets. Market participants use day-ahead markets already for many years and many of them refer to the day-ahead price as *the* power price. Therefore, we leave the exploration of the imbalance and more real-time markets for future studies. Let us proceed with the panel model we suggest to use.

2. Methodology

Quantile regression was introduced by Koenker and Bassett (1978) and build on the notion of estimating conditional quantile functions. In a quantile regression model one can locate the effect that independent variables have on the dependent variable for each quantile of the distribution function of the dependent variable. The model that we use is as follows. It is a linear model, similar to others used in different studies about power prices before.

$$p_{q,h,t} = \alpha_{q,h} + \beta_q \times mc_t + \gamma_q * D_{h,t} + \delta_q \times VRES_{h,t} + \epsilon_{q,h,t}. \quad (1)$$

The subscripts q, h, and t represent the specific quantile studied, the delivery hour, and time respectively. The dependent variable is $p_{q,h,t}$, which is the qth quantile of the day-ahead price probability distribution function for delivery during hour h in day t. This linear model follows the rationale of Hagfors et al. (2016a,c) in the choice of factors that explain $p_{q,h,t}$. Let us discuss those factors in detail.

- $\alpha_{q,h}$. This is the fixed effect as it is called in the panel literature. It represents a constant term for each specific hour h.
- mc_t. This variable captures the local past median marginal cost of supply from non-VRES at time t. One way to measure this is by using the prices of various underlying fuels. Because of the heterogeneity in the production technologies and also in the underlying fuels used, this would mean to include a series of variables like coal price, gas price, nuclear material price, CO2 emission rights and to calibrate them depending on the supply mix of the power system in cause. Another approach that reduces complexity is to create a proxy variable which comprises all underlying fuel information into one variable. That proxy variable can be formed by making use of recent power prices. Due to the merit order construction in liberalised day-ahead power markets, these prices reflect the costs of the marginal producer. Therefore, it is sensible to use recent market clearing prices as a proxy for marginal cost. We use the median of hourly power prices over the past 4 weeks: 28 days * 24 hours/day = 672 observations.[2] The model attributes the same marginal cost value for all 24 h in the day. Hence, the absence of the subscript h in $mc_{q,t}$. The logic behind this is that bidding in the day-ahead market happens in the same time for all the 24 h of the day and, consequently, the bidding decision is based on the same level of underlying fuel prices for each hour within a day. The median value is preferred over the average value since the median value is less dependent on extreme power prices, is less volatile and, therefore, it can better capture the local level of underlying fuel prices.
- $D_{h,t}$. This variable captures total demand for power during hour h in day t. It is measured from the hourly total system consumption.
- $VRES_{h,t}$. This variable is the share of total demand that is covered by wind (offshore and onshore) supply and by photovoltaic supply during hour h in day t. We do not separate between wind and solar output in this analysis as both technologies have close to zero marginal cost, both are dependent on weather and for each of them the literature proves that their supply is decreasing the wholesale power prices.[3] Percentages of supply from VRES are preferred over the volumes of supply from VRES since the share of supply from VRES can better capture how dependent the power system is on the wind and solar output in a particular moment. Volumes are less accurate in capturing this since a certain volume of VRES output in a period with a low demand is challenging more the power system's flexibility than the same volume of VRES output in a period with a high demand.
- $\epsilon_{q,t} \approx (0, \Sigma)$. This is an independent and identically distributed error term with Σ being a (24×24) covariance matrix.

Having the mc_t, $D_{h,t}$ and $VRES_{h,t}$ present in the model eliminates the need for introducing seasonality control variables as the chosen variables capture the changes that each season brings into a power system. For the volumes of load and supply from VRES, we had to make a decision between using actual/realised or expected/forecasted data. While both actual and expected data have their limitations (forecasted data is prone to player specific forecasted error; actual data is not available at the moment of day-ahead bidding), we follow Nicolosi (2010) and Kyritsis et al. (2017) by using actual volumes data. As Woo et al. (2015) explain, forecasted and actual data are highly correlated and, thus, the results not to differ much when changing from one approach to the other.[4]

To estimate the parameters in Eq. (1) in a panel framework, we follow the methodology suggested in Baltagi (2013). Because of heteroskedasticity caused by the cross-sectional covariance matrix Σ, we cannot directly estimate the parameters. We do the following steps: (i) we set-up a system of 24 seemingly unrelated regressions based on the model presented in Eq. (1); in fact 24 time-series for the 24 hourly contracts; (ii) we then estimate the system of seemingly unrelated regressions using feasible generalised least squares approach and restricting that each of the coefficients is equal across the 24 regressions (except for the hourly fixed terms); (iii) we estimate the covariance matrix Σ from the residuals; (iv) we pre-multiply the original data with the Choleski decomposition of the inverse of the estimated Σ matrix and we obtained the transformed data; (v) we estimate the parameters in Eq. (1) using quantile regression on the transformed data. The process used is not always efficient after the first transformation. Therefore, using the transformed data obtained in step (iv), we redo the all the steps above until convergence of results of step (v) is achieved. We define that convergence occurred when each δ_q estimated coefficient in Eq. (1) for each quantile level does not deviate by more than 1% from the estimated coefficient from the previous transformation panel quantile regression estimates.

Having these estimates, we then test our claim, that supply from VRES is having a stronger reducing impact on power prices at extreme quantile levels as compared to moderate quantile levels, by examining the estimates for the coefficients δ_q. These coefficients show the impact that the share of supply from VRES has on day-ahead power prices at various quantile levels. Given our claim is correct, we expect to observe significantly lower coefficient estimates for the share of supply from VRES on the lowest quantiles and on the highest quantiles compared to the quantiles in between.

3. Data

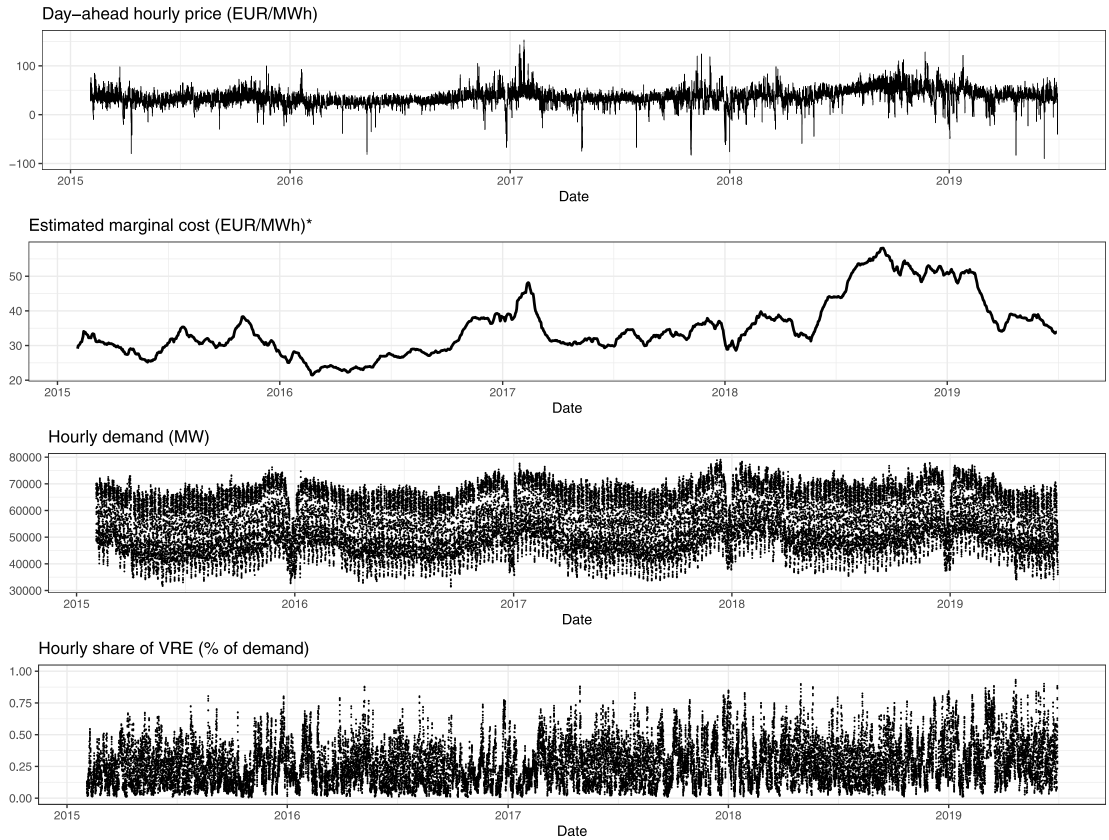
The data that we use is comprised by hourly observations from the German day-ahead power market between 6th of January 2015 to 30th of June 2019, collected from Bundesnetzagentur — SMARD.de.[5] The

[2] The length of the past data was chosen in order to: (i) include an equal number of weekdays and weekend days, eliminating in this way the within week seasonality concerns; (ii) be short enough to avoid the inclusion of prices that are not anymore relevant to the local level of prices; (iii) be long enough to allow the marginal cost variable to not be dependent on moments with a high concentration of extreme high or low prices. Shorter timeframes lead to much higher volatility for the calculated marginal cost variable and that is not in line with the volatility of the underlying fuel prices.

[3] The only economical difference between the wind power and the photovoltaics power products lays within the moments in time when they are set to produce. Solar supply is predominantly produced during peak hours and wind power can exhibit a high supply both in peak and off-peak hours.

[4] When performing robustness checks using forecasted data, the results are similar to the ones obtained using actual data.

[5] 23 days from the dataset were excluded due to unavailable data for certain hours. For 0.4% of the hourly observations, where only partial intra-hour (15 min blocks) information are available, adjustments (averaging based on available intra-hour data) had to be made in order to keep the dataset consistent.



*The estimated marginal cost is calculated as the lagged median day-ahead price for the previous 4 weeks of hourly observations.

Fig. 1. Overview of the German day-ahead market between January 2015 – June 2019.

dataset contains information about German day-ahead power prices, demand level and share of supply from VRES. The first 672 observations are used solely for estimating the initial marginal cost value of the power system, mc_t.

Fig. 1 shows the data that we use from Germany. The first (top) graph shows the hourly day-ahead prices. It shows frequent extreme high and low values, ranging from below −100 euro/MWh to over 163 euro/MWh. The second graph shows the median lagged price variable which is our proxy for marginal costs mc_t. It is less volatile as it represents a moving average. Its values range from 21 euro/MWh to 58 euro/MWh. The third graph shows system's realised demand. The fourth (lower) figure shows the share of supply from VRES and exhibits huge variability. The VRES share has hourly values from 0% to over 90%. To be noted that the variable constructed for the model represents the ratio between supply from VRES and actual demand without considering the generation related to the export/import of power. Since in all of the months included in the analysis except for one, June 2019, Germany was a net exporter of power, we would observe on average lower values when we had consider the share of VRES out of the total power generated in Germany.

To get an initial insight from the data, in Table 1 we split the dataset into day-ahead price deciles followed by a further sub segmentation by the share of supply from VRES. While not having any statistical power, already from this initial table we can observe that the share of supply from VRES is putting a much higher pressure on the German day-ahead power market during the moments when prices are more extreme, the lowest and the highest price deciles. Table 1 shows that for price deciles 0.2–0.3 to 0.7–0.8, an average increase in the VRES share of 10% decreases prices only marginally by 0.00–0.04 euro/MWh. The same average increase in the share of supply from VRES in the highest and the lowest price deciles decreases on average the day-ahead price with more than 2.8 euro/MWh. Based on Table 1, the price impact of a 10% increase in the share of VRES appears to be the highest, in absolute terms, in the two extreme cases: (i) high VRES share in the lowest price decile and (ii) low VRES share in the highest price decile. In the highest and the lowest price deciles, the price variation is also the highest, since in these moments the power system's flexibility is challenged more. The lack of flexibility in the highest and lowest price deciles, appears to lead to more abrupt price response when the share of supply from VRES changes.

4. Results

The first result that we show is to demonstrate the validity of the panel framework. Table 2 shows the (24 × 24) correlation matrix obtained from the estimate of the cross-sectional covariance matrix Σ. The table clearly shows high correlations for adjacent hours. For example, the correlation between the residuals for the (seemingly unrelated) regressions for hours 10 and 11 is 0.94 and 0.92 for hours 11 and 12. The residuals for the regression on hour 11 have a much lower correlation, of 0.36, with the residuals of hour 23. A clear correlation (and covariance) pattern occurs indicating that information is thrown away when one considers the time-series of hour 11 separate from hours 10 and 12 for instance. Similar examples can be provided for each of the 24 h within a day.[6]

[6] Another way of stating is that our approach accounts for the cross-sectional covariance between different hourly prices. To test whether this is indeed the case, we have calculated the average absolute covariance between

Table 1
German day-ahead average price behaviour by share of VRES supply and price decile.

Day ahead price decile	Minimum day ahead price	Maximum day ahead price	Price interval (max–min)	Average day-ahead price by VRES share subsample						Price change by 10% VRES share increase					
				1 0%–10%	2 10%–20%	3 20%–30%	4 30%–40%	5 40%–50%	6 50%+	(2-1)	(3-2)	(4-3)	(5-4)	(6-5)	Avg
0.0–0.1	−100.1	18.0	118.1	16.5	15.5	14.8	13.9	12.3	2.3	−0.96	−0.71	−0.88	−1.64	−9.98	−2.84
0.1–0.2	18.1	24.3	6.3	22.3	21.9	21.8	21.6	21.7	21.1	−0.38	−0.12	−0.11	0.03	−0.53	−0.22
0.2–0.3	24.3	28.2	3.8	26.4	26.4	26.3	26.3	26.3	26.2	−0.01	−0.04	0.00	0.00	−0.15	−0.04
0.3–0.4	28.2	31.1	2.9	29.8	29.7	29.7	29.7	29.7	29.7	−0.07	−0.04	0.02	−0.04	−0.01	−0.03
0.4–0.5	31.1	34.4	3.3	32.7	32.8	32.8	32.7	32.7	32.5	0.04	0.02	−0.09	0.00	−0.17	−0.04
0.5–0.6	34.4	37.9	3.5	36.1	36.1	36.1	36.1	36.1	36.0	−0.04	−0.02	0.01	0.03	−0.12	−0.03
0.6–0.7	37.9	41.9	4.0	39.8	39.8	39.8	39.7	39.8	39.8	0.03	0.03	−0.15	0.11	−0.01	0.00
0.7–0.8	42.0	47.0	5.0	44.3	44.4	44.3	44.3	44.3	44.3	0.09	−0.07	−0.05	0.05	−0.06	−0.01
0.8–0.9	47.0	54.8	7.8	50.5	50.3	50.2	50.3	50.6	49.9	−0.23	−0.09	0.13	0.28	−0.73	−0.13
0.9–1.0	54.8	163.5	108.8	70.9	65.8	63.6	60.7	58.0	56.7	−5.11	−2.18	−2.87	−2.70	−1.35	−2.84

Table 2
Correlation of residuals matrix estimated using the SUR model.

Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	1	0.91	0.83	0.80	0.76	0.72	0.58	0.39	0.38	0.41	0.40	0.41	0.41	0.38	0.34	0.37	0.29	0.20	0.18	0.22	0.31	0.39	0.41	0.44
1	0.91	1	0.94	0.90	0.85	0.80	0.66	0.44	0.41	0.42	0.41	0.42	0.41	0.39	0.36	0.38	0.29	0.22	0.18	0.20	0.27	0.35	0.36	0.41
2	0.83	0.94	1	0.96	0.90	0.83	0.67	0.44	0.42	0.44	0.43	0.44	0.44	0.41	0.37	0.38	0.30	0.22	0.18	0.17	0.24	0.32	0.33	0.39
3	0.80	0.90	0.96	1	0.96	0.88	0.69	0.46	0.44	0.45	0.44	0.45	0.45	0.42	0.38	0.40	0.31	0.22	0.18	0.17	0.24	0.34	0.34	0.41
4	0.76	0.85	0.90	0.96	1	0.92	0.69	0.46	0.43	0.44	0.43	0.45	0.44	0.41	0.37	0.39	0.31	0.23	0.19	0.17	0.24	0.33	0.33	0.40
5	0.72	0.80	0.83	0.88	0.92	1	0.80	0.55	0.49	0.48	0.46	0.46	0.45	0.41	0.38	0.41	0.34	0.25	0.23	0.22	0.30	0.40	0.38	0.44
6	0.58	0.66	0.67	0.69	0.69	0.80	1	0.80	0.73	0.65	0.60	0.56	0.51	0.47	0.44	0.49	0.45	0.40	0.40	0.39	0.42	0.43	0.33	0.35
7	0.39	0.44	0.44	0.46	0.46	0.55	0.80	1	0.93	0.83	0.75	0.67	0.59	0.55	0.53	0.59	0.59	0.60	0.59	0.54	0.49	0.37	0.23	0.24
8	0.38	0.41	0.42	0.44	0.43	0.49	0.73	0.93	1	0.91	0.83	0.75	0.66	0.60	0.57	0.62	0.60	0.61	0.60	0.55	0.50	0.39	0.25	0.26
9	0.41	0.42	0.44	0.45	0.44	0.48	0.65	0.83	0.91	1	0.94	0.86	0.78	0.70	0.64	0.69	0.67	0.65	0.62	0.55	0.52	0.42	0.31	0.31
10	0.40	0.41	0.43	0.44	0.43	0.46	0.60	0.75	0.83	0.94	1	0.94	0.85	0.76	0.69	0.72	0.69	0.64	0.59	0.50	0.49	0.41	0.33	0.32
11	0.41	0.42	0.44	0.45	0.45	0.46	0.56	0.67	0.75	0.86	0.94	1	0.92	0.83	0.74	0.76	0.72	0.64	0.56	0.45	0.46	0.40	0.35	0.36
12	0.41	0.41	0.44	0.45	0.44	0.45	0.51	0.59	0.66	0.78	0.85	0.92	1	0.92	0.84	0.81	0.75	0.60	0.52	0.42	0.44	0.41	0.37	0.36
13	0.38	0.39	0.41	0.42	0.41	0.41	0.47	0.55	0.60	0.70	0.76	0.83	0.92	1	0.95	0.90	0.79	0.59	0.48	0.37	0.39	0.36	0.32	0.38
14	0.34	0.36	0.37	0.38	0.37	0.38	0.44	0.53	0.57	0.64	0.69	0.74	0.84	0.95	1	0.94	0.83	0.61	0.49	0.38	0.39	0.36	0.32	0.37
15	0.37	0.38	0.38	0.40	0.39	0.41	0.49	0.59	0.62	0.69	0.72	0.76	0.81	0.90	0.94	1	0.91	0.71	0.58	0.45	0.45	0.41	0.36	0.41
16	0.29	0.29	0.30	0.31	0.31	0.34	0.45	0.59	0.60	0.67	0.69	0.72	0.75	0.79	0.83	0.91	1	0.84	0.70	0.56	0.54	0.46	0.38	0.35
17	0.20	0.22	0.22	0.22	0.23	0.25	0.40	0.60	0.61	0.65	0.64	0.64	0.60	0.59	0.61	0.71	0.84	1	0.86	0.67	0.55	0.39	0.28	0.21
18	0.18	0.18	0.18	0.18	0.19	0.23	0.40	0.59	0.60	0.62	0.59	0.56	0.52	0.48	0.49	0.58	0.70	0.86	1	0.83	0.68	0.46	0.32	0.21
19	0.22	0.20	0.17	0.17	0.17	0.22	0.39	0.54	0.55	0.55	0.50	0.45	0.42	0.37	0.38	0.45	0.56	0.67	0.83	1	0.84	0.62	0.44	0.29
20	0.31	0.27	0.24	0.24	0.24	0.30	0.42	0.49	0.50	0.52	0.49	0.46	0.44	0.39	0.39	0.45	0.54	0.55	0.68	0.84	1	0.84	0.66	0.47
21	0.39	0.35	0.32	0.34	0.33	0.40	0.43	0.37	0.39	0.42	0.41	0.40	0.41	0.36	0.36	0.41	0.46	0.39	0.46	0.62	0.84	1	0.87	0.70
22	0.41	0.36	0.33	0.34	0.33	0.38	0.33	0.23	0.25	0.31	0.33	0.35	0.37	0.32	0.32	0.36	0.38	0.28	0.32	0.44	0.66	0.87	1	0.81
23	0.44	0.41	0.39	0.41	0.40	0.44	0.35	0.24	0.26	0.31	0.32	0.36	0.36	0.38	0.37	0.41	0.35	0.21	0.21	0.29	0.47	0.70	0.81	1

Model: $p_{q,h,t} = \alpha_{q,h} + \beta_q \times mc_t + \gamma_q * D_{q,h,t} + \delta_q \times VRE_{q,h,t} + \epsilon_{q,h,t}$.
Data: German day-ahead prices.

Table 3
Impact of share of VRES supply on selected day-ahead price quantile levels.

Quantile	1	2	3	…	50	…	97	98	99
δ_q	−68.84	−63.77	−61.21	…	−55.85	…	−64.63	−65.72	−67.74
$\delta_q - \delta_{50}$	−12.99	−7.92	−5.36	…	–	…	−8.78	−9.87	−11.89
s.e.	(2.30)	(1.14)	(0.83)	…	(0.03)	…	(0.76)	(1.02)	(2.20)

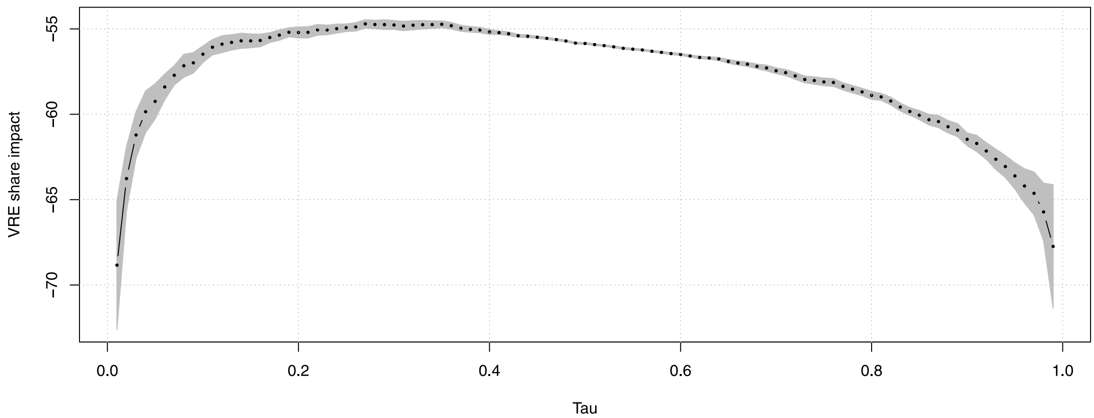
Model: $\hat{p}_{q,h,t} = \hat{\alpha}_{q,h} + \beta_q \times \widehat{mc}_t + \gamma_q * \hat{D}_{h,t} + \delta_q \times \widehat{VRE}_{h,t} + \epsilon_{q,h,t}$
Data: German day-ahead market data.

We proceed with testing the claim that an increase in supply from VRES reduces power prices more at extreme low and high quantiles than at the centre part of the power price probability distribution function. Table A.1 in the appendix shows the parameter estimates for model (1) for different quantiles. To make it readable, we summarise the main findings in Table 3. That table only shows the estimates for the parameter δ_q in model (1). That parameter can be interpreted as the ceteris paribus increase in the price of power as a result of a one unit increase in the share of demand supplied by VRES. Our hypothesis predicts that this parameter should be negative and more pronounced at extreme quantiles. This is exactly what we observe. For the extreme quantiles 1 and 99, the parameters are −68 and −67 respectively, whereas the parameter is −55 at the 50th (median) quantile. The second row in Table 3 shows the difference between the parameter for a quantile and for the median ($\delta_q - \delta_{50}$), and reveals that this difference is negative and significant (because of the low standard errors) at the extreme quantiles. Clearly, the estimates show support for the prediction that supply from VRES has a stronger impact on the extreme price quantiles than on the median price quantile.

Fig. 2 provides the complete picture by showing the δ_q estimates for all the quantiles 1 through 99.[7] This figure, while not being a

the pairs of hourly prices before and after convergence. We observe that the average absolute covariance between a pair of hours decreases by a factor of 4 from about 30 to 7. This is not equal to zero, although we think that a value of zero would be unlikely to achieve for the following reasons. First, we calculate the average of the absolute values. Second, we only focus on the cross-sectional covariance and assume that variation over time is constant, which might not be the case within our sample. To deal with this, is another topic and we think it is beyond the scope of this paper. We do conclude, based on this test, that we adequately account for the heteroskedastic structure (within the limits set by the scope of this paper).

[7] In Fig. 2, τ represents the various quantiles considered.



The black dots show the estimates for δ_q from the transformed equation 1. The grey shaded area show 95% confidence intervals for δ_q for quantiles 1 through 99

Fig. 2. VRES share impact across the German day-ahead price quantiles (τ).

focal point of our research,[8] it illustrates two aspects which are worth mentioning. First, it is clear that δ_q is negative for all quantiles, supporting the existing view from the literature that an increase in supply from VRES reduces power prices (because of its near zero marginal cost). Second, it shows that the impact is most negative at the higher and lower quantiles. When predicting power price ranges, one should keep in mind that supply from VRES has a different impact on power prices for different quantiles; the impact is relatively low when one is interested in predicting mean or median prices and more dramatic when one is interested in predicting high and low price ranges. This is what owners of flexibility offering assets are interested in since price ranges can help them optimise their bidding strategies. Because of this, we argue that is more important to use the model proposed in Eq. (1) for investigating the behaviour of extreme power prices rather than the one of moderate power prices.

Another takeaway from Table 3 and Fig. 2 is that the coefficient δ_q has similar values at the lowest and highest price quantiles. This means that extreme low and high German day-ahead power prices are affected similarly by an increase in supply from VRES. While the values of the coefficients δ_q are similar at the lowest and highest day-ahead power price quantiles, the reasons for them occurring are different. We explain this as follows. High prices occur when demand is high and the share of supply from VRES is low. During these moments, the higher marginal cost producers are the ones setting the power price. Many power plants produce to supply the high demand and there is competition to ramp down production when the VRES share increases. In this situation, an increase in share of VRES will reduce the power price fast as it will replace in the merit order curve the high marginal cost producers. On the other end of the power price distribution function, at extreme low prices, the fast decrease of power prices that comes with VRES share increases is due to less competition and inflexibility of base load power producers[9] to ramp down production. Competition to ramp down is low during low demand periods as only a few power plants operate. An increase in supply from VRES puts higher pressure to ramp down production on the few base load producers that are still operating in such moments than the same increase in supply from VRES when demand is moderate. If the base load producers are inflexible, in the sense that it is less costly for them to temporarily accept producing at price levels below their marginal cost rather than to ramp down and up their production level, the impact of a change in VRES share is getting bigger at extreme low power price quantile levels than at moderate power price quantile levels.

4.1. The impact of VRES share on quantile power prices conditional on demand level

Interpreting the difference between the estimates of δ_q in Eq. (1) is our means to examine the claim that VRES are having a varying impact on power prices. This model has similar variables as other models proposed in the literature that we discussed before. There is one aspect we want to discuss here. When we look in Table A.1 in the appendix, we see that the demand coefficients, γ_q, have all positive values and are statistically different from 0. This means that, the higher the demand level is, the higher the power price[10] will be. At the same time, a part of that demand is catered by supply from VRES. Furthermore, as Fig. 2 shows, the VRES share coefficient δ_q is always significantly negative. We can then infer that an increase in demand will put upward pressure on power prices but, if that increase in demand is catered supply from VRES, that upward pressure on prices will be diminished by supply from VRES. We therefore expect that an interplay between demand and share of VRES should provide important information to better predict the impact of VRES share on power prices. We therefore suggest to use a revised model expressed in equation (2):

$$p_{q,h,t} = \alpha_{q,h} + \beta_q \times mc_t + \gamma_q * D_{h,t} + \delta_q \times VRES_{h,t} + \zeta_q \times D_{h,t} \times VRES_{h,t} + \epsilon_{q,h,t}, \tag{2}$$

Compared with model (1), we include the interaction term $D_{h,t} \times VRES_{h,t}$. Note that the interaction term represents the actual supply of VRES. While it might appear counterintuitive to include in a model both the share and actual volume of supply from VRES,[11] this technique allows the model to control for the interplay between demand and share of VRES. Thus, the coefficient ζ_q, is aimed at capturing the effect of the interaction between demand and share of VRES on power prices. We estimate the parameters in Eq. (2) by following the same steps as we did for Eq. (1).

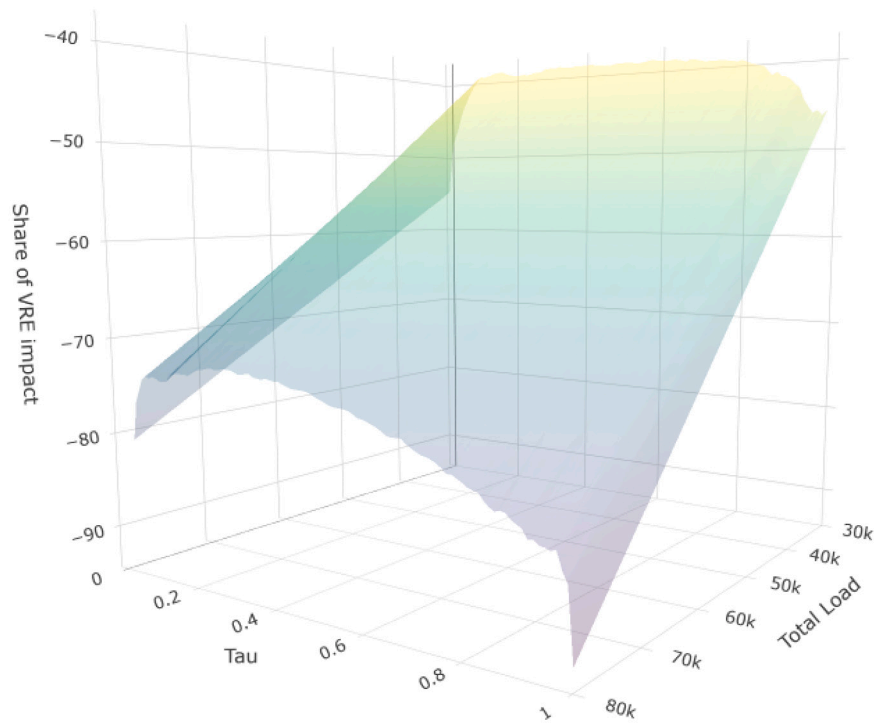
Using the revised model, we perform the same analysis as for the initial model in order to isolate the impact of VRES share on power

[8] The model proposed in Eq. (1) is aimed at investigating the extreme ends of the probability distribution function of power prices and not the specific moderate price quantiles.

[9] We refer to base load producers as conventional fuel producers that usually generate power at relatively constant levels for all hours of the day.

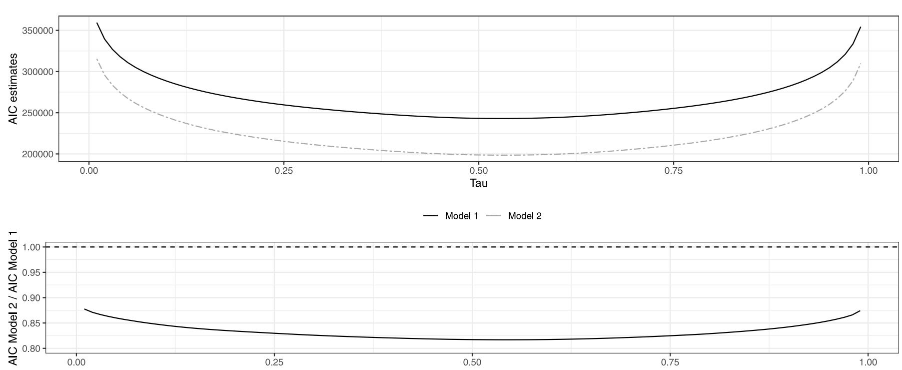
[10] While Table A.1 presents the γ_q coefficients only for a selection of price quantiles, for each analysed quantile, from the 1st to the 99th, the γ_q values are statistically significantly higher than 0

[11] The actual volume of supply from VRES is represented in the model by the interaction between demand and the share of supply from VRES.



The shaded area indicates the impact of VRES share on the quantiles of German day-ahead prices conditional on demand level. Estimates are calculated using the first order derivative of the transformed equation 2 with respect to share of VRES.

Fig. 3. VRES share impact on German day-ahead price quantiles, conditional on demand level.



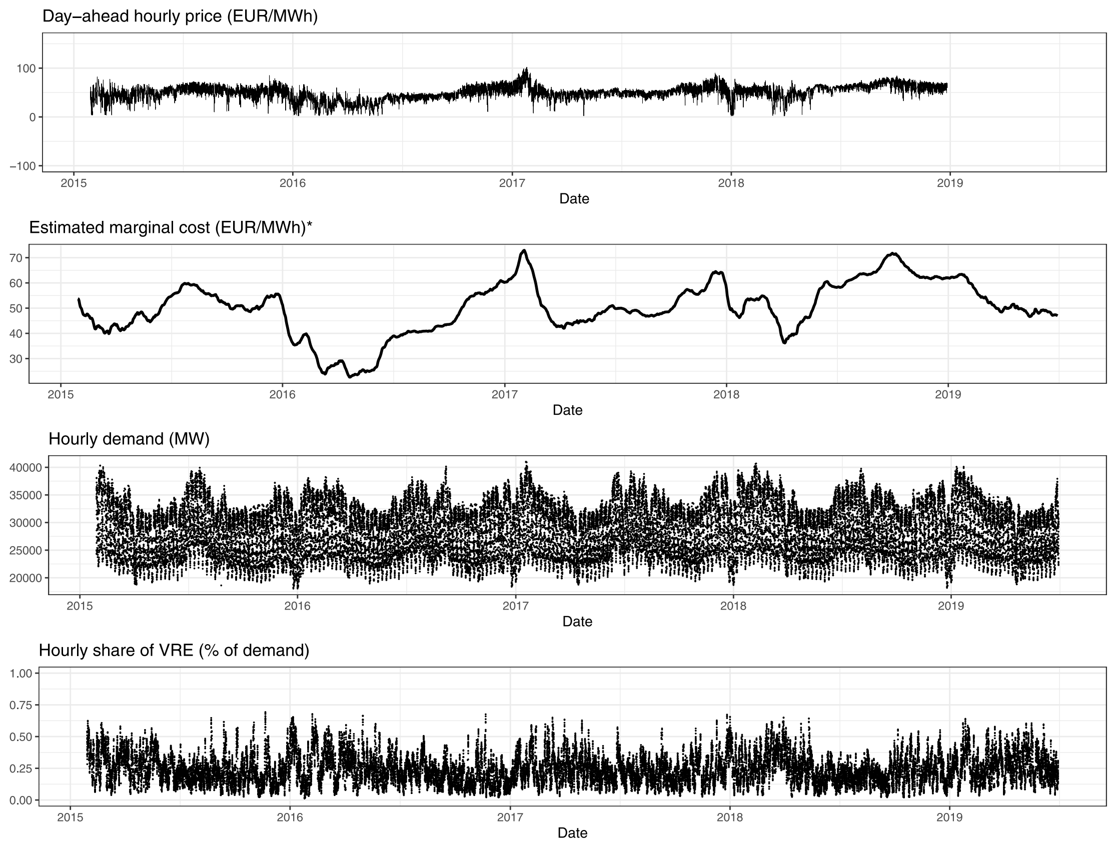
The lines in the upper part of the figure contain the AIC estimated for models 1 and 2 at each quantile (τ), from the 1^{st} to the 99^{th} quantile. The lower part of the figure shows the ratio between the AIC estimates for the model 2 and 1.

Fig. 4. AIC comparison between models (1) and (2) estimated on the German day-ahead market.

prices conditional on a fixed demand level. To calculate this, we take the first order derivative of the estimated model (2) with respect to share of VRES. Thus, the impact of the share of VRES on power prices is: $\delta_q + \zeta_q \times D$. To be noted that in this estimation of the impact of share of VRES on power prices demand is exogenous to the estimation. This simplification is necessary for making it easier to exemplify the results of the second model, results that are shown in Fig. 3. Similar as for the first model, in the appendix Table A.2 we present the coefficients for all the variables included in the model estimated on Eq. (2) at selected extreme and at median price quantile levels.

Fig. 3 shows the impact the share of supply from VRES has on quantile power prices conditional on the demand level. The demand level axis is formed by all the values comprised between the minimum and the maximum observed demand level in the German day-ahead power market. Conditional on a fixed demand level, results show similar patterns as for the first model. For any fixed demand level, in the lowest and highest price quantiles, the impact of VRES share on power prices is much more negative than for moderate quantiles. For example, let us consider a fixed moderate hourly demand of 50,000 MWh. Conditional on this demand level, all else equal, an increase in the share of supply from VRES leads to a higher power price decrease when power prices are very low (1st quantile coefficient for share of VRES being −65) or very high (99th quantile coefficient for share of VRES being −64) than when prices are moderate (50th quantile coefficient for share of VRES being −53).

While for this chosen fixed demand level of 50,000 MWh the estimated share of VRES impact on power prices is similar to the one estimated in the first model, for other demand levels, the estimates



*The estimated marginal cost is calculated as the lagged median day-ahead price for the previous 4 weeks of hourly

Fig. A.1. Overview of the Spanish day-ahead market between January 2015 – June 2019.

differ. The differences come from the fact that in the second model, the share of VRES impact on power prices is conditional on a fixed selected demand level. When reading Fig. 3 and comparing it with 2 we have to keep in mind the fact that Fig. 2 presents the average impact of VRES share on power prices and that Fig. 3 separates the impact based on demand level. Furthermore, it is important to note that, while Fig. 3 presents an estimate for the share of VRES impact for each demand level at each quantile, the frequency of a certain pair of price quantile and demand level varies greatly. For example, it is unlikely that high prices appear on low demand levels or that low prices appear on high demand levels. Thus, the results in Fig. 3 should be read as an indication on what is the VRES share impact on power prices at specific power price quantile and demand level.

To compare the two models, Fig. 4 presents the AIC for both models. In the upper part of the figure, the AIC values for the two models are shown. The model estimated on Eq. (1) is represented with by the solid line and the model estimated on Eq. (2) is represented by the dashed line. For all the quantiles investigated, the second model has a lower AIC value, indicating a better performance of model (2). In the lower part of Fig. 4, the ratio between the AIC values of the model (2) and model (1) is illustrated, indicating that the second model (estimated on Eq. (2)) has values between 0.14% – 0.18% lower than the first model (estimated on Eq. (1)). From here, we can conclude that the interaction between demand and share of VRES is a factor that adds value to models aiming to predict German day-ahead power prices. This is another important finding that can help flexibility offering asset owners in Germany as it shows that, for this market, the interplay between demand and supply from VRES influences day-ahead power prices.

4.2. Challenge: the Spanish day-ahead market

The results presented so far provide a clear picture on how a alteration in output from VRES changes day-ahead power prices in Germany. Having a significant share of coal and nuclear supply in its power mix, the German power market is relatively inflexible. This fact reveals itself through the frequent price spikes that appear in the German day-ahead price. In this section, we challenge our findings and apply the same analysis to a more flexible power market which is not directly linked to the German power market: the Spanish power market. Spain has a relatively high share of supply from VRES in its power mix, and compared to Germany, the Spanish power mix has a higher share of hydro, hydro pumped and gas supply and a lower share of coal supply. This is why we label the Spanish power market as more flexible than the German power market. Moreover, the policies of the Spanish power market do not allow for negative day-ahead power prices, limiting in this way the price reduction impact in periods with extreme low demand and high share of VRES.

To investigate the Spanish day-ahead power market, we use data collected from ENTSOE Transparency platform and use a timeframe similar to the one for the German market: from 1st of January 2015 to 30th of June 2019.[12] A visual representation of the data used for this exercise is presented in the appendix Fig. A.1. In the upper part of this figure, we can observe that the Spanish hourly day-ahead power prices are exhibiting, on the high end, less extreme high spikes as compared

[12] 25 days from the Spanish data were excluded due to unavailable data for certain hours. The same as for the German market, the presented results are based on actual realised demand and share of VRES data.

Table A.1
A selection of quantile regression coefficients estimated using the transformed Eq. (1).

Quantile level	1	2	3	...	50	...	97	98	99
Marginal cost (β_q)	0.82	0.73	0.70	...	0.68	...	0.56	0.51	0.56
	(0.09)	(0.05)	(0.03)	...	(0.001)	...	(0.03)	(0.04)	(0.09)
Demand (γ_q)	0.00067	0.00064	0.00062	...	0.00057	...	0.00064	0.00068	0.00078
	(0.00005)	(0.00002)	(0.00002)	...	(0.00000)	...	(0.00001)	(0.00002)	(0.00005)
VRE share (δ_q)	−68.84	−63.77	−61.21	...	−55.85	...	−64.63	−65.72	−67.74
	(2.30)	(1.14)	(0.83)	...	(0.03)	...	(0.76)	(1.02)	(2.20)
Hour 0 ($\alpha_{q,0}$)	−394.57	−282.23	−228.47	...	−4.66	...	190.88	233.14	328.68
	(19.07)	(10.81)	(9.45)	...	(0.24)	...	(6.89)	(9.51)	(18.64)
Hour 1 ($\alpha_{q,1}$)	−398.13	−285.14	−226.35	...	−4.74	...	191.53	234.69	330.47
	(19.97)	(12.78)	(8.31)	...	(0.24)	...	(6.97)	(9.62)	(19.06)
Hour 2 ($\alpha_{q,2}$)	−399.13	−288.86	−234.17	...	−5.14	...	192.63	237.17	335.55
	(21.40)	(11.10)	(8.64)	...	(0.25)	...	(7.04)	(10.17)	(21.35)
Hour 3 ($\alpha_{q,3}$)	−397.60	−284.39	−231.09	...	−6.53	...	190.00	232.39	328.42
	(19.26)	(10.69)	(9.49)	...	(0.24)	...	(6.79)	(9.51)	(18.89)
Hour 4 ($\alpha_{q,4}$)	−401.45	−288.03	−229.95	...	−6.85	...	190.77	233.58	329.92
	(19.84)	(12.85)	(8.31)	...	(0.24)	...	(6.85)	(9.59)	(19.24)
Hour 5 ($\alpha_{q,5}$)	−401.67	−291.81	−236.72	...	−6.51	...	191.72	236.49	334.45
	(21.23)	(11.25)	(8.63)	...	(0.25)	...	(7.07)	(10.15)	(21.51)
Hour 6 ($\alpha_{q,6}$)	−397.57	−283.31	−230.59	...	−4.45	...	191.96	233.81	328.93
	(19.13)	(10.62)	(9.44)	...	(0.25)	...	(6.91)	(9.24)	(18.78)
Hour 7 ($\alpha_{q,7}$)	−395.70	−283.03	−225.01	...	−0.81	...	196.07	238.66	334.38
	(19.65)	(12.84)	(8.40)	...	(0.24)	...	(6.71)	(9.79)	(19.19)
Hour 8 ($\alpha_{q,8}$)	−394.80	−284.45	−229.97	...	1.25	...	199.05	243.33	340.31
	(21.51)	(11.14)	(8.50)	...	(0.26)	...	(7.09)	(10.19)	(21.52)
Hour 9 ($\alpha_{q,9}$)	−391.56	−278.16	−225.33	...	1.21	...	198.28	239.67	333.27
	(19.33)	(10.73)	(9.50)	...	(0.25)	...	(6.95)	(9.36)	(18.86)
Hour 10 ($\alpha_{q,10}$)	−393.07	−280.93	−222.41	...	0.89	...	197.46	239.65	334.59
	(19.84)	(13.09)	(8.47)	...	(0.24)	...	(6.86)	(9.55)	(19.28)
Hour 11 ($\alpha_{q,11}$)	−393.77	−283.20	−228.63	...	0.95	...	198.83	243.50	340.23
	(21.76)	(11.14)	(8.60)	...	(0.27)	...	(7.09)	(10.22)	(21.87)
Hour 12 ($\alpha_{q,12}$)	−390.03	−277.80	−225.16	...	0.25	...	196.88	238.05	332.09
	(19.21)	(10.78)	(9.43)	...	(0.26)	...	(6.86)	(9.07)	(18.89)
Hour 13 ($\alpha_{q,13}$)	−390.96	−280.82	−222.81	...	−0.52	...	196.18	237.34	331.54
	(19.60)	(12.84)	(8.34)	...	(0.24)	...	(6.88)	(9.42)	(18.88)
Hour 14 ($\alpha_{q,14}$)	−393.08	−283.65	−229.66	...	−1.32	...	195.28	239.68	335.67
	(21.38)	(10.99)	(8.51)	...	(0.26)	...	(6.92)	(10.16)	(21.62)
Hour 15 ($\alpha_{q,15}$)	−388.57	−276.97	−224.68	...	−1.19	...	194.49	235.37	328.33
	(19.03)	(10.78)	(9.13)	...	(0.26)	...	(6.64)	(9.04)	(18.47)
Hour 16 ($\alpha_{q,16}$)	−390.31	−280.14	−222.27	...	−1.43	...	193.95	235.40	329.17
	(19.64)	(12.59)	(8.20)	...	(0.23)	...	(6.95)	(9.27)	(18.78)
Hour 17 ($\alpha_{q,17}$)	−389.92	−280.94	−227.13	...	−0.15	...	195.99	239.88	336.19
	(20.82)	(11.12)	(8.20)	...	(0.26)	...	(6.91)	(10.41)	(21.60)
Hour 18 ($\alpha_{q,18}$)	−386.03	−275.44	−222.16	...	0.77	...	195.58	236.65	329.20
	(18.60)	(10.61)	(9.27)	...	(0.26)	...	(6.74)	(9.19)	(18.39)
Hour 19 ($\alpha_{q,19}$)	−389.39	−278.83	−220.42	...	0.60	...	194.62	236.73	330.71
	(19.72)	(12.44)	(8.13)	...	(0.23)	...	(7.04)	(9.48)	(18.61)
Hour 20 ($\alpha_{q,20}$)	−393.84	−284.10	−229.82	...	−1.28	...	193.55	237.68	333.55
	(21.07)	(11.08)	(8.36)	...	(0.26)	...	(7.02)	(10.30)	(20.58)
Hour 21 ($\alpha_{q,21}$)	−392.47	−280.72	−226.65	...	−3.07	...	190.28	231.69	324.68
	(18.87)	(10.77)	(9.48)	...	(0.24)	...	(6.79)	(9.38)	(18.39)
Hour 22 ($\alpha_{q,22}$)	−396.05	−283.56	−224.54	...	−2.82	...	191.06	233.73	327.97
	(19.90)	(12.71)	(8.29)	...	(0.24)	...	(7.03)	(9.50)	(18.74)
Hour 23 ($\alpha_{q,23}$)	−399.07	−288.46	−233.65	...	−4.65	...	191.80	236.11	333.09
	(21.31)	(11.21)	(8.55)	...	(0.25)	...	(7.10)	(10.24)	(20.96)

Model: $\hat{p}_{q,h,t} = \hat{\alpha}_{q,h} + \beta_q \times \widehat{mc}_t + \gamma_q * \hat{D}_{h,t} + \delta_q \times \widehat{VRE}_{h,t} + \epsilon_{q,h,t}$.
Note: Standard errors in parenthesis–German day-ahead market data used.

to the German day-ahead prices, and, on the low end, always positive prices.

In this additional analysis on the Spanish day-ahead market we use the same steps as for the German day-ahead market. The results for the impact of share of VRES on the Spanish day-ahead quantile power prices using the model detailed in Eq. (1) are presented in the appendix Table A.3 and appendix Fig. A.2.[13] These results show that also for a more flexible power market, such as the Spanish one, the impact of the share of supply from VRES on the day-ahead power prices is significantly stronger on the extreme low and extreme high day-ahead price quantiles than in the middle of the power price distribution function.

At the median price quantile level the share of VRES parameter value is −54. At the 1st and at the 99th price quantiles the parameters for the share of VRES are lower being −0.61 and, respectively, −0.59. The values for δ_q coefficients on the Spanish data at moderate price quantiles are similar to the ones obtained on the German data. At the extreme price quantiles, the Spanish δ_q coefficients are not as low as the German ones. This indicates that Spanish conventional producers can adapt faster their output level to changes in supply from VRES than German conventional producers in moments when the power market is challenged the most. This confirms the fact that the Spanish day-ahead market is indeed more flexible than the German one. Thus, an increase in the share of supply from VRES at the extreme low and high price

[13] For space limitations reasons the paper presents only the coefficients for the VRES share impact. On request, the coefficients for all the other variables included in the model can be made available.

Table A.2
A selection of quantile regression coefficients estimated using the transformed Eq. (2).

Quantile level	1	2	3	...	50	...	97	98	99
Marginal cost (β_q)	0.78	0.68	0.68	...	0.65	...	0.53	0.48	0.51
	(0.08)	(0.05)	(0.04)	...	(0.001)	...	(0.03)	(0.04)	(0.08)
Demand (γ_q)	0.00087	0.00081	0.00079	...	0.00079	...	0.00088	0.00093	0.00105
	(0.00007)	(0.00004)	(0.00003)	...	(0.00000)	...	(0.00003)	(0.00003)	(0.00007)
VRE share (δ_q)	−37.76	−31.24	−28.94	...	−15.74	...	−19.68	−19.97	−14.72
	(9.46)	(6.53)	(4.94)	...	(0.12)	...	(4.22)	(4.33)	(9.23)
Interaction (ζ_q)*	−0.00054	−0.00057	−0.00059	...	−0.00074	...	−0.00083	−0.00084	−0.00099
	(0.00019)	(0.00012)	(0.00009)	...	(0.00000)	...	(0.00008)	(0.00008)	(0.00017)
Hour 0 ($\alpha_{q,0}$)	−400.23	−297.38	−239.35	...	−14.46	...	177.16	220.89	309.59
	(20.98)	(11.25)	(8.67)	...	(0.26)	...	(7.30)	(7.49)	(18.36)
Hour 1 ($\alpha_{q,1}$)	−405.18	−292.27	−239.68	...	−14.74	...	179.05	220.45	300.47
	(21.12)	(12.34)	(8.41)	...	(0.26)	...	(7.38)	(8.88)	(19.39)
Hour 2 ($\alpha_{q,2}$)	−416.76	−303.95	−245.45	...	−15.07	...	178.68	229.98	311.17
	(19.30)	(12.25)	(9.63)	...	(0.23)	...	(6.90)	(9.77)	(20.49)
Hour 3 ($\alpha_{q,3}$)	−403.00	−299.55	−242.04	...	−16.11	...	176.40	220.55	310.21
	(20.99)	(11.17)	(8.60)	...	(0.27)	...	(7.29)	(7.54)	(18.32)
Hour 4 ($\alpha_{q,4}$)	−409.14	−295.57	−242.85	...	−16.86	...	178.50	219.94	300.97
	(20.95)	(12.46)	(8.32)	...	(0.26)	...	(7.38)	(9.03)	(19.38)
Hour 5 ($\alpha_{q,5}$)	−419.83	−306.86	−248.28	...	−16.68	...	178.61	229.92	311.54
	(18.92)	(12.25)	(9.66)	...	(0.23)	...	(6.82)	(9.90)	(20.49)
Hour 6 ($\alpha_{q,6}$)	−403.29	−299.56	−241.37	...	−14.82	...	178.01	222.02	310.97
	(20.91)	(11.38)	(8.46)	...	(0.28)	...	(7.38)	(7.45)	(17.75)
Hour 7 ($\alpha_{q,7}$)	−404.63	−291.62	−238.74	...	−11.81	...	182.75	224.05	304.69
	(20.62)	(12.30)	(8.27)	...	(0.25)	...	(7.46)	(9.25)	(19.51)
Hour 8 ($\alpha_{q,8}$)	−414.00	−300.27	−242.43	...	−9.72	...	184.74	236.09	316.47
	(19.18)	(12.32)	(9.65)	...	(0.24)	...	(6.95)	(9.91)	(20.52)
Hour 9 ($\alpha_{q,9}$)	−398.07	−294.73	−236.38	...	−9.24	...	183.99	227.15	315.50
	(21.10)	(11.37)	(8.62)	...	(0.28)	...	(7.40)	(7.58)	(18.13)
Hour 10 ($\alpha_{q,10}$)	−402.73	−289.27	−236.28	...	−9.44	...	184.79	225.46	305.39
	(20.90)	(12.25)	(8.43)	...	(0.25)	...	(7.35)	(9.30)	(19.89)
Hour 11 ($\alpha_{q,11}$)	−413.43	−298.52	−240.98	...	−9.39	...	185.63	236.33	316.28
	(19.47)	(12.45)	(9.77)	...	(0.24)	...	(6.94)	(10.02)	(20.94)
Hour 12 ($\alpha_{q,12}$)	−397.40	−294.52	−235.92	...	−9.54	...	183.73	226.23	315.84
	(21.06)	(11.35)	(8.76)	...	(0.26)	...	(7.37)	(7.53)	(18.60)
Hour 13 ($\alpha_{q,13}$)	−400.92	−289.35	−236.62	...	−10.47	...	183.61	224.46	304.22
	(20.81)	(12.13)	(8.47)	...	(0.26)	...	(7.33)	(9.27)	(19.40)
Hour 14 ($\alpha_{q,14}$)	−413.59	−299.28	−242.02	...	−11.70	...	182.44	232.81	311.70
	(19.13)	(12.42)	(9.68)	...	(0.24)	...	(6.82)	(9.92)	(21.07)
Hour 15 ($\alpha_{q,15}$)	−395.99	−293.86	−236.21	...	−11.41	...	180.94	223.03	311.28
	(20.92)	(11.24)	(8.71)	...	(0.26)	...	(7.23)	(7.36)	(18.80)
Hour 16 ($\alpha_{q,16}$)	−399.48	−289.16	−236.42	...	−11.90	...	181.21	221.72	300.93
	(20.86)	(11.86)	(8.51)	...	(0.26)	...	(7.28)	(9.31)	(18.70)
Hour 17 ($\alpha_{q,17}$)	−409.98	−297.40	−239.82	...	−11.09	...	182.64	232.80	310.98
	(18.86)	(12.36)	(9.53)	...	(0.21)	...	(6.94)	(9.77)	(20.80)
Hour 18 ($\alpha_{q,18}$)	−393.71	−291.49	−234.10	...	−9.90	...	181.39	223.70	311.14
	(20.50)	(11.27)	(8.57)	...	(0.27)	...	(7.29)	(7.47)	(18.64)
Hour 19 ($\alpha_{q,19}$)	−398.23	−287.15	−234.85	...	−10.14	...	181.84	222.07	301.06
	(20.80)	(11.98)	(8.35)	...	(0.26)	...	(7.38)	(9.23)	(18.89)
Hour 20 ($\alpha_{q,20}$)	−412.93	−300.25	−242.45	...	−12.04	...	179.54	230.08	308.50
	(18.95)	(12.31)	(9.55)	...	(0.21)	...	(6.99)	(9.79)	(20.10)
Hour 21 ($\alpha_{q,21}$)	−399.43	−296.41	−238.27	...	−13.41	...	176.17	219.16	306.04
	(20.78)	(11.25)	(8.64)	...	(0.25)	...	(7.27)	(7.45)	(18.59)
Hour 22 ($\alpha_{q,22}$)	−403.75	−290.93	−238.28	...	−13.31	...	178.51	219.50	298.28
	(21.10)	(12.22)	(8.46)	...	(0.25)	...	(7.49)	(8.87)	(19.26)
Hour 23 ($\alpha_{q,23}$)	−417.21	−303.78	−245.28	...	−14.71	...	178.01	228.48	308.24
	(19.07)	(12.37)	(9.71)	...	(0.22)	...	(6.91)	(9.73)	(20.26)

Model: $\hat{p}_{q,h,t} = \hat{\alpha}_{q,h} + \beta_q \times \widehat{mc}_t + \gamma_q * \hat{D}_{h,t} + \delta_q \times \widehat{VRE}_{h,t} + \zeta_q \times \widehat{Interaction}_{h,t} + \epsilon_{q,h,t}$
Note: Standard errors in parenthesis–German day-ahead market data used.
Note: Interaction variable* $= D_{h,t} \times VRE_{h,t}$.

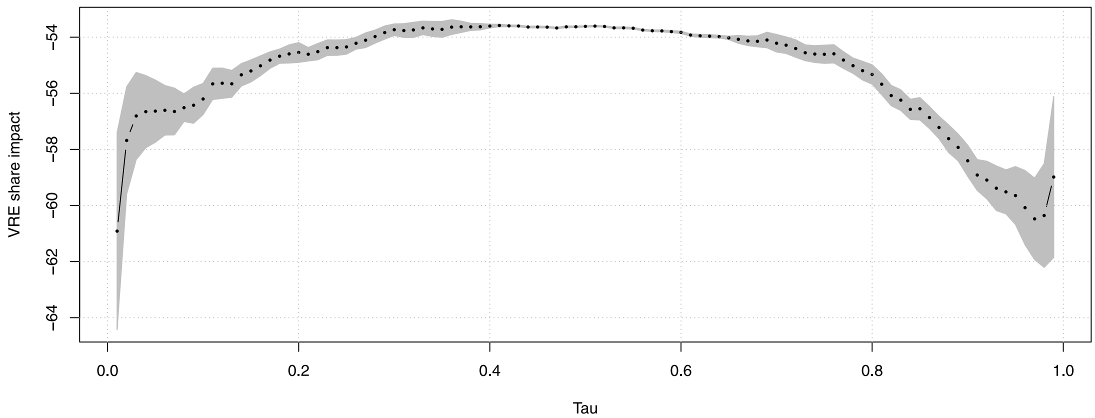
Table A.3
Impact of share of VRES supply on selected day-ahead price quantile levels.

Quantile	1	2	3	...	50	...	97	98	99
δ_q	−60.91	−57.68	−56.81	...	−53.61	...	−60.48	−60.36	−58.98
$\delta_q - \delta_{50}$	−7.30	−4.07	−3.20	...	–	...	−6.87	−6.75	−5.37
s.e.	(2.13)	(1.16)	(0.94)	...	(0.01)	...	(0.88)	(1.12)	(1.74)

Model: $\hat{p}_{q,h,t} = \hat{\alpha}_{q,h} + \beta_q \times \widehat{mc}_t + \gamma_q * \hat{D}_{h,t} + \delta_q \times \widehat{VRE}_{h,t} + \epsilon_{q,h,t}$.
Data: Spanish day-ahead market data.

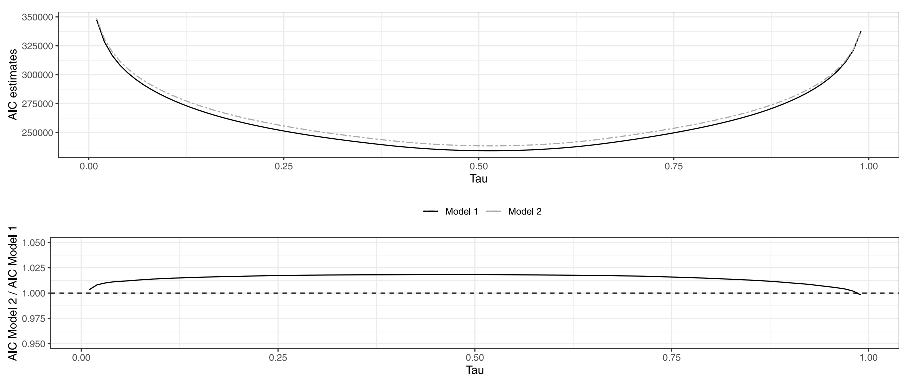
quantiles does not induce in the Spanish power market a price shock as big as in the German power market. The comparison between the flexibility of the German and Spanish day-ahead markets is relevant at the extreme price quantile levels, since it is in those moments that the power markets are most challenged. When prices are moderate, most power markets have enough conventional flexible supply available to shift their production levels in order to cater changes in supply from VRES. This result suggests that, as compared to an inflexible power market, for a more flexible power market, the value of flexibility offering assets, such as storage facilities, is lower, since the occurrence of extreme prices is limited.

The results for the Spanish day-ahead market on the second model, the one estimated on Eq. (2), are similar with the ones presented in appendix Fig. A.2 for the first model (1). Conditional on a fixed demand level, at extreme price quantiles VRES share is inducing a stronger



The black dots show the estimates for δ_q from the transformed equation 1. The grey shaded area show the 95% confidence intervals for δ_q for quantiles 1 through 99

Fig. A.2. VRES share impact across the Spanish day-ahead price quantiles (τ).



The lines in the upper part of the figure contain the AIC estimated for models 1 and 2 at each quantile (τ), from the 1^{st} to the 99^{th} quantile. The lower part of the figure shows the ratio between the AIC estimates for the model 2 and 1.

Fig. A.3. AIC comparison between models (1) and (2) estimated on the Spanish day-ahead market.

negative impact on Spanish day-ahead power prices than at moderate price quantile levels.[14]

Fig. A.3 compares the relative quality of the two models for the Spanish power market. In the upper part of the figure, the dashed line and the solid line represent the quantile specific AIC values for the second model (2) and, respectively for the first model (1). In the lower part of the figure, the per quantile ratio between the AIC for model (2) and model (1) is exhibited. As opposed to the results for the German day-ahead market, Fig. A.3 shows that for the Spanish day-ahead market, the second model (2) does not perform better than the first model (1). For most quantile levels investigated model (1) has a lower AIC estimate than model (2). This indicates that for a flexible power markets, such as the Spanish day-ahead market, adding a term for the interaction between VRES share and demand level does not add explanatory value to a panel quantile regression model trying to explain power prices. While not expected, this result is not totally surprising. Having increased flexibility, the conventional producers in Spanish power market can more easily adapt their production levels to shifts in VRES share, regardless of demand level, as compared to conventional producers in an inflexible power market. Thus, the interplay between demand and VRES share becomes less relevant for a flexible power market, as opposed to an inflexible power market. For owners of flexibility offering assets this result suggest once again that it is in the inflexible power markets that their flexibility offering assets will be worth the most.

[14] There is one exception from this on the moments when the Spanish day-ahead market is in a situation of extreme high demand and extreme high prices.

5. Conclusion

With increasing supply from wind and solar sources, the share of power demand supplied by variable renewable energy sources (VRES) becomes an important factor that influences power prices. We build upon the existing literature by presenting a panel quantile regression approach, showing that the share of demand supplied by VRES has a varying impact on power prices, with significantly higher impact when the power prices are in extreme low or high price quantiles ranges. This result proves that when the flexibility of a power market is challenged the most (in moments when extreme prices occur) the impact of an increase in supply from VRES leads to much more drastic downward adjustments in price than in periods when power markets are more flexible (when moderate prices occur). We observe this effect in both the German and Spanish day-ahead markets.

The paper also proves that in periods when power prices are extremely low or high, in a more inflexible power market, such as the German day-ahead market, an increase in VRES share decreases the day-ahead power price more than the same increase in VRES share for a relatively more flexible power market, such as the Spanish day-ahead market. This means that the higher the flexibility and capacity of the conventional producers to adjust their production levels in function of changes in supply from VRES, the lower the variation in the impact that supply from VRES has on power prices at extreme price quantile levels. When comparing the results for the two markets investigated, the paper also indicates that for a relatively inflexible power market (the German day-ahead power market), the interaction between demand level and VRES share adds value in understanding day-ahead price movements. For the relatively more flexible Spanish day-ahead power market, the interaction between demand level and VRES share does not appear to add value in understanding day-ahead price movements. This means that in a flexible power market, conventional producers have enough flexibility in adjusting their production output to cater for changes in supply from VRES such that the interplay between demand and VRES share becomes less relevant. The result suggests that policy makers should adjust their measures related to further integration of supply from VRES based also on the pre-existing individual (in)flexibility conditions of each power market. For example, one policy that could increase power market flexibility is to stimulate investments in power storage assets attached to VRES facilities. However, based on our results, policy makers should keep in mind that the utility of a such a policy will be higher in an inflexible power market than in a flexible one. Besides looking at our results, this conclusion can be deduced also from the concept of cannibalisation of extreme power prices. In a more flexible power market, because of the increased competition between flexibility offering assets, extreme prices become rarer. In such a setting, both the need for flexibility and the profitability of flexibility offering assets is lower.

The results of this paper are important for investments in assets that make the power markets more flexible in accommodating fluctuating supply from variable renewables. Power storage facilities or demand response applications are such assets and, in effect, they are flexibility offering assets that give the option to charge/discharge or to adjust consumption levels. Those options are worth more when the range in which power prices behave in becomes wider. Our model demonstrates how one should incorporate (expected) output from renewables in predicting that price range through understanding the impact of supply from VRES at different price quantile levels. Furthermore, the panel framework allows for simultaneous predictions for all hours during a delivery day, which is more in line with the microstructure of international power markets.

CRediT authorship contribution statement

Ronald Huisman: Conceptualization, Methodology, Validation, Investigation, Writing – review & editing, Supervision. **Cristian Stet:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Investigation, Writing – original draft, Visualisation.

Appendix A

See Figs. A.1–A.3 and Tables A.1–A.3.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105685.

References

Baltagi, B., 2013. Econometric Analysis of Panel Data, fifth ed. Wiley, ISBN: 978-1-118-67232-7.

Benhmad, F., Percebois, J., 2018. Photovoltaic and wind power feed-in impact on electricity prices: The case of Germany. Energy Policy 119 (May), 317–326. http://dx.doi.org/10.1016/j.enpol.2018.04.042.

Borenstein, S., 2002. The trouble with electricity markets: understanding California's restructuring disaster. J. Econ. Perspect. 16 (1), 191–211.

Bunn, D., Andresen, A., Chen, D., Westgaard, S., 2016. Analysis and forecasting of electricity price risks with quantile factor models. Energy J. 37 (1), 101–122. http://dx.doi.org/10.5547/01956574.37.1.dbun.

Chen, W., Lei, Y., 2018. The impacts of renewable energy and technological innovation on environment-energy-growth nexus: New evidence from a panel quantile regression. Renew. Energy 123, 1–14.

Goodarzi, S., Perera, H.N., Bunn, D., 2019. The impact of renewable energy forecast errors on imbalance volumes and electricity spot prices. Energy Policy 134 (June), 110827. http://dx.doi.org/10.1016/j.enpol.2019.06.035.

Hagfors, L.I., Bunn, D., Kristoffersen, E., Staver, T.T., Westgaard, S., 2016a. Modeling the UK electricity price distributions using quantile regression. Energy 102, 231–243. http://dx.doi.org/10.1016/j.energy.2016.02.025.

Hagfors, L.I., Kamperud, H.H., Paraschiv, F., Prokopczuk, M., Sator, A., Westgaard, S., 2016b. Prediction of extreme price occurrences in the german day-ahead electricity market. Quant. Finance 16 (12), 1929–1948. http://dx.doi.org/10.1080/14697688.2016.1211794.

Hagfors, L.I., Paraschiv, F., Molnar, P., Westgaard, S., 2016c. Using quantile regression to analyze the effect of renewables on EEX price formation. Renew. Energy Environ. Sustain. 1, 32. http://dx.doi.org/10.1051/rees/2016036.

Huisman, R., Huurman, C., Mahieu, R., 2007. Hourly electricity prices in day-ahead markets. Energy Econ. 29 (2), 240–248. http://dx.doi.org/10.1016/j.eneco.2006.08.005.

Huisman, R., Kyritsis, E., Stet, C., 2022. Fat tails due to variable renewables and insufficient flexibility: evidence from Germany. Energy J. 43 (5), 231–247. http://dx.doi.org/10.5547/01956574.43.5.rhui.

Jónsson, T., Pinson, P., Madsen, H., Nielsen, H.A., 2014. Predictive densities for day-ahead electricity prices using time-adaptive quantile regression. Energies 7 (9), 5523–5547. http://dx.doi.org/10.3390/en7095523.

Ketterer, J.C., 2014. The impact of wind power generation on the electricity price in Germany. Energy Econ. 44, 270–280. http://dx.doi.org/10.1016/j.eneco.2014.04.003.

Koenker, R., Bassett, G., 1978. Regression quantiles. Econometrica 46 (1), 33. http://dx.doi.org/10.2307/1913643.

Kyritsis, E., Andersson, J., 2019. Causality in quantiles and dynamic relations in energy markets: (De)tails matter. Energy Policy 133, 110933.

Kyritsis, E., Andersson, J., Serletis, A., 2017. Electricity prices, large-scale renewable integration, and policy implications. Energy Policy 101 (September 2016), 550–560. http://dx.doi.org/10.1016/j.enpol.2016.11.014.

Lindstrom, E., Regland, F., 2012. Modeling extreme dependence between European electricity markets. Energy Econ. 34 (4), 899–904. http://dx.doi.org/10.1016/j.eneco.2012.04.006.

Maciejowska, K., 2020. Assessing the impact of renewable energy sources on the electricityprice level and variability – A quantile regression approach. Energy Econ. 85, http://dx.doi.org/10.1016/j.eneco.2019.104532.

Maciejowska, K., Nowotarski, J., Weron, R., 2016. Probabilistic forecasting of electricity spot prices using factor quantile regression averaging. Int. J. Forecast. 32 (3), 957–965. http://dx.doi.org/10.1016/j.ijforecast.2014.12.004.

Martin de Lagarde, C., Lantz, F., 2018. How renewable production depresses electricity prices: Evidence from the german market. Energy Policy 117 (December 2017), 263–277. http://dx.doi.org/10.1016/j.enpol.2018.02.048.

Nicolosi, M., 2010. Wind power integration and power system flexibility-An empirical analysis of extreme events in Germany under the new negative price regime. Energy Policy 38 (11), 7257–7268. http://dx.doi.org/10.1016/j.enpol.2010.08.002.

Paraschiv, F., Erni, D., Pietsch, R., 2014. The impact of renewable energies on EEX day-ahead electricity prices. Energy Policy 73, 196–210. http://dx.doi.org/10.1016/j.enpol.2014.05.004.

Rintamäki, T., Siddiqui, A.S., Salo, A., 2017. Does renewable energy generation decrease the volatility of electricity prices? An analysis of Denmark and Germany. Energy Econ. 62, 270–282. http://dx.doi.org/10.1016/j.eneco.2016.12.019.

Rodríguez, R.A., Becker, S., Andresen, G.B., Heide, D., Greiner, M., 2014. Transmission needs across a fully renewable European power system. Renew. Energy 63, 467–476. http://dx.doi.org/10.1016/j.renene.2013.10.005, arXiv:1306.1079.

Sapio, A., 2019. Greener, more integrated, and less volatile? A quantile regression analysis of Italian wholesale electricity prices. Energy Policy 126, 452–469. http://dx.doi.org/10.1016/j.enpol.2018.10.017.

Troster, V., Shahbaz, M., Uddin, G.S., 2018. Renewable energy, oil prices, and economic activity: A Granger-causality in quantiles analysis. Energy Econ. 70, 440–452. http://dx.doi.org/10.1016/j.eneco.2018.01.029.

Woo, C.K., Moore, J., Schneiderman, B., Olson, A., Jones, R., Ho, T., Toyama, N., Wang, J., Zarnikau, J., 2015. Merit-order effects of day-ahead wind generation forecast in the hydro-rich Pacific northwest. Electr. J. 28 (9), 52–62. http://dx.doi.org/10.1016/j.tej.2015.10.001.

Würzburg, K., Labandeira, X., Linares, P., 2013. Renewable generation and electricity prices: Taking stock and new evidence for Germany and Austria. Energy Econ. 40, S159–S171. http://dx.doi.org/10.1016/j.eneco.2013.09.011.