The impact of variable renewables on the distribution of hourly electricity prices and their variability: A panel approach

BY Kyriaki Tselika

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The impact of variable renewables on the distribution of hourly electricity prices and their variability: A panel approach

Kyriaki Tselika*

Department of Business and Management Science, Norwegian School of Economics, Helleveien 30, 5045, Bergen, Norway

Abstract

This paper investigates the impact of intermittent renewable generation on the distribution of electricity prices and their variability in Denmark and Germany. We exploit hourly data from 2015 to 2020 and employ a novel panel quantile approach - the Quantiles via moments (MMQR) method. The combination of hourly-specific effects and the quantile approach allow us to estimate the renewable sources effect on various price quantiles while controlling for market dynamics. The results suggest that the merit-order effect occurs in both countries, with wind and solar generation having diverse effects on the electricity price distribution. Thus, policy makers should consider this diversifying effect to develop efficient renewable support schemes. We also explore non-linearities by including different demand levels in our model and investigate price variability. The outcomes indicate that wind generation increases (decreases) the occurrence of price fluctuations for low demand (high demand) in both countries. Meanwhile, in Germany, solar power stabilizes price fluctuations for high demand levels, stronger than wind. Market risk information could be useful for organizations in recognizing beneficial investment opportunities or hedging strategies. We finally aggregate the hourly observations into daily and compare the estimation outcomes. Hourly-related features seem to affect the merit-order effect and its robustness, and a panel approach shall be considered when investigating electricity markets.

Keywords: electricity prices, panel quantile regression, renewable sources, merit-order effect, price variability

1. Introduction

Over the last decades, European (EU) initiatives encourage sustainable practices aiming at a climate-neutral continent by 2050. Electricity markets have been accentuated by these efforts and initiatives. Structural and operational changes, such as market integration, intend to reform electricity markets and improve their resilience. Electricity is sold in power exchange markets such as the European Energy Exchange (EEX). These markets include various economic characteristics that originate from the microstructure of power systems.

Technological improvement has triggered new objectives and regulations in the EU energy sector, which has encouraged the continuous growth of renewable energy sources (RES). Wind and solar energy– two rapidly developed renewable energy sources - play a key part in the energy sector transformation towards the new green era. The current EU climate action plan focuses on market decarbonization promoting a 55% greenhouse gas emissions reduction by 2030 (European Commission, 2019). In addition, the new Green Deal introduced goals

*Corresponding author
e-mail: kyriaki.tselika@nhh.no

regarding RES penetration to reduce emissions further, and initiate alternative flexible electricity usage. The new EU target for RES is set to 32% by 2030.

The adoption of RES and their inclusion in the electricity grid poses many new challenges. The intermittent nature of RES, which depend highly on geographical attributes and weather conditions, incite technical issues in the electricity grid. Variable RES generation does not follow electricity demand patterns, which can create imbalances in electricity markets. Moreover, new regulatory frameworks are bound to create new challenges for power systems. For instance, the EU directives promote the phasing out from coal and nuclear power in the following years, and countries are required to modify their energy policies and comply to the new regulations. The excess changes that power systems have undergone, and the new energy transition schemes, have profound consequences for electricity markets and their microstructure. Market inefficiencies have arisen in the form of extreme price fluctuations and spikes (see Hagfors et al., 2016) making it essential to explore electricity price dynamics.

A potential solution to market inefficiencies could be increased system flexibility, such as flexible consumption technologies. Real-option investments are needed to establish these flexible systems. Real options refer to tangible investment opportunities that are available to companies. Such investments in the power sector involve demand-response systems, power storage systems and alternative fuel generation technologies. For instance, a demand-response system provides the opportunity to charge when RES supply is high and power demand low. On the other hand, the system can discharge when RES supply is low and power demand is high. In this way, power consumption is scaled up and down, depending on RES supply, making the power system more flexible and improving electricity supply security. However, real-option investments depend on long-term returns and investment risks, which are closely connected to power prices and their fluctuations (Black and Scholes, 1973; Cox et al., 1979). In particular, power storage companies could benefit from high electricity price variability by charging when prices are low and discharging when prices are high. It becomes obvious that RES penetration, electricity prices and real-option investments are strongly interconnected. Hence, it is important for market stability to explore how the structure and penetration of RES affect prices and, by extension, the value of real-option assets.

In this article, a panel quantile approach with hourly-specific effects is applied both for the case of Denmark and Germany. Both countries are appealing cases due to their high renewable penetration and distinct power features. The panel framework involves two dimensions; the individual and time element, which are the hours and days, respectively. We investigate various electricity price quantiles and how RES can impact them and model the electricity price distribution in two settings, accounting for different demand levels. The electricity price distribution is defined by quantiles, specifically $\tau = 0.1,..,0.9$. Each electricity price quantile is estimated using a vector of exogenous variables, and various indicators to control for short-term dynamics and seasonal effects. The methodology allows us to investigate the RES impact on electricity price levels, but also the entire distribution, and account for hourly factors common across all hours and diverse between a specific hour. Finally, the price variability is evaluated through the scale estimate, which can provide crucial insights on market risk.

The effect of RES has attracted a lot of attention in the electricity market literature. The effect has been explored in numerous countries with different institutional settings (Gelabert et al., 2011; Clo et al., 2015; Gullì and Balbo, 2015; Lagarde and Lantz. 2018; Csereklyei et al., 2019;

Prol et al., 2020; Marshman et al., 2020). Cludius et al. (2014), Paraschiv et al. (2014) and Wurzburg et al. (2013) show that wind and solar power in Germany seem to relate negatively to electricity price levels, with their effect being independent on the market since solar is available during daylight while wind is generally higher during the night. Jonsson et al. (2010), focusing on the Scandinavian market of Denmark, employ a non-parametric approach to investigate the effect of wind energy forecasts on day-ahead prices. The results imply that higher wind penetration decreases electricity prices. On the other hand, Mauritzen (2013) applies a simple distributed lag model to explore the wind generation impact on trade, electricity prices and hydropower production in Denmark. He finds that Denmark stores excess wind power in hydro reservoirs in neighboring Norway and an extra unit of wind would result in a 5% reduction of prices in Denmark. Thus, it has been shown, that variable renewable sources reduce electricity price levels, which is called in the literature as the merit-order effect. The electricity supply curve shifts due to increased low-cost RES penetration in the market, which leads to decreased prices.

Renewable energy and its intermittent nature have changed another key feature of electricity prices, their variation. The early empirical studies concentrated on renewable sources and their effect on electricity prices but later extended to electricity price volatility. The important relation between renewable sources, the source type, and electricity price variability is empirically supported by a large body of the literature (Ketterer et al., 2014; Kyritsis et al., 2017, Rintamäki et al., 2017). Kyritsis et al. (2017) apply a GARCH-in-Mean model to explore the impact of wind and solar power on electricity price volatility in Germany. They show that an increase in wind generation will result in higher price volatility. In contrast, an increase in solar power is shown to reduce price volatility. The RES effect on electricity price volatility for two distinct cases – Denmark and Germany - was investigated by Rintamäki et al. (2017). The results illustrate how market dynamics play a central role in RES penetration and their impact on price volatility. They show that renewable energy reduces price volatility in Denmark due to its connection with other Scandinavian countries, that have hydro storage capacity. On the other hand, wind power production is shown to increase electricity price volatility in Germany due to its off-peak hours effect. Finally, solar power appears to decrease price volatility since it mainly contributes during peak hours.

The literature over the last years has used a wide range of datasets and established multiple settings to explore electricity prices. However, research has mainly focused on investigating daily electricity prices, ignoring the hourly-specific effect and the influence it has on power markets. Several papers have split daily electricity price data on peak-off peak[†] hours to stress out the diverse RES impact, within the day, on electricity prices and their movements (Paraschiv et al., 2014; Kyritsis et al., 2017, Rintamaki et al., 2017). Although the high dependence of RES on the hour within the day and its attributes have been highlighted, it has not been fully explored. Electricity produced by renewable sources is highly variable within a day due to the intermittent nature of renewables. In addition, different RES categories showcase different production patterns. For example, wind power is generally abundant during night hours while solar power is only available during sunlight hours. These market characteristics urge us to account for the hourly-specific effect and its embedded information on electricity prices.

[†] Peak hours refer to the time period from 8am to 8pm while the rest refer to off-peak hours.

Although the merit-order effect has been illustrated by multiple studies and settings, literature on the repercussions of RES on the shape of electricity price distributions has been spare (Hagfors et al., 2016a; Bunn et al., 2016; Sapio, 2019; Maciejowska, 2020; Sirin and Yilmaz, 2020; Apergis et al., 2019). Electricity prices are characterized by large fluctuations, spikes, and excess kurtosis, which have motivated studies regarding the tails of the electricity price distribution. Bunn et al. (2016) use quantile regression to evaluate the dependence of electricity price risks on fundamental market variables. More recently, Maciejowska (2020) employs a semi-parametric approach to investigate the shape of the electricity price distribution. They examine the RES impact on the electricity price distribution and conclude that while wind has a stronger effect on lower quantiles, solar power's influence is intensified for upper price quantiles. Furthermore, they analyze the electricity price variability, through which they demonstrate the diverse RES impact dynamics. Lastly, Apergis et al. (2020) explore the tail dependence of electricity prices through copulas in the Australian market. They divide the chosen time frame into pre-during-post carbon tax periods and conclude that tail dependence highly differs between the investigated periods.

Denmark and Germany have been pioneers in the renewable energy field. In both countries, the power markets have also undergone important regulatory changes. Denmark, after the 1970s oil crisis, decided to establish a long-term energy plan to avoid energy shortage in the future. Through this plan, they have encouraged the development and use of energy efficient technologies such as wind turbines. Denmark aims currently at a 70% emission reduction and 55% renewables share by 2030 (Danish Ministry of Climate, Energy and Utilities, 2019). In Denmark, RES receive various types of financial support such as tenders and premium tariffs (Danish Energy Agency, 2019). In Germany, the renewable energy field started to blossom in the 2000s. The German Renewable Energy Act has been the key mechanism to promote energy transition in the country. The energy action plan has been modified twice since its introduction to accommodate RES inclusion, reduce financial pressure to final consumers, promote competition, and eventually, improve cost efficiency in the market. Regarding the German market composition and energy plan, emissions are expected to decline by 55% while the RES share to rise to 65% by 2030 (IEA, 2020).

This study aims to analyze the complex behavior of electricity prices and renewable energy penetration, as well as facilitate investment and regulatory decisions in the power sector. Our empirical findings contribute to the literature in various aspects. First, to account for the intraday time effect, we employ hourly data. The high frequency of the data offers a wider information range that allows us to control for various market characteristics. Few studies employ hourly data with most not acknowledging and accounting for the hourly-specific effect. Second, we investigate the distributional effect of RES on day-ahead electricity prices. By doing so, we can understand the RES role on power market inefficiencies, such as extreme prices, and recognize market systems and regulatory frameworks that can reduce uncertainty and promote long-term flexibility. Lastly, we explore two cases, Denmark and Germany, that although being close neighbors, their power markets carry distinct attributes and specific challenges. Germany, although in the heart of Europe, has limited access to flexible storage systems, while Denmark stores electricity in Norwegian hydro-reservoirs.

2. Data

The data employed concern the period from January 1, 2015 to November 30, 2020 for Denmark and January 6, 2015 to November 30, 2020 for Germany, providing a very rich dataset with 2154 and 2149 days, respectively. Thus, the entire dataset includes 51696 hours for Denmark and 51576 hours for Germany. Hourly data for electricity day-ahead prices (€/MWh), forecasted loads, and forecasted wind power (GWh) in Denmark were obtained by Nordpool AS, the power market operator for the Nordic region. The hourly day-ahead prices, forecasted loads[‡], wind and solar power forecasts in Germany were retrieved from EEX and the European Network of Transmission System Operators for Electricity[§] that collects and shares information from Transmission System Operators (TSO) around Europe.

A potential matter that should be mentioned, concerning the chosen underlying variables, is data exogeneity. Renewable energy is dispatched with regulatory priority and its production depends on weather or natural conditions. We, thus, can assume that wind and solar generation will be exogenous in our models. It is also believed that renewable energy is unlikely to be sensitive to price signals. RES producers have high motives, such as financial incentives, to maintain production levels even when electricity prices are extremely low (Mauritzen, 2013).

The EU electricity system includes three key markets– the day-ahead, intraday, and balancing market - depending on power exchange frequency. The day-ahead market (or spot market) clears supply and demand with a price for each of the 24 hours of the following day. Thus, the buyers and sellers in the market, place their bids in an hourly resolution for the following day. These bids are aggregated, and the system price is determined by the intersection between demand and supply. The last required generation technology to meet demand determines the

Table 1
Descriptive Statistics

Variable	Mean	Min	Max	St. dev.	Skewness	Kurtosis
Denmark						
Price	31.175	-58.8	200.04	15.04	0.345	4.99
Wind	1.316	0	4.503	0.963	0.673	2.468
Load	2.280	1.202	3.545	0.452	0.142	2.044
Germany						
Price	34.51	-130.09	200.04	16.47	-0.272	8.897
Wind	46.27	1.254	188.923	36.10	1.163	3.834
Solar	18.19	0	129.914	27.58	1.541	4.391
Load	219.42	115.29	345.633	37.99	-0.056	1.943

price through a marginal price setting procedure (Huisman et al., 2015). Electricity prices can be affected by generation capacity, transmission constraints and meteorological factors (Nord Pool, n.d.). The intraday and balancing markets, in which the participants trade closer to the physical delivery time, aim to correct forecast errors, and eventually secure a balance between electricity supply and demand. Day-ahead prices have been the main field of investigation regarding RES influence on electricity prices. The liberalization of electricity markets increased trade interest in day-ahead markets, and although complementary markets (e.g., intraday) emerged through the years, the role of day-ahead markets remained prominent until today.

[‡] There were 48 hourly observations of forecasted loads in Germany missing, for which we used realized values.
[§] https://transparency.entsoe.eu/

Table 1 presents the descriptive statistics for electricity prices, forecasted renewables and loads. In both countries, the per hour distribution of prices is leptokurtic, indicating the asymmetric effect of extreme prices for their distribution. In the German market, the kurtosis level is much higher than in the Danish case. We use the Pesaran (2015) CD statistic to test for cross-sectional dependence and second-generation unit root tests to examine the stationarity of the panel. Since our panel is balanced and long, in terms of time, we apply Breitung and Das's (2005) panel unit root test which indicates that the series are stationary, and we can proceed with the analysis without further modifications to the data. The cross-sectional dependence and unit-root results are available in Appendix A.

Another important illustration is the time-series evolution of electricity prices, RES and loads during the examined period. Figures 1 and 2 demonstrate the underlying variables in Denmark and Germany. The fact that electricity prices show great fluctuations that contain extreme positive and negative values is apparent and in line with the kurtosis of the distribution. It is also evident in the figures that wind and solar generation vary widely throughout the year. This is mainly attributed to their dependence weather conditions and hourly sunlight. Forecasted wind, solar and load follow a strong yearly seasonal pattern. While load and wind generation have higher values in winter and lower values in the summer, solar generation peaks during summer periods.

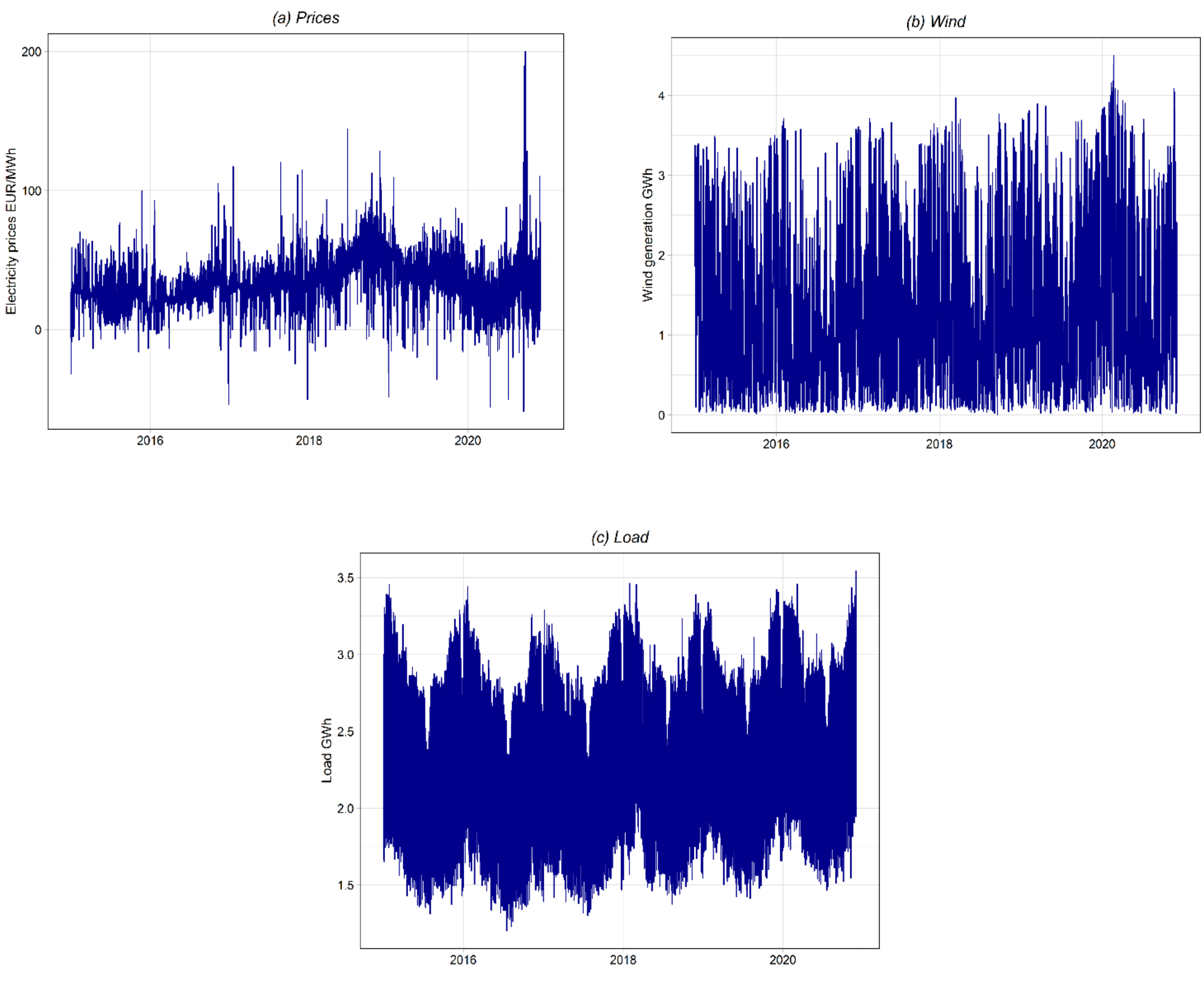

Fig. 1. Fundamental variables in Denmark.

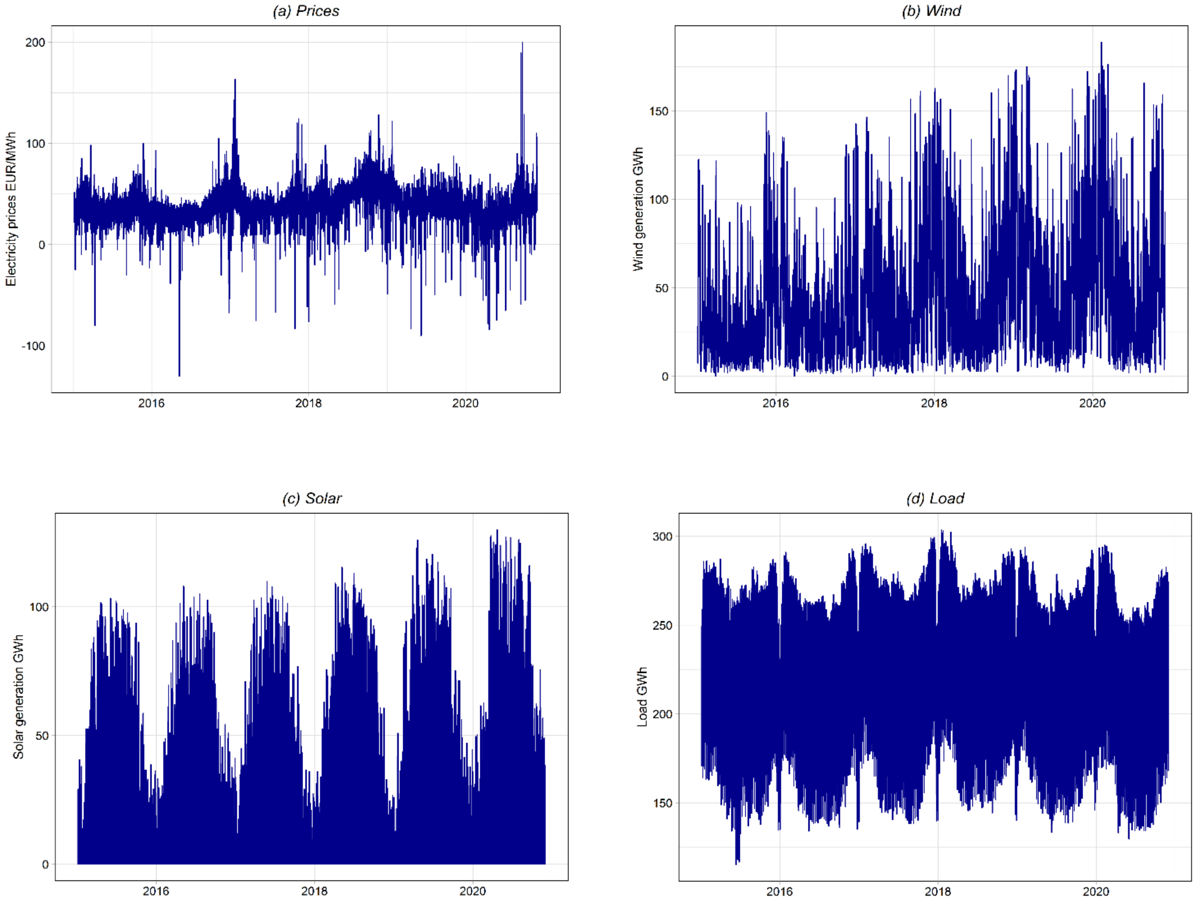

Fig. 2. Fundamental variables in Germany.

In Figure 3, we demonstrate individual boxplots for three electricity price levels (low, intermediate, and high) categorized by the hours of the day. The figures indicate that the electricity price distributions vary greatly, in both countries, during a day. We also notice that Denmark shows a lower price variability than Germany. Denmark has established strong interconnections with other Scandinavian countries, which allows access to flexible storage systems, contributing to lower price fluctuations. Electricity prices exhibit extreme values, in both countries, for almost all hours, but in Germany we observe a higher frequency of negative electricity spikes. This shows how diverse electricity markets are, even within Europe, and how important market integration can be to establish efficient electricity markets. Finally, figure 3 implies that the distribution of prices is linked to the hour itself. For instance, during the morning and afternoon hours, when industrial activities take place, higher electricity prices are observed. Therefore, it is obvious that the distributional effects of RES on electricity prices are linked to hourly-specific effects which our research accounts for.

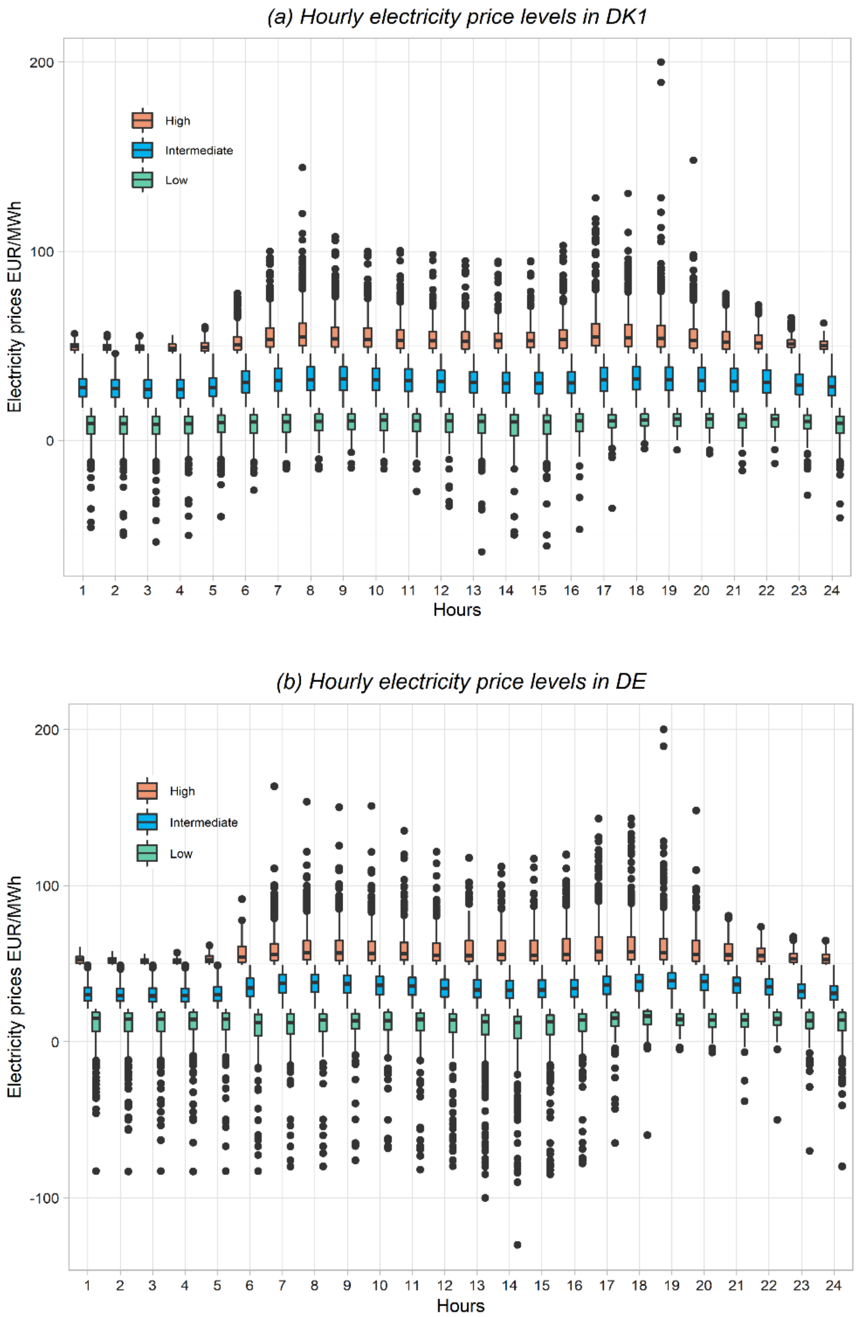

Fig. 3. Boxplots of three electricity price levels (low, intermediate, and high) for each hour of the day in a) Denmark, and b) Germany.

3. Methodology

Electricity markets are characterized by distinct features that cause various methodological challenges for researchers. The need for a day-ahead market stems from electricity's poor storage capabilities, as well as supply and demand variability. To formulate an efficient econometric model, key electricity price dynamics should be considered. As mentioned earlier, day-ahead prices are set simultaneously for the 24 hours of the following day. Therefore, the 24 determined prices, resulting from submitted bids, correspond to the same information, and should be treated as a panel rather than a time series element (Huisman et al., 2007). As was initially proposed by Huismal et al. (2007), day-ahead prices should be treated in a panel framework rather than a time-series. They highlighted the need to consider the market microstructure characteristics in electricity research and include the cross-sectional hourly effect. More recently, the individual-specific effects were incorporated in their research by Keppler et al. (2016). They investigate the RES and market coupling impact on electricity price spreads between Germany and France. The hourly-specific effect can be deemed extremely important when exploring interconnections between markets since transmission capacities can be rather diverse across the hours of a day, and congestion can prevent market integration.

In addition, by using daily data, we can overlook valuable information regarding important time variation. Therefore, a panel framework would be an appropriate setting for investigating the various links between electricity prices and fundamental variables. In the panel setting we establish a common dynamic across all hours and a varying factor for each hour. A panel framework for electricity prices has been established by previous research (Huisman et al., 2007; Karakatsani and Bunn, 2008; Pena, 2012; Keppler et al., 2016; Pham, 2019) but to the best of our knowledge has not been applied in a quantile scope.

Quantile regression was introduced by Koenker and Bassett (1978) and has been applied in various economic applications. It is used to estimate the predictive value of independent variables on the quantiles of the dependent variable and is especially robust to outliers. In this empirical investigation, a novel approach by Machado and Silva (2019), called Method of Moments Quantile Regression (MMQR), is employed. The MMQR method is particularly relevant when individual effects or endogenous variables are recognized in a panel. Machado and Silva (2019) have established an estimator that combines the location-scale functions and estimates the conditional quantile functions. Additionally, the MMQR does not allow the quantile estimates to cross which is an important condition in empirical research (He, 1997; Chernozhukov et al., 2010). Finally, the MMQR estimator allows the hourly-specific effects to impact the entire electricity price distribution. As an initial point of analysis, a linear specification for exploring the RES effect on the electricity price distribution is explored. Then, we further include non-linearities in the model to assess the stability of the variables across different demand levels. Taking into consideration the link between electricity prices and demand, we examine the RES effect on the shape of the electricity price distribution conditional on three demand levels.

The conditional quantile estimation of the location-scale is described as follows:

$$\begin{aligned} Q_p(\tau) = \big(a_i + \delta_i q(\tau)\big) + \beta^L L_{it} + \beta^W W_{it} + \beta^S S_{it} + \\ + \theta_1 P_{i,t-1} + \theta_2 P_{i,t-7} + \varphi C_{it} + Z'_{it} \gamma q(\tau), \tau \in (0,1) \qquad (1) \end{aligned}$$

With $\Pr\{\delta_i + Z'_{it}\gamma > 0\} = 1$. Z is a k-vector of known differentiable (with probability 1) transformations of the components of X with element l given by $Z_l = \Xi_l(X), l = 1, \ldots, k$. We denote *i* the hour group and *t* the day, with *i* =1….24, and T with *t* =1….*T*.

Eq (1) connects the τ^{th} electricity price quantile with the vector of independent variables. The scalar coefficient $a_i(\tau) \equiv \alpha_i + \delta_i q(\tau)$ is called the quantile-τ fixed effect for individual i. We denote L_{it} the forecasted load, S_{it} the forecasted solar power generation, W_{it} the forecasted wind generation and C_{it} a set of binary indicators[1] to consider the effect of weekends, holidays, and seasonal parameters. We also use lagged prices to control for short-term price dynamics. According to Nickell (1981) dynamic models with fixed effects are biased by $1/T$. Hence, the bias due to the dynamic formulation is expected to be small and we highly doubt it will affect the estimates since our time dimension - both in Denmark and Germany - can be considered large. Lastly, in the case of Denmark, solar power is minimal, hence only wind generation is accounted for, regarding this empirical analysis.

Electricity consumption and renewable sources are often shown to have a reverse effect on price levels; load often increases prices while renewable sources reduce them. Ketterer (2014) showed that wind and solar share; the forecasted wind/solar generation divided by the forecasted load, has a negative impact on electricity prices. In addition, Maciejowska (2020) demonstrated the diverse effect of RES on electricity prices depending on demand levels. High interaction between load and renewable generation would be expected with the possibility of the demand effect overriding the RES price reduction. Thus, we could expect a higher predictive power of the model by including the interaction between the renewable generation and different demand levels.

The three demand levels were drawn by the unconditional distribution of loads. We include an indicator in our model: $D_{1it} = 1_{L_{it} \leq L(\tau_L)}$, $D_{2it} = 1_{L(\tau_L) < L_{it} < L(\tau_H)}$ and $D_{3it} = 1_{L_{it} \leq L(\tau_L)}$ where the demand quantile thresholds are $\tau_L = 0.15$ and $\tau_H = 0.85$. These thresholds were selected in a manner that allows the inclusion of a sufficient number of observations for the estimation. Furthermore, these thresholds allow us to explore the electricity price distribution in connection to the demand level extremes. We also used different demand thresholds to test the robustness of our results and did not find any qualitative deviations between them. The robustness checks can be found in Appendix D.

Equation (1) then becomes:

$$Q_p(\tau) = \left(a_i + \delta_i q(\tau)\right) + \sum_{m=1}^{3} \beta_m^L \, L_{mit} + \sum_{m=1}^{3} \beta_m^W \, W_{mit} + \sum_{m=1}^{3} \beta_m^S \, S_{mit} +$$

$$+\theta_1 P_{i,t-1} + \theta_2 P_{i,t-7} + \varphi C_{it} + Z'_{it} \gamma q(\tau) \qquad (2)$$

where $L_{mit} = D_{mit} L_{it}$, $W_{mit} = D_{mit} W_{it}$ and $S_{mit} = D_{mit} S_{it}$.

According to Angrist and Pischke (2008, p.227) bootstrapping standard errors can be useful in settings like quantile regression, that the asymptotic distributions are characterized by unknown densities. Thus, we use the bootstrap clustered by group standard errors to treat potential heteroskedasticity and serial correlation in the panel.

4. Results

4.1 Distributional impacts of RES on electricity prices

The empirical estimates for model 1, eq (1), are presented in Table 2. All coefficients for wind and solar are negative and significant for all price quantiles at 1% level. Thus, a unit increase in wind or solar will reduce electricity prices in all quantiles. The findings clearly reflect the merit-order effect that has been explored extensively in the literature (e.g., Mauritzen, 2013; Cludius et al., 2014). The merit-order effect originates by the low short-term marginal costs of RES. Hence, RES

Table 2
The estimates of baseline model 1.

Variables	Quantiles								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Denmark									
Wind	-6.159***	-5.935***	-5.782***	-5.653***	-5.534***	-5.409***	-5.273***	-5.110***	-4.848***
Load	3.756***	4.971***	5.803***	6.506***	7.154***	7.833***	8.571***	9.458***	10.88***
Observations	51,696	51,696	51,696	51,696	51,696	51,696	51,696	51,696	51,696
Germany									
Wind	-0.233***	-0.22***	-0.211***	-0.203***	-0.196***	-0.187***	-0.178***	-0.168***	-0.15***
Solar	-0.131***	-0.132***	-0.132***	-0.133***	-0.133***	-0.1335***	-0.134***	-0.1345***	-0.135***
Load	0.175***	0.182***	0.187***	0.19***	0.195***	0.199***	0.204***	0.209***	0.218***
Observations	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576

Notes: (i) Standard errors are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

can replace conventional higher-cost power plants (coal, gas, etc.), shifting the supply curve and pulling electricity prices down. RES type-specific characteristics such as generation patterns and capacity levels, and their interchange with unique power system economics distinguish the effect of one renewable source to another on electricity prices. While wind generation can be considered as a rather stable-producing energy source, solar production occurs during sunlight hours which mainly include high demand periods. Maciejowska (2020) was the first to explicitly compare the influence of two RES on the electricity price distribution. She concluded that energy policies should consider the high interaction between different RES to maximize power stability.

The results imply that although, there is a universal RES impact on electricity prices, this impact is heterogeneous depending on price levels and renewable energy source type. Our findings verify previous claims concerning the relationship between renewable sources and market fundamentals. In both Denmark and Germany, the estimates show that wind reduces electricity prices more on lower quantiles than in upper ones. The reason behind this result lies in the relationship between electricity prices and market-specific characteristics. During off-peak hours, demand is low and electricity prices are sometimes pressed down to zero or even below zero. The system inflexibility pressures conventional power plants to bid in negative prices when it is cost efficient, in short-time segments, than shutting down. An increase in wind production could further stress baseload producers to shut down, establishing a more prominent effect of wind during these times. Additionally, conventional plants will opt out of bidding in case production costs are much higher than costs induced by operational restrictions such as shut down costs. Then again, the relation of wind power and electricity prices is stronger in the case of lower quantiles – surging lower-level electricity prices. It is evident that while the direction of the wind coefficients is similar in both countries, the magnitudes are different since they have diverse power production systems such as generation mixes, and renewable production capacities.

In Germany, solar has a slightly weaker effect on low prices than on high ones. Thus, solar generation seems to reduce the occurrence of extreme positive electricity prices and could be used as a tool to improve system balance. The market involves intense competition when demand is high resulting in high-cost technologies setting electricity prices. However, solar generation is mainly available during high-demand hours and can be a setting price technology during these periods. This results in solar having a stronger impact on electricity prices than other energy sources at these times. We also notice that wind overpowers solar for all electricity price quantiles. The underlying reason behind this could be that wind capacity and availability is more extensive than solar power. Maciejowska (2020) has shown, using aggregated daily data, that solar generation has a stronger impact than wind on upper price quantiles. The solar power generation patterns reveal a great dependence on the hour of the day. For instance, it has been shown that solar induces a higher merit-order effect during peak hours when its production is high (Kyritsis et al., 2017). The addition of hourly fixed effects, combined with the distributional effect, has the potential to describe in more detail the renewables effect on electricity prices. Finally, the load seems, as expected, to increase electricity prices in all quantiles with a higher impact on upper quantiles.

Table 3 presents the model estimates for electricity price averages and variability. While load increases electricity prices average, renewable sources seem to reduce it. All the estimates are statistically significant at 1% level except solar which is significant at 5% level. The wind coefficients suggest that an increase in forecasted wind will give a rise to price variability in Denmark and Germany. This result is in accordance with previous research for Germany, but not for Denmark. We would expect wind to reduce price variability in Denmark (Rintamäki et al., 2017) since they are well-connected to neighboring countries such as Norway and Sweden, which grants Denmark access to flexible systems (hydro-reservoir) with high storage opportunities. Hence, one would expect that excess electricity from wind would be transferred to Norway and stored in its hydro-reservoirs, reducing the pressure in the market, and flatten the impact of wind. Instead, we notice that wind power increases price variability disregarding the favorable power market structure in Denmark. The positive wind estimates could be connected to the fact that wind exhibits a stronger impact on low price quantiles. An increase in forecasted wind could reduce already low prices further, displacing conventional energy producers and rendering the market inefficient even if they have access to hydro systems. We will further investigate this result in the following section where non-linearities are included in the model.

Table 3
Baseline model 1 location and scale estimates.

Baseline Model (1)	Location	Scale
Denmark		
Wind	-5.515***	0.429***
Load	7.251***	2.334***
Germany		
Wind	-0.193***	0.027***
Solar	-0.133***	-0.001
Load	0.196***	0.014***

Notes: (i) Standard errors are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

On the other hand, Germany has limited access to flexible systems and the concentration of wind generation in the North (Paraschiv et al., 2014) often challenges the power system causing greater price fluctuations. In the case of solar power in Germany, the scale estimate is negative, which indicates that an increase in forecasted solar could result in lower electricity price variability. This could relate to the fact that solar has a more intense effect on upper electricity price quantiles. The solar scale coefficient, though negative, does not seem to hold statistical significance. Model 2 (eq. 2) could reveal more information about the relationship between solar power and price variability. Finally, load exhibits a significant positive impact on electricity price variability in both countries.

4.2 Distributional impacts of RES on electricity prices conditional on demand

Analyzing first the Danish distributional effect of wind, conditional on demand, the results of model 2 (Table 4) suggest that wind more strongly impacts upper price quantiles when demand is high and lower price quantiles for low and intermediate demand. Overall, the effect is more prominent for high demand levels and all the results are statistically significant at 1% level. This result is in line with our analysis in the previous section and provide a detailed illustration of the market effects. In higher demand quantiles, high-cost marginal technologies will bid more intensely in the market and increase competition. Thus, an increase in the forecasted wind will induce a sharp price dampening effect during these periods. The forecasted load estimates, contrarily, have a positive sign in all price quantiles which indicates that a rise in forecasted consumption will increase electricity prices. The effect, as expected from previous literature, is more prominent on higher demand levels.

Also in Germany, wind generation has a stronger price reducing effect on lower electricity price quantiles when demand is low than when it is high. In the intermediate demand level, the impact is diminishing from lower to upper price quantiles. On the other hand, solar forecasts follow a similar pattern to wind, but the magnitude of the estimates is different. What is noteworthy, is that in all three demand levels, wind estimates exceed solar estimates. The equality hypotheses between the two RES estimates in all quantiles have been tested and found significant at 1% level. The results suggest that both renewable sources impact similarly the median of electricity prices but not the tails of the distribution. Therefore, the aggregated influence of both renewable sources can be particularly employed when investigating the median of electricity prices. Finally, forecasted loads increase electricity prices for all quantiles in all demand levels with the coefficients for the upper price - higher demand quantiles being the strongest.

Table 4
The estimates of the demand level model 2.

	Denmark			Germany					
τ	Wind			Wind			Solar		
	$\beta^{w}_{1,L}$	$\beta^{w}_{2,M}$	$\beta^{w}_{3,H}$	$\beta^{w}_{1,L}$	$\beta^{w}_{2,M}$	$\beta^{w}_{3,H}$	$\beta^{S}_{1,L}$	$\beta^{S}_{2,M}$	$\beta^{S}_{3,H}$
0.1	-6.944***	-6.284***	-5.283***	-0.347***	-0.238***	-0.151***	-0.156***	-0.149***	-0.082***
0.2	-6.209***	-5.964***	-5.723***	-0.315***	-0.223***	-0.164***	-0.155***	-0.145***	-0.104***
0.3	-5.699***	-5.742***	-6.028***	-0.291***	-0.212***	-0.174***	-0.155***	-0.142***	-0.120***
0.4	-5.274***	-5.557***	-6.283***	-0.271***	-0.203***	-0.182***	-0.155***	-0.140***	-0.133***
0.5	-4.884***	-5.388***	-6.516***	-0.251***	-0.193***	-0.190***	-0.155***	-0.138***	-0.146***
0.6	-4.478***	-5.211***	-6.759***	-0.231***	-0.184***	-0.198***	-0.154***	-0.136***	-0.160***
0.7	-4.044***	-5.022***	-7.019***	-0.208***	-0.173***	-0.207***	-0.154***	-0.133***	-0.175***
0.8	-3.522***	-4.795***	-7.331***	-0.181***	-0.161***	-0.218***	-0.154***	-0.130***	-0.193***
0.9	-2.682***	-4.43***	-7.834***	-0.138***	-0.140***	-0.235***	-0.153***	-0.125***	-0.222***
Obs	51,696	51,696	51,696	51,576	51,576	51,576	51,576	51,576	51,576

Notes: (i) Standard errors are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Moving forward to the electricity prices average and variability estimates in Denmark (Table 5), the average electricity prices are shown to be reduced by forecasted wind for low, intermediate, and high demand levels. Wind significantly also impacts price variability for all demand levels. The wind estimates are positive for low and intermediate demand levels and negative for high demand. This ambiguous result indicates that price variability and wind generation depend strongly on electricity demand. Generally, during low electricity demand, wind power would suffice to cover electricity consumption, which combined with the renewable sources pressure on conventional power plants, could result in excess electricity supply in the market. Hence, an extra unit of forecasted wind could urge greater price fluctuations and marker uncertainty. On the contrary, when demand is high, the entrance of high-cost technologies in the market intensifies competition. During these times, an increase in wind power, a low-cost generator, would pull electricity prices down, reduce extreme fluctuations and enhance electricity security. The results also show that forecasted load increases electricity prices on average as well as their variability and may, thus, cause electricity price fluctuations including positive price spikes.

Table 5
Model 2 (conditional on demand) location and scale estimates.

Demand level Model (2)		Location	Scale
Denmark			
Wind	W_L	-4.837***	1.392***
	W_M	-5.367***	0.605***
	W_H	-6.545***	-0.833***
Load	L_L	7.277***	1.671***
	L_M	7.481***	2.221***
	L_H	7.986***	3***
Germany			
Wind	W_L	-0.245***	0.066***
	W_M	-0.19***	0.031***
	W_H	-0.192***	-0.026***
Solar	S_L	-0.154***	0.0008
	S_M	-0.137***	0.007*
	S_H	-0.15***	-0.044***
Load	L_L	0.204***	-0.007*
	L_M	0.19***	0.002
	L_H	0.192***	0.022***

Notes: (i) Standard errors are computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Wind and solar, carrying diverse characteristics, can influence differently electricity price variability in Germany. It is shown that wind increases price variability for low and intermediate loads, while solar increases price variability only for low demand levels. The wind estimates are statistically significant at 1% for all three demand levels while the solar estimate for low demand is insignificant, and the intermediate and high demand variables are significant at 10% and 1% respectively. More importantly, the results indicate that when demand is high the negative relation between solar generation and price variability is stronger compared to the equivalent effect of wind power. Solar availability and generation capacity characteristics compared to wind production patterns could relate to this. Additionally, geographical characteristics may also contribute to this result especially when the results are used for comparative analysis. In Germany, energy consumption is mainly concentrated in the southern part while wind power is mostly produced in the northern part (Paraschiv et al., 2014). Thus, transmission constraints and congestion across the country, could prevent wind generation from covering electricity demand, allowing solar power to impact electricity prices during these times. The graphical representations of the results are available in Appendix C.

5. Aggregated data

A large portion of the literature has employed aggregated daily data to investigate the RES effect on electricity price distributions. In this paper we use high-frequency data that allow us to control for hourly-specific effects which could impact the research outcomes. We would anticipate differences between the two methods and procedures; thus, it could be essential to examine the aggregated model as well. The data are transformed from hourly into daily observations and an autoregressive quantile regression (Koenker and Xiao, 2006) including the same set of variables, as in models 1 and 2, is applied. The empirical results can be found in Tables B4, B5, B6 and B7 in Appendix B.

Figure 5 illustrates the baseline Method of Moments Quantile Regression (MMQR) and daily estimates for wind, solar and load in Germany. While the MMQR wind and solar coefficients follow approximately the same pattern as the daily estimates, the hourly results reveal strongest impacts than the aggregated in all price quantiles. Only in the case of solar power and for high electricity price quantiles the daily estimate exceeds the MMQR. Additionally, load exhibits a more prominent impact in the hourly resolution compared to the daily. What is noteworthy, is that solar estimates seem to show the highest divergence which prompts us to suspect that the hourly-specific effect can be crucial in the case of RES production-specific characteristics and their influence in the market. Figure 4 also shows the wind and load estimates in Denmark. We notice that the coefficients follow the same trend as in Germany, with the MMQR wind impacting stronger lower quantiles and daily wind influencing mostly low and upper price quantiles.

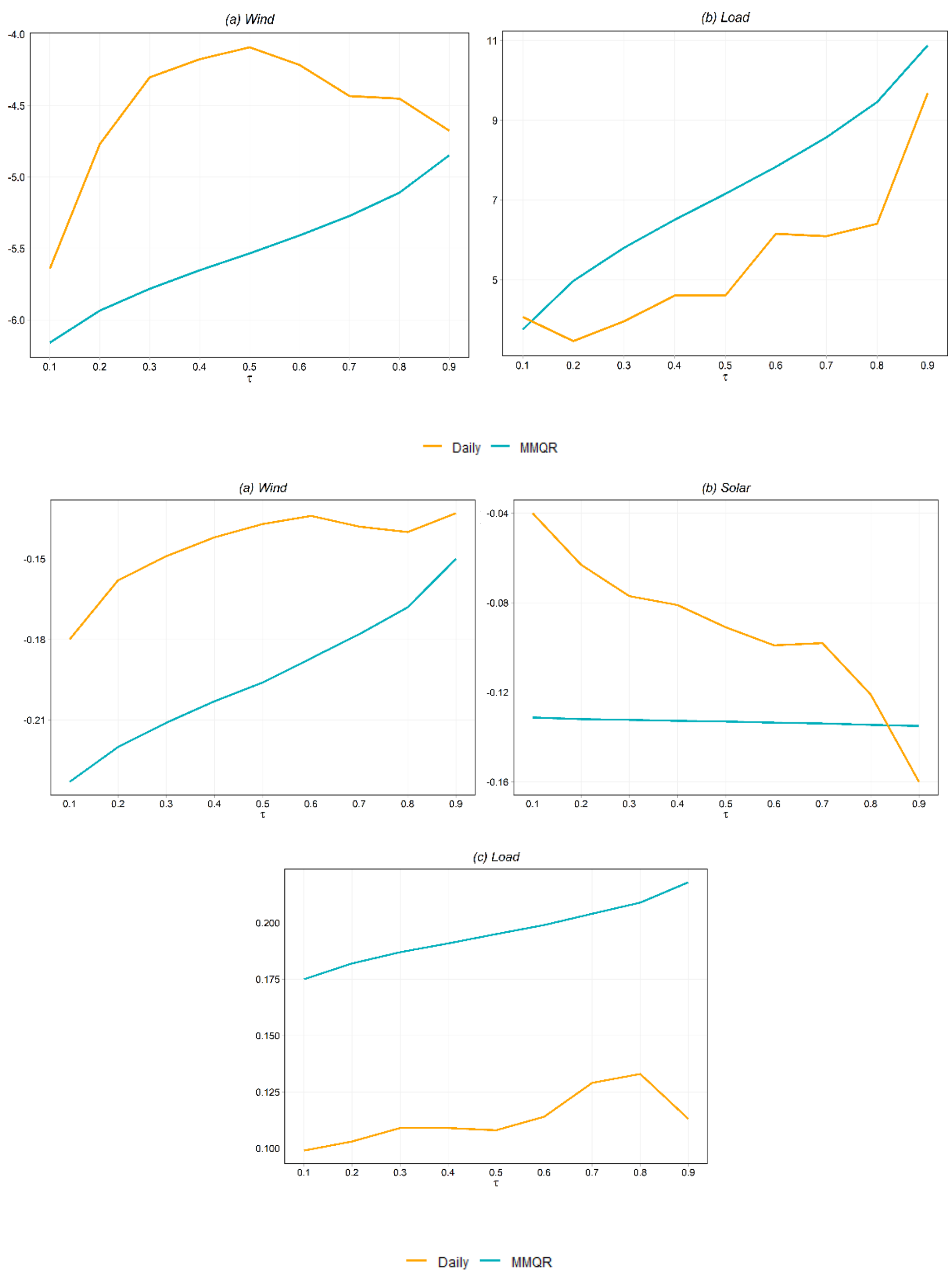

Fig. 5. Baseline model 1 daily vs MMQR estimates in DE.

Figure 6 demonstrates the non-linear MMQR model and daily estimates in Germany. It can be observed that the daily and MMQR wind estimates for low and intermediate demand exhibit approximately the same pattern. As for high demand levels, the daily wind estimates are stronger for upper and lower price quantiles while the MMQR approach indicates that the wind impact is monotonically decreasing, having a higher impact on lower price quantiles. On the other contrary, solar displays a highly diversified influence on electricity price quantiles. The daily coefficients show sharp fluctuations for all demand levels while the MMQR approach presents a smoother RES effect on the electricity price distribution. Especially for low demand, there is a striking contrast between the two results and their implications. In addition, the wind and solar MMQR coefficients show a higher negative impact than daily estimates for all demand levels and price quantiles. Finally, in the case of load, we notice great diversity between the hourly and daily estimates, with hourly-resolution results displaying much higher impacts than the daily aggregated.

When the non-linear case of the daily and MMQR results in Denmark (Figure 7) is explored, it is observed that for low demand the two approaches outcomes follow a very similar pattern. For intermediate demand, the MMQR coefficient is increasing across quantiles while the daily result is strongest for low and upper quantiles. Furthermore, it is noted that in extreme positive price quantiles and for intermediate demand, the daily impact exceeds the MMQR. In the case of loads, the MMQR results show a smoother and stronger effect than the daily ones. Finally, both the daily wind and load results display again high fluctuations compared to the hourly estimates.

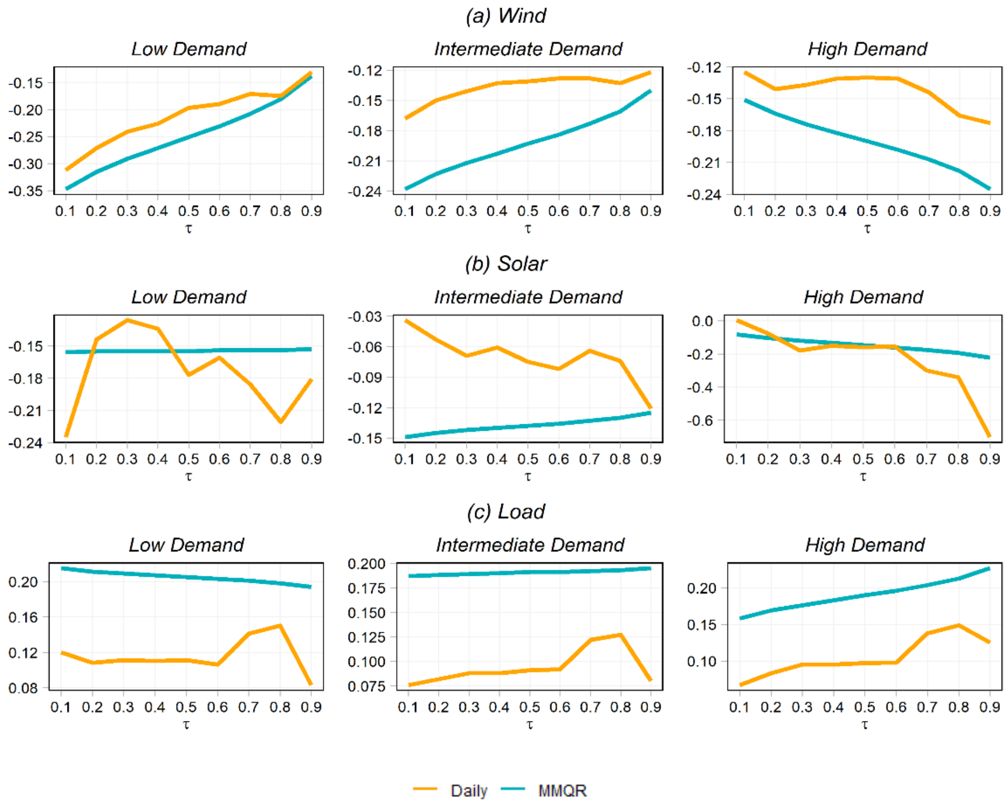

Fig. 6. Model 2 – conditional on demand daily vs MMQR estimates in Germany.

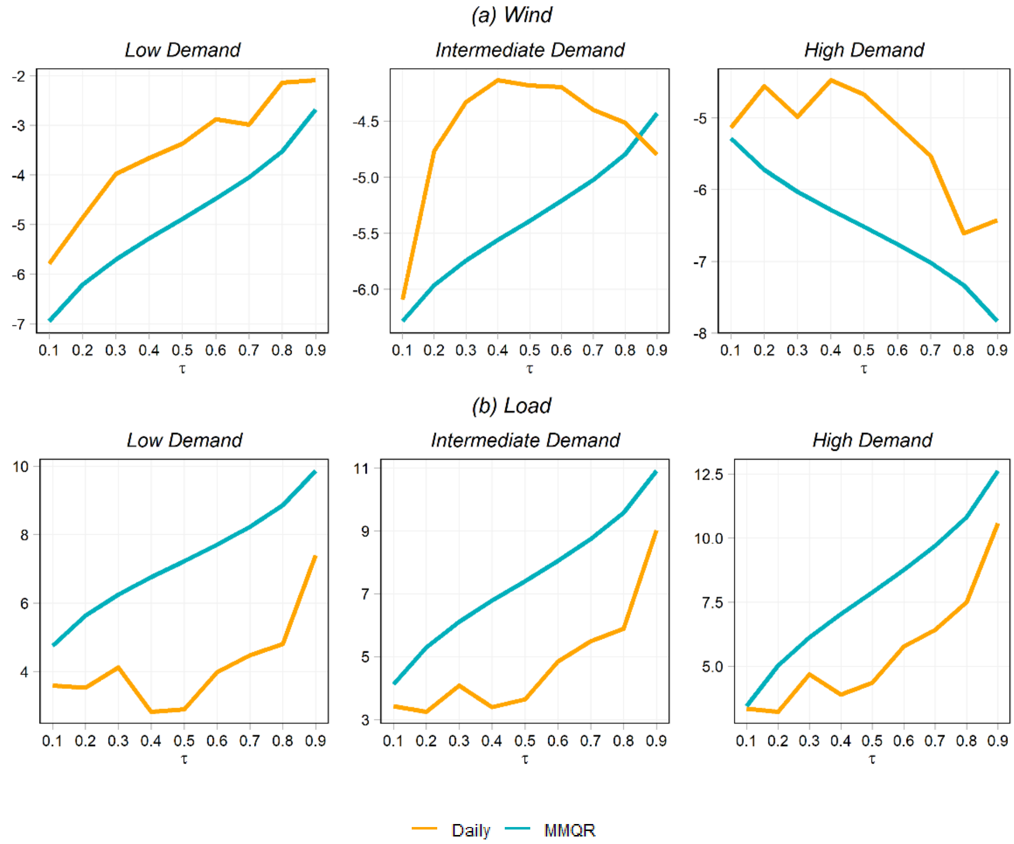

Fig. 7. Model 2 – conditional on demand daily vs MMQR estimates in Denmark.

Individual hours and their specific characteristics can be highly significant in the case of renewable sources which depend on weather conditions and can display rapid and extreme variations. The analysis and comparison of aggregated time-series and hourly-panel results can verify, to some extent, this hypothesis. The diversity of the outcomes reveals that accounting for this hour-specific effect could be important for investigating the RES influence on electricity prices. Overall, the panel setting uncovers a higher distributional impact of renewable sources on electricity prices. It should be noted that in this section we do not compare the quality of the daily and panel estimates since the estimation methods are very different. We essentially attempt to illustrate the diversity between the aggregated and hourly coefficients and elaborate on the importance of using the electricity high-frequency data.

6. Robustness check

The robustness of the RES effect on the distribution of electricity prices and their variability is corroborated by altering model 2. Since the results depend highly on the chosen demand thresholds, new chosen thresholds are applied to verify the estimates. The new demand thresholds are set at $\tau_L = 0.2$ and $\tau_H = 0.8$. The use of high-frequency hourly data, while providing richer information, can create many challenges, especially in the case of solar power. Hourly solar data are zero when there is no sunlight. Hence, we believe that lower demand thresholds can bias the solar estimates by including an inadequate number of observations. The robustness check results can be found in Appendix D.

In the renewable sources and electricity prices literature, another common way to verify the estimation results has been the addition of fuel prices (e.g., gas, coal) in regressions. Unfortunately, gas (or coal) prices are provided in daily resolutions and would need to be extrapolated to be incorporated in this research. Furthermore, it has been shown that although fuel prices impact electricity prices, they do not affect the RES estimates on them (Gelabert et al., 2011; Cludius et al., 2014; Maciejowska, 2020; Sirin and Yilmaz, 2020).

The results reported in Appendix D confirm the RES impacts obtained in previous sections. There are slight quantitative differences in the solar coefficients and variability effects in Germany, but this is to be expected due to the sensitivity of solar on the number of observations as explained earlier. Nevertheless, the final interpretation of the results is not affected by these minor differences.

7. Conclusion

The increasing variable renewable energy has become an important factor in power markets that affects market fundamentals, such as electricity prices. In this paper, a panel quantile approach is applied to investigate the distributional impact of RES on electricity prices. The analysis focuses on both the effect on electricity price levels and price variability. We apply two models, including a non-linear case through the interaction between RES and electricity demand, which draws a more accurate picture of the electricity market. We explore three demand levels – low, intermediate, and high - chosen by the unconditional quantile distribution of loads.

The results confirm the merit-order effect from wind and solar. The findings show similar patterns concerning wind power in both Denmark and Germany. Wind power shows to have a stronger impact on the lower tail of the price distribution, a result connected to market dynamics. In Germany, the renewable energy source type seems to be important for the electricity market structure. In contrast to wind, solar power impacts stronger upper electricity price quantiles. Thus, the strong interaction between renewable source types could yield important benefits to governments and organizations, if recognized and managed accordingly. Moreover, wind and solar appear to influence the electricity price median in a similar manner, limiting potential gains from the RES type interplay in the market. Our findings complement results from previous studies such as Paraschiv et al. (2014), Rintamaki et al. (2017) and Maciejowska (2020).

In this paper, the relationship between RES and price variability is also examined. The results show that wind increases price variability in both countries. While this result is already established in Germany (Paraschiv et al., 2014; Rintamaki et al., 2017), it comes as a surprise in Denmark. Rintamaki et al. (2017) has shown that the flexible electricity system structure in Denmark curtails the variability impact of wind on electricity prices. Our results imply that the strong wind influence on the low tail of electricity prices, and higher wind capacity could increase uncertainty-in the form of price variability-, although Denmark has one of the most flexible systems in Europe. When we investigate the RES impact on price variability, acknowledging potential non-linearities, we notice that the results insinuate extra information on the explored relationships. Wind power appears to increase electricity price variability for lower and intermediate demand levels, while reduces variability for high demand levels. In Germany, wind and solar seem to impact variability in a similar pattern, with solar having a stronger influence than wind for high demand.

Finally, the difference between exploiting hourly data and aggregated daily data is explored. It is shown that the results are highly diversified in both countries, and between the different renewable source type. The aggregated data appear to underestimate the RES impact on the electricity price distribution with the difference being more prominent on solar power. This suggests that solar is more sensitive on data aggregation which could emerge from the solar-specific generation patterns – solar is only available during sunlight hours. The results illustrate that exploiting higher frequency electricity data, without aggregating them, could provide significantly different information in the market. Thus, a panel setting with hourly-specific effects should be further considered in future electricity research.

The findings of this analysis are important for policy makers and practitioners since they illustrate the importance of renewable sources on the structure and operation of power markets. The results could be used by governments and organizations for different course of action. Understanding the fundamental variables that control electricity price fluctuations could help policy makers to strategically design energy plans that optimize variable renewable sources inclusion in electricity systems. For instance, regulators could consider the disproportionate impact of wind power on electricity prices and apply RES support schemes that could minimize these imbalances in the market. Another important aspect drawn by the results is the diverse impact of renewable source type (wind and solar) on electricity price levels and variability. This interaction is important to governments for regulating energy markets. They could allocate future RES infrastructure in strategic positions to improve electricity flow in the system or recognize the need to expand the electricity grid and establish stronger interconnections. Moreover, organizations could use the information on market uncertainty to discover future profit opportunities. In particular, real-option investors, such as power storage companies, could benefit from higher electricity price fluctuations. In such way, investments on flexible systems which are set to play a crucial role in market decarbonization and energy security in the following years, could be further employed

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APPENDIX A

Table A1

Diagnostic tests for Denmark and Germany.

Variable	*Denmark* Price	Wind	Load	*Germany* Price	Wind	Solar	Load
Cross-sectional dependence							
CD-Pesaran (2004)	604.041***	615.183***	668.386***	575.403***	672.018***	378.329***	685.906***
P-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Unit root							
Breitung and Das (2006)	-6.803***	-4.636***	-2.081**	-5.4454***	-6.037***	-2.725***	-3.046***
P-value	<0.01	<0.01	0.018	<0.01	<0.01	<0.01	<0.01
Breitung and Das with trend	-5.886***	-8.015***	-1.481*	-5.1245***	-8.958***	-2.369***	-3.802***
P-value	<0.01	<0.01	0.069	<0.01	<0.01	<0.01	<0.01

Notes: i) p-values close to zero indicate data are correlated across panel groups, ii) the unit root hypothesis is rejected when the p-value is lower than the chosen significance level

APPENDIX B

Table B1

Model 1 estimates with standard errors.

Variables	Quantiles 0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Denmark									
Wind	-6.159***	-5.935***	-5.782***	-5.653***	-5.534***	-5.409***	-5.273***	-5.110***	-4.848***
	(0.093)	(0.086)	(0.094)	(0.107)	(0.124)	(0.143)	(0.165)	(0.194)	(0.243)
Load	3.756***	4.971***	5.803***	6.506***	7.154***	7.833***	8.571***	9.458***	10.88***
	(0.289)	(0.232)	(0.225)	(0.238)	(0.265)	(0.308)	(0.365)	(0.431)	(0.552)
Observations	51,696	51,696	51,696	51,696	51,696	51,696	51,696	51,696	51,696
Germany									
Wind	-0.233***	-0.22***	-0.211***	-0.203***	-0.196***	-0.187***	-0.178***	-0.168***	-0.15***
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Solar	-0.131***	-0.132***	-0.132***	-0.133***	-0.133***	-0.1335***	-0.134***	-0.1345***	-0.135***
	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
Load	0.175***	0.182***	0.187***	0.19***	0.195***	0.199***	0.204***	0.209***	0.218***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Observations	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576

Notes: (i) Standard errors in parentheses computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table B2

Model 2 estimates in Denmark with standard errors.

τ	Wind			Load		
	$\beta_{1,L}^{w}$	$\beta_{2,M}^{w}$	$\beta_{3,H}^{w}$	$\beta_{1,L}^{L}$	$\beta_{2,M}^{L}$	$\beta_{3,H}^{L}$
0.1	-6.944***	-6.284***	-5.283***	4.748***	4.119***	3.445***
	(0.220)	(0.122)	(0.248)	(0.416)	(0.364)	(0.358)
0.2	-6.209***	-5.964***	-5.723***	5.630***	5.291***	5.029***
	(0.190)	(0.108)	(0.260)	(0.357)	(0.331)	(0.344)
0.3	-5.699***	-5.742***	-6.028***	6.241***	6.104***	6.127***
	(0.173)	(0.105)	(0.269)	(0.374)	(0.350)	(0.367)
0.4	-5.274***	-5.557***	-6.283***	6.752***	6.782***	7.043***
	(0.159)	(0.105)	(0.276)	(0.423)	(0.391)	(0.401)
0.5	-4.884***	-5.388***	-6.516***	7.220***	7.404***	7.883***
	(0.150)	(0.110)	(0.284)	(0.487)	(0.443)	(0.446)
0.6	-4.478***	-5.211***	-6.759***	7.708***	8.053***	8.759***
	(0.142)	(0.117)	(0.294)	(0.570)	(0.511)	(0.505)
0.7	-4.044***	-5.022***	-7.019***	8.228***	8.745***	9.694***
	(0.139)	(0.127)	(0.305)	(0.668)	(0.591)	(0.575)
0.8	-3.522***	-4.795***	-7.331***	8.854***	9.577***	10.82***
	(0.136)	(0.143)	(0.318)	(0.784)	(0.683)	(0.654)
0.9	-2.682***	-4.43***	-7.834***	9.862***	10.917***	12.63***
	(0.149)	(0.172)	(0.344)	(0.986)	(0.845)	(0.796)
Obs	51,696	51,696	51,696	51,696	51,696	51,696

Notes: (i) Standard errors in parentheses computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table B3

Model 2 estimates in Germany with standard errors.

τ	Wind			Solar			Load		
	$\beta_{1,L}^{w}$	$\beta_{2,M}^{w}$	$\beta_{3,H}^{w}$	$\beta_{1,L}^{S}$	$\beta_{2,M}^{S}$	$\beta_{3,H}^{S}$	$\beta_{1,L}^{L}$	$\beta_{2,M}^{L}$	$\beta_{3,H}^{L}$
0.1	-0.347***	-0.238***	-0.151***	-0.156***	-0.149***	-0.082***	0.215***	0.187***	0.158***
	(0.012)	(0.011)	(0.003)	(0.031)	(0.012)	(0.011)	(0.011)	(0.011)	(0.008)
0.2	-0.315***	-0.223***	-0.164***	-0.155***	-0.145***	-0.104***	0.211***	0.188***	0.169***
	(0.011)	(0.009)	(0.003)	(0.026)	(0.010)	(0.009)	(0.010)	(0.010)	(0.007)
0.3	-0.291***	-0.212***	-0.174***	-0.155***	-0.142***	-0.120***	0.209***	0.189***	0.176***
	(0.011)	(0.009)	(0.002)	(0.023)	(0.009)	(0.008)	(0.010)	(0.009)	(0.007)
0.4	-0.271***	-0.203***	-0.182***	-0.155***	-0.140***	-0.133***	0.207***	0.190***	0.183***
	(0.010)	(0.008)	(0.002)	(0.021)	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
0.5	-0.251***	-0.193***	-0.190***	-0.155***	-0.138***	-0.146***	0.205***	0.191***	0.190***
	(0.009)	(0.007)	(0.002)	(0.019)	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)
0.6	-0.231***	-0.184***	-0.198***	-0.154***	-0.136***	-0.160***	0.203***	0.191***	0.196***
	(0.009)	(0.007)	(0.003)	(0.018)	(0.006)	(0.007)	(0.008)	(0.007)	(0.006)
0.7	-0.208***	-0.173***	-0.207***	-0.154***	-0.133***	-0.175***	0.201***	0.192***	0.204***
	(0.008)	(0.006)	(0.003)	(0.018)	(0.006)	(0.008)	(0.008)	(0.007)	(0.006)
0.8	-0.181***	-0.161***	-0.218***	-0.154***	-0.130***	-0.193***	0.198***	0.193***	0.213***
	(0.008)	(0.005)	(0.004)	(0.018)	(0.006)	(0.010)	(0.008)	(0.006)	(0.007)
0.9	-0.138***	-0.140***	-0.235***	-0.153***	-0.125***	-0.222***	0.194***	0.195***	0.227***
	(0.008)	(0.004)	(0.006)	(0.022)	(0.008)	(0.013)	(0.009)	(0.007)	(0.008)
Obs	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576

Notes: (i) Standard errors in parentheses computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table B5

Daily estimates of the baseline model in Germany.

Variables	Quantiles								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Wind	-0.180***	-0.158***	-0.149***	-0.142***	-0.137***	-0.134***	-0.138***	-0.140***	-0.133***
	(0.009)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.009)	(0.014)
Solar	-0.040*	-0.063***	-0.077***	-0.081***	-0.091***	-0.099***	-0.098***	-0.121***	-0.160***
	(0.022)	(0.017)	(0.019)	(0.017)	(0.017)	(0.014)	(0.016)	(0.021)	(0.030)
Load	0.099***	0.103***	0.109***	0.109***	0.108***	0.114***	0.129***	0.133***	0.113***
	(0.019)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.020)	(0.029)
Constant	-8.965**	-8.994**	-9.351***	-7.807**	-6.119*	-5.883*	-7.059**	-4.321	4.807
	(4.249)	(3.524)	(3.489)	(3.272)	(3.248)	(3.064)	(3.407)	(4.492)	(7.109)
Observations	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149

Notes: (i) Standard errors in parentheses computed with the bootstrapped approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table B4

Daily estimates of the baseline model in Denmark.

Variables	Quantiles								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Wind	-5.641***	-4.770***	-4.302***	-4.177***	-4.092***	-4.215***	-4.433***	-4.452***	-4.676***
	(0.364)	(0.264)	(0.222)	(0.204)	(0.198)	(0.242)	(0.230)	(0.231)	(0.337)
Load	4.067***	3.465***	3.959***	4.603***	4.602***	6.153***	6.093***	6.404***	9.683***
	(1.092)	(0.790)	(0.856)	(0.776)	(0.797)	(0.699)	(0.731)	(0.959)	(1.423)
Constant	-1.607	-0.521	-0.750	-0.504	0.615	-1.183	1.083	2.722	-1.449
	(2.578)	(1.722)	(1.893)	(1.817)	(1.748)	(1.619)	(1.815)	(2.172)	(3.504)
Observations	2,154	2,154	2,154	2,154	2,154	2,154	2,154	2,154	2,154

Notes: (i) Standard errors in parentheses computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table B6

Daily estimates of model 2 in Denmark.

τ	Wind			Load		
	$\beta_{1,L}^{w}$	$\beta_{2,M}^{w}$	$\beta_{3,H}^{w}$	$\beta_{1,L}^{L}$	$\beta_{2,M}^{L}$	$\beta_{3,H}^{L}$
0.1	-5.787***	-6.092***	-5.137***	3.588	3.427*	3.341**
	(0.927)	(0.412)	(0.634)	(2.361)	(1.836)	(1.697)
0.2	-4.862***	-4.767***	-4.555***	3.518**	3.247**	3.224***
	(0.778)	(0.280)	(0.487)	(1.616)	(1.355)	(1.207)
0.3	-3.979***	-4.331***	-4.984***	4.118***	4.079***	4.682***
	(0.377)	(0.269)	(0.509)	(1.263)	(1.094)	(1.026)
0.4	-3.659***	-4.135***	-4.474***	2.822**	3.398***	3.894***
	(0.476)	(0.260)	(0.503)	(1.426)	(1.305)	(1.175)
0.5	-3.366***	-4.181***	-4.673***	2.891*	3.643***	4.357***
	(0.573)	(0.226)	(0.473)	(1.481)	(1.332)	(1.230)
0.6	-2.877***	-4.197***	-5.105***	3.981***	4.847***	5.772***
	(0.546)	(0.264)	(0.415)	(1.467)	(1.294)	(1.120)
0.7	-2.986***	-4.398***	-5.533***	4.471***	5.488***	6.414***
	(0.696)	(0.238)	(0.523)	(1.288)	(1.131)	(1.012)
0.8	-2.143***	-4.513***	-6.610***	4.799***	5.892***	7.499***
	(0.744)	(0.241)	(0.654)	(1.589)	(1.313)	(1.221)
0.9	-2.092***	-4.798***	-6.427***	7.396***	9.026***	10.575***
	(0.593)	(0.345)	(0.728)	(2.115)	(1.805)	(1.679)
Obs.	2,154	2,154	2,154	2,154	2,154	2,154

Notes: (i) Standard errors in parentheses computed with the bootstrapped approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

Table B7

Daily estimates of model 2 in Germany.

τ	Wind			Solar			Load		
	$\beta_{1,L}^{w}$	$\beta_{2,M}^{w}$	$\beta_{3,H}^{w}$	$\beta_{1,L}^{S}$	$\beta_{2,M}^{S}$	$\beta_{3,H}^{S}$	$\beta_{1,L}^{L}$	$\beta_{2,M}^{L}$	$\beta_{3,H}^{L}$
0.1	-0.312***	-0.168***	-0.125***	-0.235***	-0.034	0.004	0.120***	0.076***	0.067***
	(0.029)	(0.010)	(0.017)	(0.083)	(0.027)	(0.121)	(0.026)	(0.022)	(0.023)
0.2	-0.271***	-0.150***	-0.141***	-0.144*	-0.053***	-0.077	0.108***	0.082***	0.083***
	(0.032)	(0.009)	(0.016)	(0.075)	(0.017)	(0.089)	(0.023)	(0.019)	(0.020)
0.3	-0.241***	-0.141***	-0.137***	-0.126***	-0.069***	-0.179	0.111***	0.088***	0.095***
	(0.024)	(0.007)	(0.014)	(0.048)	(0.019)	(0.111)	(0.020)	(0.017)	(0.017)
0.4	-0.226***	-0.133***	-0.131***	-0.134***	-0.061***	-0.150	0.110***	0.088***	0.095***
	(0.021)	(0.007)	(0.013)	(0.041)	(0.018)	(0.091)	(0.020)	(0.017)	(0.017)
0.5	-0.197***	-0.131***	-0.130***	-0.177***	-0.075***	-0.159*	0.111***	0.091***	0.097***
	(0.021)	(0.007)	(0.011)	(0.041)	(0.019)	(0.089)	(0.020)	(0.017)	(0.016)
0.6	-0.190***	-0.128***	-0.131***	-0.161***	-0.082***	-0.153	0.106***	0.092***	0.098***
	(0.020)	(0.008)	(0.011)	(0.048)	(0.021)	(0.102)	(0.023)	(0.019)	(0.018)
0.7	-0.171***	-0.128***	-0.144***	-0.186***	-0.064***	-0.299**	0.141***	0.122***	0.138***
	(0.023)	(0.008)	(0.015)	(0.047)	(0.020)	(0.143)	(0.026)	(0.021)	(0.020)
0.8	-0.175***	-0.133***	-0.166***	-0.221***	-0.074***	-0.340**	0.150***	0.127***	0.149***
	(0.026)	(0.013)	(0.017)	(0.054)	(0.023)	(0.143)	(0.028)	(0.025)	(0.023)
0.9	-0.131**	-0.122***	-0.173***	-0.181*	-0.121***	-0.701***	0.083**	0.080**	0.125***
	(0.055)	(0.014)	(0.029)	(0.095)	(0.034)	(0.222)	(0.041)	(0.032)	(0.033)
Obs.	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149

Notes: (i) Standard errors in parentheses computed with the bootstrapped approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

APPENDIX C

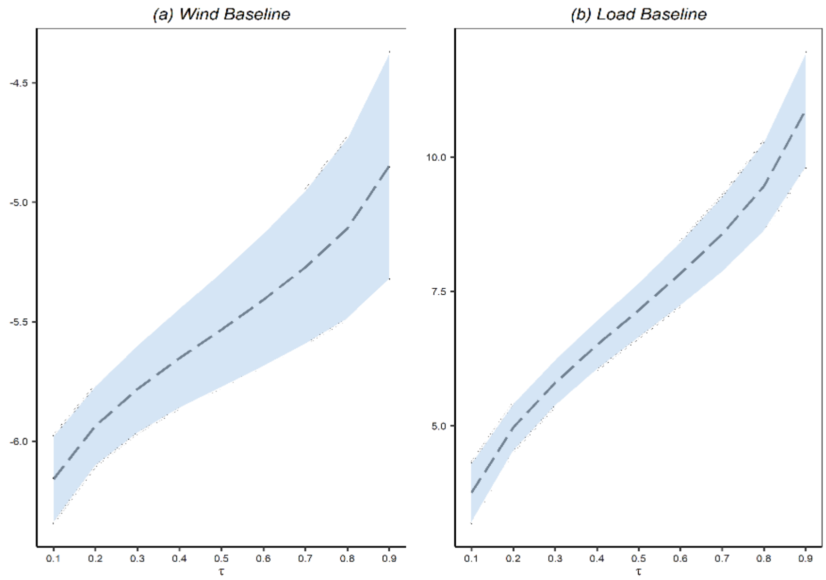

Fig. C1. Baseline model estimates in Denmark. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

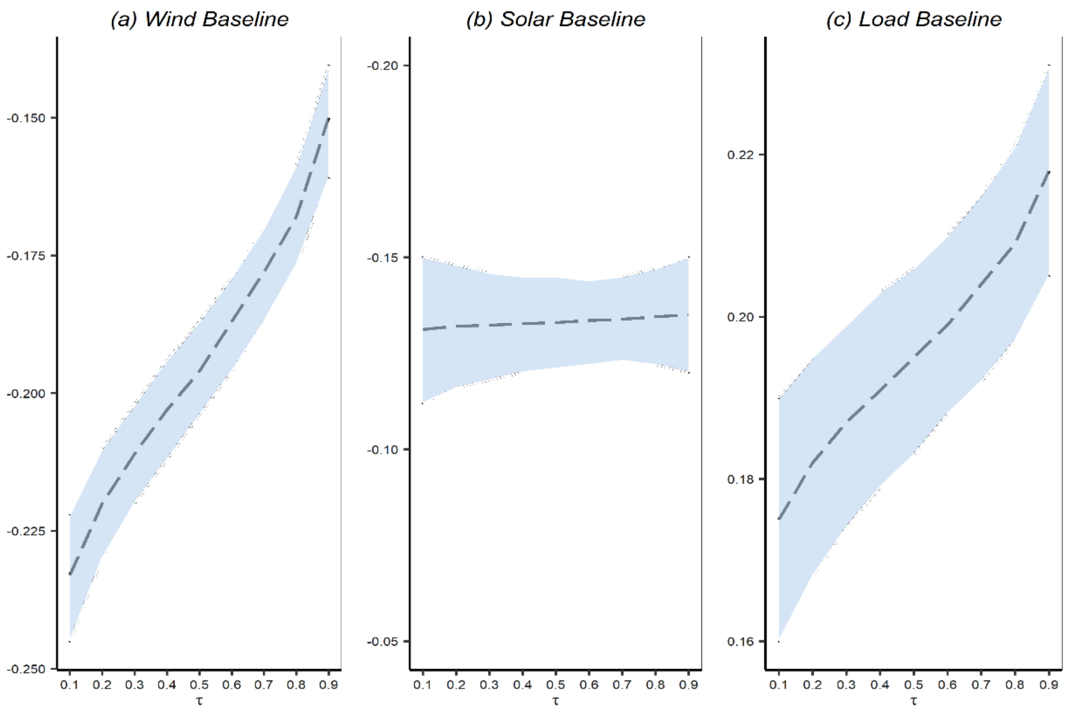

Fig. C2. Baseline model estimates in Germany. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

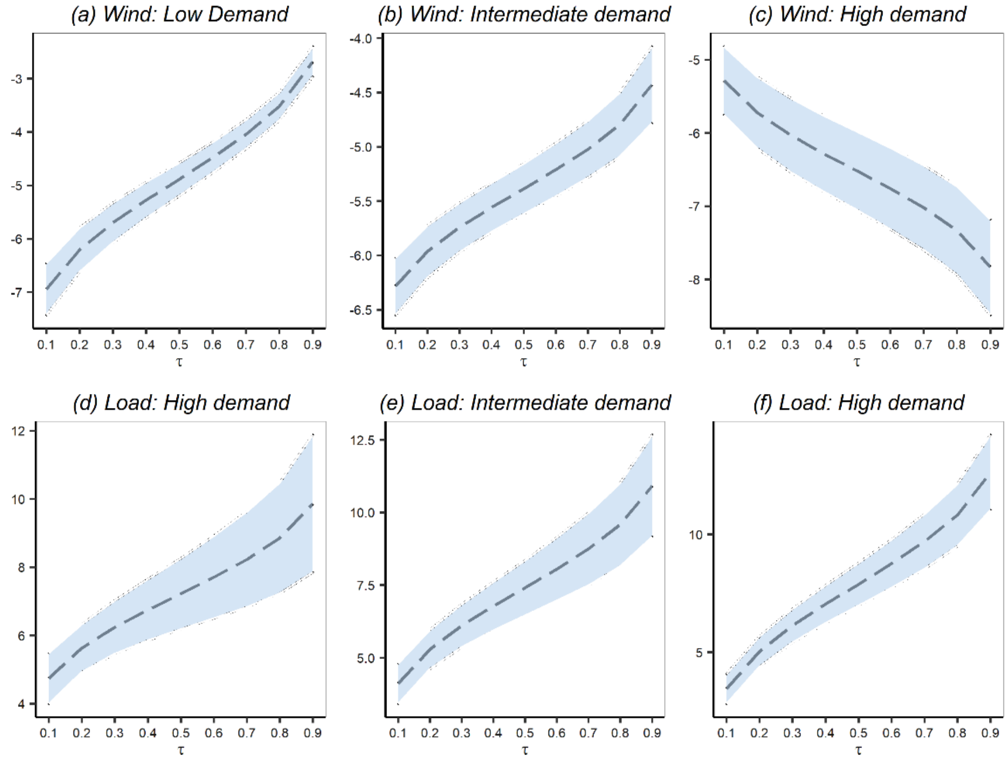

Fig. C3. Conditional on demand estimates-model 2 in Denmark. τ = 0.1, 0.2, …, 0.9 with 95% confidence intervals.

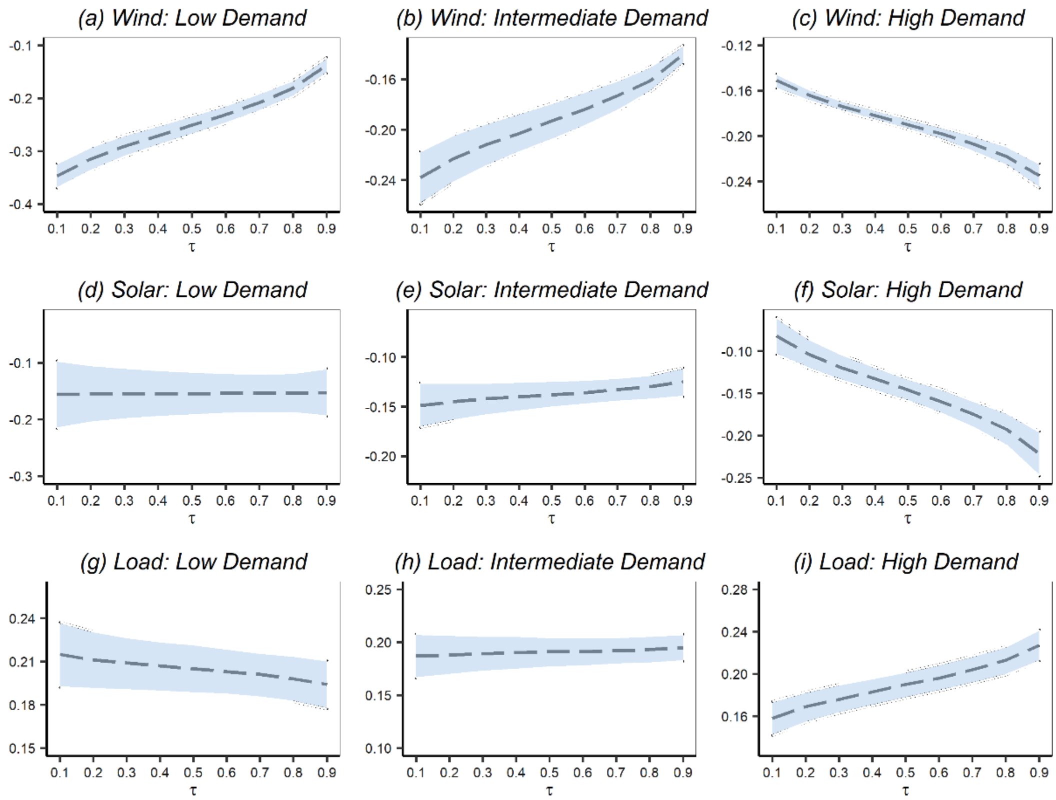

Fig. C4. Conditional on demand estimates-model 2 in Germany. τ = 0.1, 0.2, …, 0.9 with 95% confidence intervals.

APPENDIX D

Table D1

Model 2 estimates with different demand thresholds (τ = 0.2-0.8)

τ	Denmark						Germany								
	Wind			Load			Wind			Solar			Load		
	$\beta^{w}_{1,L}$	$\beta^{w}_{2,M}$	$\beta^{w}_{3,H}$	$\beta^{L}_{1,L}$	$\beta^{L}_{1,M}$	$\beta^{L}_{1,H}$	$\beta^{w}_{1,L}$	$\beta^{w}_{2,M}$	$\beta^{w}_{3,H}$	$\beta^{S}_{1,L}$	$\beta^{S}_{2,M}$	$\beta^{S}_{3,H}$	$\beta^{L}_{1,L}$	$\beta^{L}_{2,M}$	$\beta^{L}_{3,H}$
0.1	-7.014**	-6.350***	-5.184***	4.779***	4.169***	3.420***	-0.334***	-0.239***	-0.151***	-0.213***	-0.155***	-0.071***	0.217***	0.190***	0.160***
	(0.177)	(0.140)	(0.222)	(0.419)	(0.359)	(0.346)	(0.014)	(0.013)	(0.004)	(0.028)	(0.014)	(0.011)	(0.012)	(0.011)	(0.008)
0.2	-6.387**	-6.003***	-5.592***	5.612***	5.270***	4.948***	-0.304***	-0.224***	-0.163***	-0.197***	-0.150***	-0.092***	0.215***	0.192***	0.170***
	(0.157)	(0.120)	(0.232)	(0.380)	(0.336)	(0.340)	(0.012)	(0.011)	(0.003)	(0.022)	(0.012)	(0.009)	(0.011)	(0.010)	(0.007)
0.3	-5.781**	-5.762***	-5.875***	6.192***	6.035***	6.011***	-0.281***	-0.212***	-0.171***	-0.186***	-0.147***	-0.106***	0.214***	0.193***	0.178***
	(0.146)	(0.112)	(0.240)	(0.384)	(0.345)	(0.359)	(0.011)	(0.010)	(0.002)	(0.018)	(0.010)	(0.008)	(0.010)	(0.009)	(0.007)
0.4	-5.250**	-5.561***	-6.112***	6.675***	6.673***	6.897***	-0.263***	-0.202***	-0.178***	-0.177***	-0.144***	-0.119***	0.212***	0.194***	0.185***
	(0.136)	(0.109)	(0.247)	(0.408)	(0.369)	(0.386)	(0.010)	(0.009)	(0.002)	(0.015)	(0.009)	(0.007)	(0.010)	(0.009)	(0.007)
0.5	-4.968**	-5.375***	-6.331***	7.123***	7.264***	7.717***	-0.245***	-0.193***	-0.185***	-0.167***	-0.141***	-0.131***	0.211***	0.195***	0.191***
	(0.129)	(0.112)	(0.253)	(0.443)	(0.401)	(0.421)	(0.009)	(0.009)	(0.002)	(0.013)	(0.008)	(0.006)	(0.009)	(0.008)	(0.007)
0.6	-4.560**	-5.184***	-6.554***	7.580***	7.869***	8.557***	-0.226***	-0.183***	-0.192***	-0.158***	-0.138***	-0.144***	0.210***	0.196***	0.198***
	(0.124)	(0.119)	(0.261)	(0.491)	(0.444)	(0.466)	(0.009)	(0.008)	(0.002)	(0.012)	(0.007)	(0.006)	(0.009)	(0.008)	(0.007)
0.7	-4.122**	-4.977***	-6.798***	8.079***	8.527***	9.471***	-0.205***	-0.172***	-0.199***	-0.147***	-0.135***	-0.158***	0.208***	0.198***	0.205***
	(0.121)	(0.129)	(0.271)	(0.555)	(0.501)	(0.524)	(0.008)	(0.007)	(0.003)	(0.012)	(0.006)	(0.006)	(0.009)	(0.008)	(0.007)
0.8	-3.616**	-4.730***	-7.088***	8.672***	9.310***	10.558***	-0.180***	-0.159***	-0.209***	-0.135***	-0.131***	-0.175***	0.206***	0.199***	0.214***
	(0.119)	(0.146)	(0.283)	(0.634)	(0.569)	(0.591)	(0.007)	(0.006)	(0.003)	(0.015)	(0.006)	(0.007)	(0.009)	(0.008)	(0.007)
0.9	-2.782**	-4.334***	-7.554***	9.626***	10.569***	12.306***	-0.140***	-0.138***	-0.224***	-0.114***	-0.125***	-0.201***	0.203***	0.201***	0.228***
	(0.127)	(0.179)	(0.303)	(0.774)	(0.688)	(0.708)	(0.007)	(0.004)	(0.004)	(0.021)	(0.007)	(0.009)	(0.010)	(0.008)	(0.008)
Obs	51,696	51,696	51,696	51,696	51,696	51,696	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576	51,576

Notes: (i) Standard errors in paratheses computed with the bootstrap clustered approach. (ii) ***, **,* respectively denotes rejection of the null hypothesis of insignificant coefficient at 1%, 5% and 10% significance levels.

NHH

NORGES HANDELSHØYSKOLE
Norwegian School of Economics

Helleveien 30
NO-5045 Bergen
Norway

T +47 55 95 90 00
E nhh.postmottak@nhh.no
W www.nhh.no