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

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A R T I C L E I N F O

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A B S T R A C T

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. Previous research has mainly used aggregated-daily data and have applied a time-series setting. We argue that since the electricity price formation and renewable energy generation can show great variations during a day, a panel setting with 24 individuals-hours could offer higher accuracy. Therefore, we apply a panel approach that accounts for both the time and cross-sectional dimension of electricity prices. The panel allows us to control for time-invariant (hourly-specific) characteristics and can reveal hidden market dynamics that exist during a day. The combination of hourly-specific effects and the quantile approach enable us to estimate the renewable sources effect on various price quantiles while controlling for market dynamics. In this way, we investigate extreme market cases accounting for the range and distribution of the electricity prices data. 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. The results prompt us to believe that aggregated time-series tend to underestimate the RES impact on prices. In addition, we estimate the same models using hourly data in a time-series approach in order to verify that the diverse effect between aggregated time-series and hourly panel data is driven by the time-invariant characteristics, and not the data resolution. We find that the hourly time-series underestimate the merit-order effect, like in the aggregated time-series case, which supports our claims that the results are steered by the cross-sectional dimension. Thus, a panel approach could provide higher accuracy estimates of the RES influence on electricity prices. In conclusion, hourly-related features seem to affect the merit-order effect and its robustness, and a panel approach should be considered when investigating electricity markets.

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 regarding RES

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

In this article, we use a novel methodology to model power systems and show how the impact of renewable sources on electricity prices vary across their distribution depending on market dynamics. We focus on Denmark and Germany, which are appealing cases due to their high renewable penetration and distinct power features. Furthermore, investigating these two countries can allow us to compare our results with previous literature. The main advantage of using a quantile regression model is its ability to examine the relationship between electricity prices and RES across the entire price distribution. Therefore, the quantile approach allows us to 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. Bunn et al. (2016) highlight the advantages of using quantile regression to explore power prices, characterizing it as a semi-parametric method that allows the inclusion of fundamental variables. They also state that it could be used as an alternative methodology to regime-switching models. Furthermore, quantile regression does not assume a parametric distributional form for the error term (Davino et al., 2013) and allows the investigation of nonlinear relationships among variables. Overall, quantile regression could provide greater predictive accuracy and insights. It can, thus, be an important tool for market participants and stakeholders such as producers, regulators, etc., who should be able to model and gain information on the extremes of electricity prices in order to recognize market risks and adjust their actions.

The investigation of the effect of RES on electricity prices, through a quantile approach, is not a new research subject, but it has been quite spare. Nonetheless, our empirical findings contribute to the literature in various aspects. The main contribution is the use of the hourly data in a panel setting that accounts for time-invariant (or fixed) hourly effects. 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, the methodology allows us to investigate the price variability, approximated by the scale estimate. The method assumes that the scale function is linear which facilitates comparison with other methods. The scale parameter is a measure of dispersion (also called variability) and shows how spread is a distribution (Pham, 2006). Thus, the scale estimate provides information about the distributional heterogeneity of prices (Haylock, 2022) and is closely related to price variance. The MMQR approach estimates the parameter in the scale function, through which we approximate the effect on price variability. To the best of our knowledge, the electricity price variability effect has been studied only using aggregated-daily data. For instance, Maciejowska (2020) uses the Interquartile range - another measure of dispersion - based on the quantile estimates to investigate the variability effect of RES on electricity prices in Germany. Lastly, most studies apply linear quantile regression models while we incorporate non-linear effects in our approach. We would expect that the impact of renewable generation on electricity prices varies depending on the demand level. For instance, when the market struggles to accommodate the fluctuating supply by renewable generation due to lack of flexibility (storage capacity, etc.), we would anticipate the effect from RES intermittent generation to vary when demand is low (high) and renewable sources supply is high (low). Thus, we think it is important to incorporate the non-linear effects by including different demand levels in our regressions.

It would be logical to wonder about our methodological approach and the reasons for choosing it over more established time-series methods. 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. In the day-ahead market, the electricity prices are set the day prior to the delivery day. The market participants need to submit their bids before a specific time with delivery time the following day. Thus, the prices are set simultaneously for the 24 h of the following day. For instance, the bids to cover supply for hour 8 are submitted the same time as the bids to cover supply for hour 19. Therefore, the 24 determined prices correspond to the same set of information since they are determined at the exact same time. Therefore, treating day-ahead prices as a time-series could be misleading. Huisman et al. (2007) argued that day-ahead prices should be treated as a panel framework rather than a time-series. They showed that electricity prices mean-revert around a specific price level which differs over hours – especially between peak and off-peak hours. Their results unveil that day-ahead electricity prices show cross-sectional correlation among hours, and one should consider day-ahead electricity prices, in a panel framework, as the behavior of individuals (24 h) observed across time (time-series).

Previous research on the power sector has mainly used time-series models to investigate daily data or hours in isolation by choosing a representative hour based on group of hours that share similar characteristics (Hagfors et al., 2016b; Do et al., 2019; Keles et al., 2020). Some studies have focused on the daily average price of peak and off-peak hours examining the dynamics of the average price of a group of hours (Kyritsis et al., 2017; Maciejowska, 2020). All these studies ignore the cross-sectional information included in the electricity market microstructure and provide information about average or one-hour prices. Therefore, we deem important to consider these market microstructure characteristics and include the cross-sectional hourly effect in our research. But what advantages does the panel approach hold for the market? Our method suggests that group hours are heterogeneous. For instance, group hour 4 is very different than group hour 10. Time-series do not control for this heterogeneity and could obtain biased results. Hence, in a technical aspect, the panel framework allows us to control for time-invariant (group hours) characteristics. Panel data also give a large number of data points, increasing the degrees of freedom and improving the efficiency of the econometric estimates. They are also suited to study dynamic relationships based on inter-individual differences reducing the collinearity between current and former variables providing unrestricted time-adjustment estimates (Hsiao, 2007). Therefore, panels provide several methodological benefits in comparison to time-series or cross-sectional methods, providing greater predictive power and insights. The main methodological challenge for panel data with fixed effects is the incidental parameter problem. According to Nickell (1981) dynamic panel models with fixed effects are biased by $1/T$. In our case, 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.

In our case, the group hours can hide a multitude of changes such as abrupt weather changes and policy implementations that panel can help us detect. Additionally, electricity price formation and risk vary highly during the day and renewable generation can be highly diverse among hours. Thus, many market agents are exposed to dynamics that depend on hourly variation. For instance, different production plants need more accurate tools to predict electricity price levels and fluctuations, as well as the effects on the market as a whole, in order to develop efficient bidding strategies. Another important example would be flexible storage facilities which need high predictive accuracy (hence less risk) to charge (discharge) when prices are low (high). If market agents realize higher gains, the market could benefit in the long-run by increased investments in new technologies (flexible systems, demand response technologies, etc.). Therefore, in this paper we revisit electricity markets to apply a highly realistic framework that accounts for important market features and can support market participants recognize profitable opportunities and adjust to market risks.

Explaining a little bit more on the methodological approach: 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.

2. Literature review

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.

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	2.28	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	36.1	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

Endogeneity?

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, 2019; 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.

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; Clò and D'Adamo, 2015; Gullì and Balbo, 2015; de 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 Würzburg 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. Jónsson 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, 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[1] hours to stress out the diverse RES impact, within the day, on

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

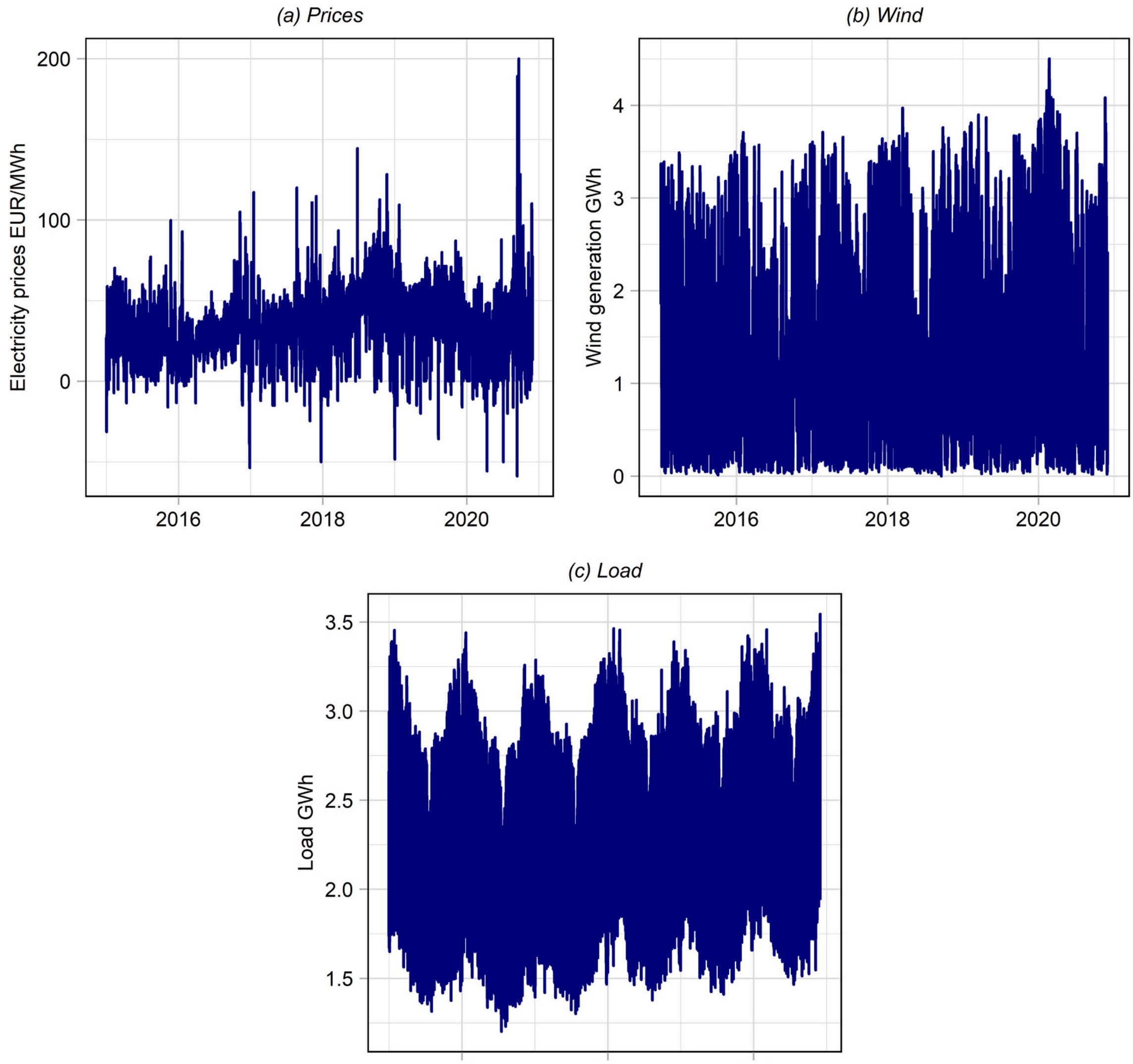

Fig. 1. Fundamental variables in Denmark.

electricity prices and their movements (Paraschiv et al., 2014; Kyritsis et al., 2017; Rintamäki 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.

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.

3. 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 51,696 h for Denmark and 51,576 h 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

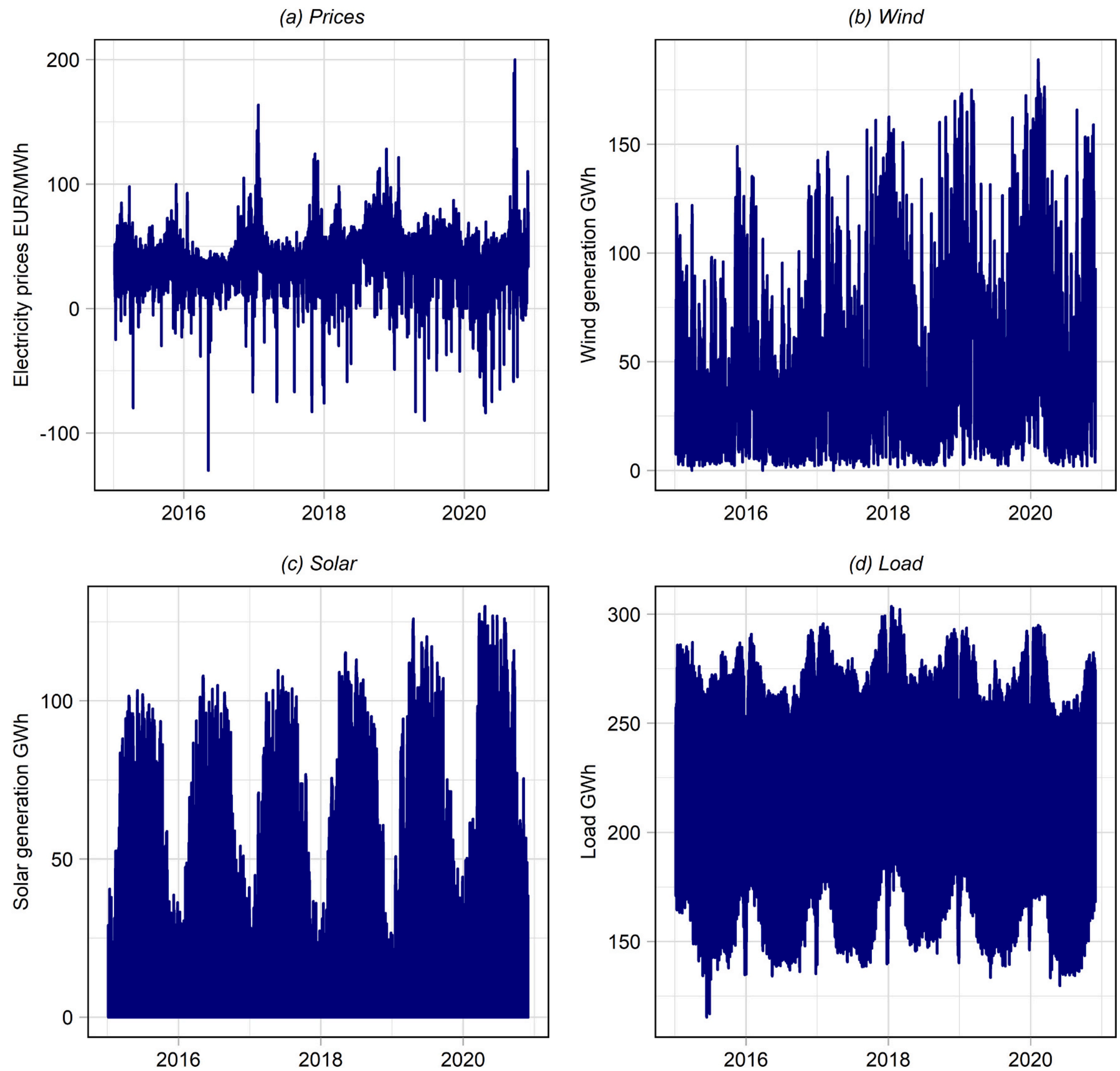

Fig. 2. Fundamental variables in Germany.

operator for the Nordic region. The hourly day-ahead prices, forecasted loads,[2] wind and solar power forecasts in Germany were retrieved from EEX and the European Network of Transmission System Operators for Electricity[3] that collects and shares information from Transmission System Operators (TSO) around Europe. For an explanation of the electricity market in Europe, refer to Appendix A.

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 B.

Another important illustration is the time-series evolution of electricity prices, RES and loads during the examined period. Figs. 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 on 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.

Lastly, in Fig. 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,

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

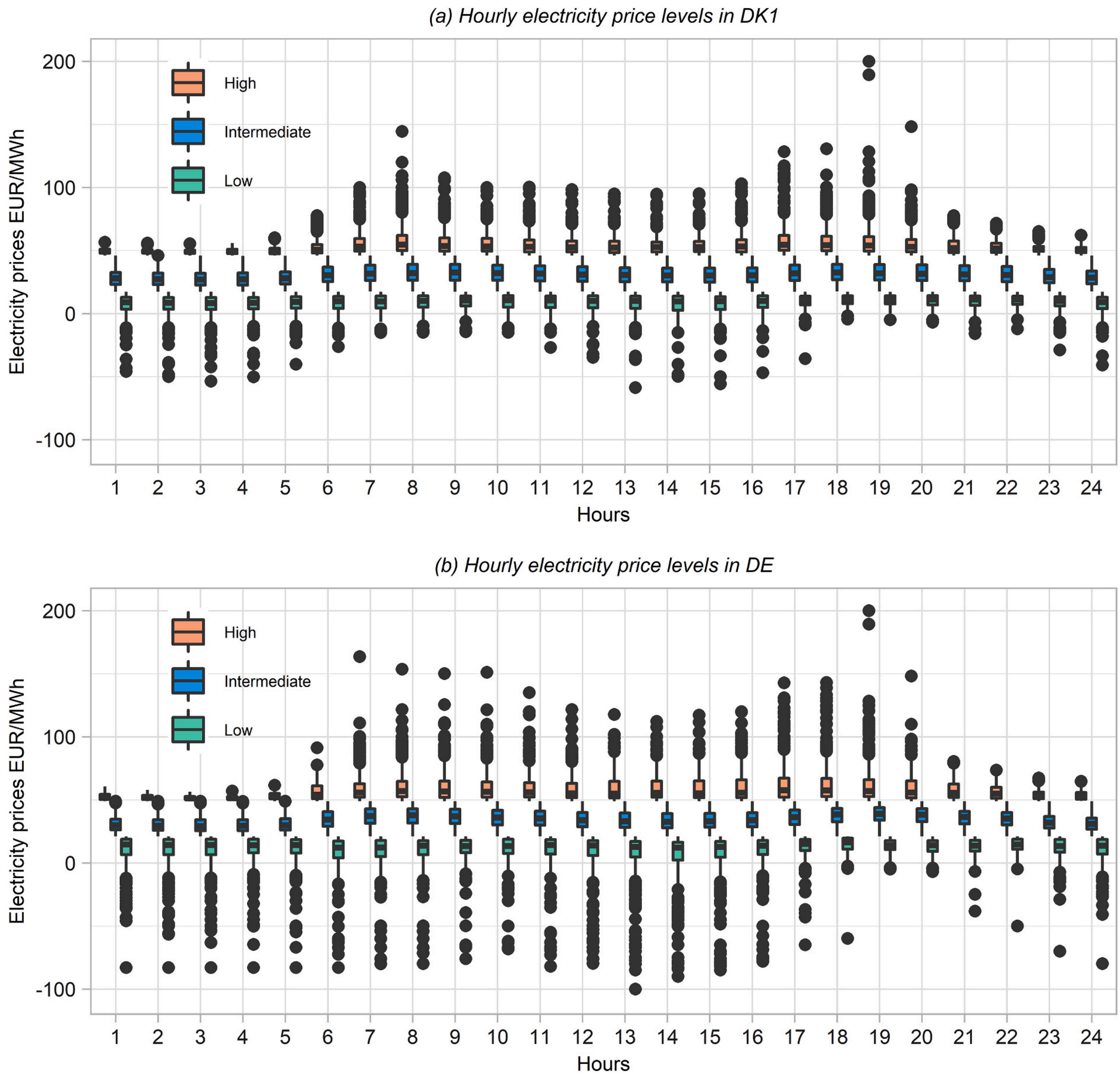

Fig. 3. Boxplots of three electricity price levels (low, intermediate, and high) for each hour of the day in a) Denmark, and b) Germany.

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.

Fig. 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.

4. Methodology

Quantile regression was introduced by Koenker and Bassett Jr (1978) and has been applied in various economic applications. It is used to estimate the predictive value of independent variables on the quantiles

 Because median instead of mean

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.

As previously discussed, the panel framework in electricity market research was initially proposed by Huisman et al. (2007). 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. They showed that 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; Peña, 2012; Keppler et al., 2016; Pham, 2019) but to the best of our knowledge has not been applied in a quantile scope.

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

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

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 $i = 1\ldots0.24$, and T with $t = 1\ldots.T$.

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[4] and C_{it} a set of binary indicators 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.

The scale parameter is a measure of dispersion (also called variability) and shows how spread is a distribution (Pham, 2006). For instance, for the normal distribution, the scale parameter corresponds to the standard deviation. According to Koenker and Zhao (1996), the scale is closely related to price variance, but provides a more natural dispersion concept. In our case, the scale effect measures how much the distribution will contract closer or expand away from the conditional mean. Thus, it can provide information about the distributional heterogeneity of prices (Haylock, 2022). The MMQR approach estimates an auxiliary regression to obtain the scale coefficients, through which we approximate the effect on price variability. Machado and Silva (2019) interpret a positive (negative) scale estimate of an independent variable, as the increase (decrease) in the dispersion of the observed dependent variable. Thus, this specification and estimation of the scale function can provide information on how the regressors affect elements of the conditional distribution that we are interested in, not focusing only its central tendency. Maciejowska (2020) used the Interquartile range – another measure of dispersion – to evaluate the effect of RES on the variability of electricity prices. There are some studies in other fields that interpret the scale estimate from the MMQR approach in a similar manner as us (Ike et al., 2020; Polemis, 2020; Haylock, 2022). Henceforth, the term price variability used in the rest of the paper refers to the scale coefficients drawn by the model.

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: $D_{1it} = 1_{L_{it} \le L(\tau_L)}$, $D_{2it} = 1_{L(\tau_L) < L_{it} < L(\tau_H)}$ and $D_{3it} = 1_{L_{it} \le L(\tau_L)}$ 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 F.

Eq. (1) then becomes:

$$Q_p(\tau) = (a_i + \delta_i q(\tau)) + \sum_{m=1}^{3} \beta_m^L L_{mit} + \sum_{m=1}^{3} \beta_m^W W_{mit} + \sum_{m=1}^{3} \beta_m^S S_{mit} + + \theta_1 P_{i,t-1} + \theta_2 P_{i,t-7} + \varphi C_{it} + Z_{it}' \gamma q(\tau) \tag{2}$$

interaction terms!!

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 (2009, 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.

5. Results

5.1. Distributional effects 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

[4] We assume that wind and solar generation are exogenous in our model since they are dispatched with regulatory priority and their production depends on weather conditions. For more information see Mauritzen (2013).

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 results imply that although, there is a global RES impact on electricity prices, this impact is heterogeneous depending on price levels and renewable energy source type. 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. 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.

Focusing on 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. Additionally, the load seems, as expected, to increase electricity prices in all quantiles with a higher impact on upper quantiles. More demand during peak hours means steeper curve is engaged

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. interaction terms = non linearities

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.

Table 3
Baseline model 1 location and scale estimates. dispersion

Baseline Model (1)	Location average	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.

5.2. Distributional effects 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.

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 results suggest that both renewable sources impact similarly the median of electricity prices but not the tails of the distribution. 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.

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.

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. More

Table 4
The estimates of the demand level model 2.

τ	Denmark			Germany					
	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.

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.

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 D.

Although our results reflect the well-known merit order effect, our estimates diversify from previous research that uses individual hours or aggregate time-series methods. Focusing on the extensively researched case of the German electricity market, we can notice that empirical results have been underestimated or overestimated compared to our findings. Regarding the median of the electricity price distribution, a stronger effect of renewable sources on prices has been found in contrast to our results (Cludius et al., 2014). When individual hours are investigated an underestimation of the renewable sources effect for most hours in different quantiles has been revealed (Hagfors et al., 2016b; Do et al., 2019). On the other hand, Maciejowska (2020) has shown that solar power has a much stronger effect on upper price quantiles than in lower quantiles which is in contrast with our research findings. Specifically, we illustrate that considering the hourly-specific characteristics, the merit-order effect could be uniform for all price quantiles. This could be reasonable since solar power generation patterns reveal a great dependence on the hour of the day due to the sunlight. Thus, we consider the addition of the hourly fixed effects a potential to provide higher accuracy outcomes. In the next section, we clarify that our results differ from previous findings due to the time-invariant (hour-specific) characteristic, rather than the high frequency of the data.

Research to date has measured price variability in various ways, using different frequencies, and reaching diverse findings (for instance Ketterer, 2014; Rintamäki et al., 2017; Maciejowska, 2020). Therefore, even if our measure of variability differs greatly from previous studies, we still think it is important to highlight the differences in our results, and the potential implications for electricity research. Kyritsis et al. (2017) has shown that solar has a significant negative impact on price variability in Germany, considering daily aggregated data, but no significant effect in off-peak hours. On the other hand, we illustrate that solar has no significant relationship with the electricity price variability. Furthermore, we show that solar generation reduces price variability only when demand is high, while Maciejowska (2020) demonstrates that solar has a stronger negative and statistically important impact when demand is intermediate. These differences could provide crucial evidence on the dependence of solar generation on the hour of the day and its characteristics. In the case of Denmark, Rintamäki et al. (2017) have presented, using daily data, that wind power decreases price volatility in Denmark while we have revealed the opposite effect. Therefore, the diverse results steer us to think that the cross-sectional dimension plays an important role in RES and electricity research and should be considered in future research. In the following section we directly analyze the results between the panel and time series approach and describe the benefits of our chosen method.

6. Daily time-series vs hourly panel data

A large portion of the literature has employed aggregated daily (time-series) 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 time-series model and discuss the findings. 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 C4, C5, C6 and C7 in Appendix C.

Fig. 5 illustrates the baseline Method of Moments Quantile Regression (MMQR) and daily estimates for wind, solar and load in Germany.

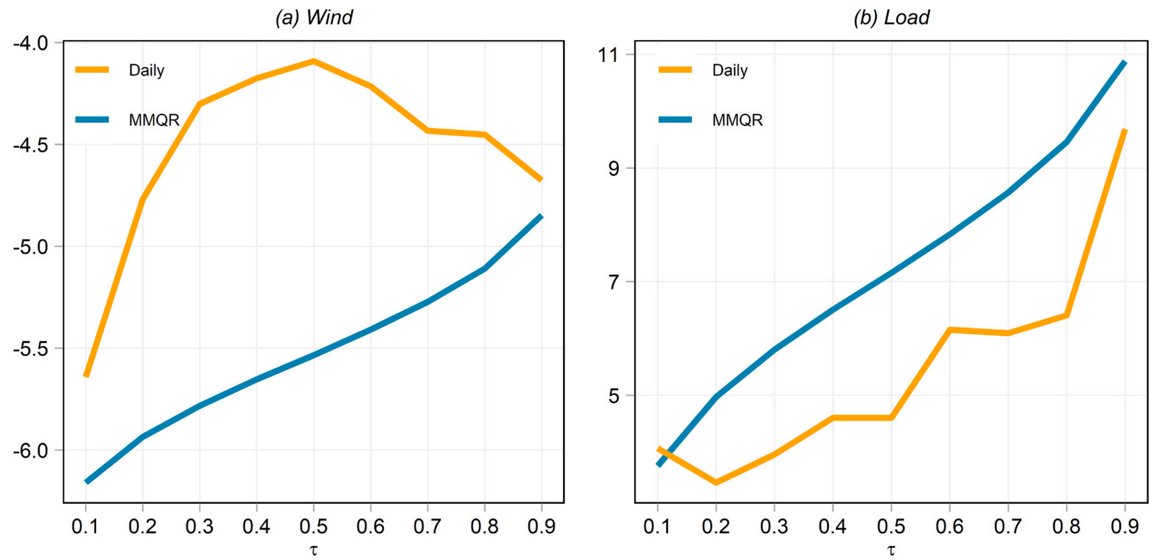

Fig. 4. Baseline model 1 daily vs MMQR estimates in DK1.

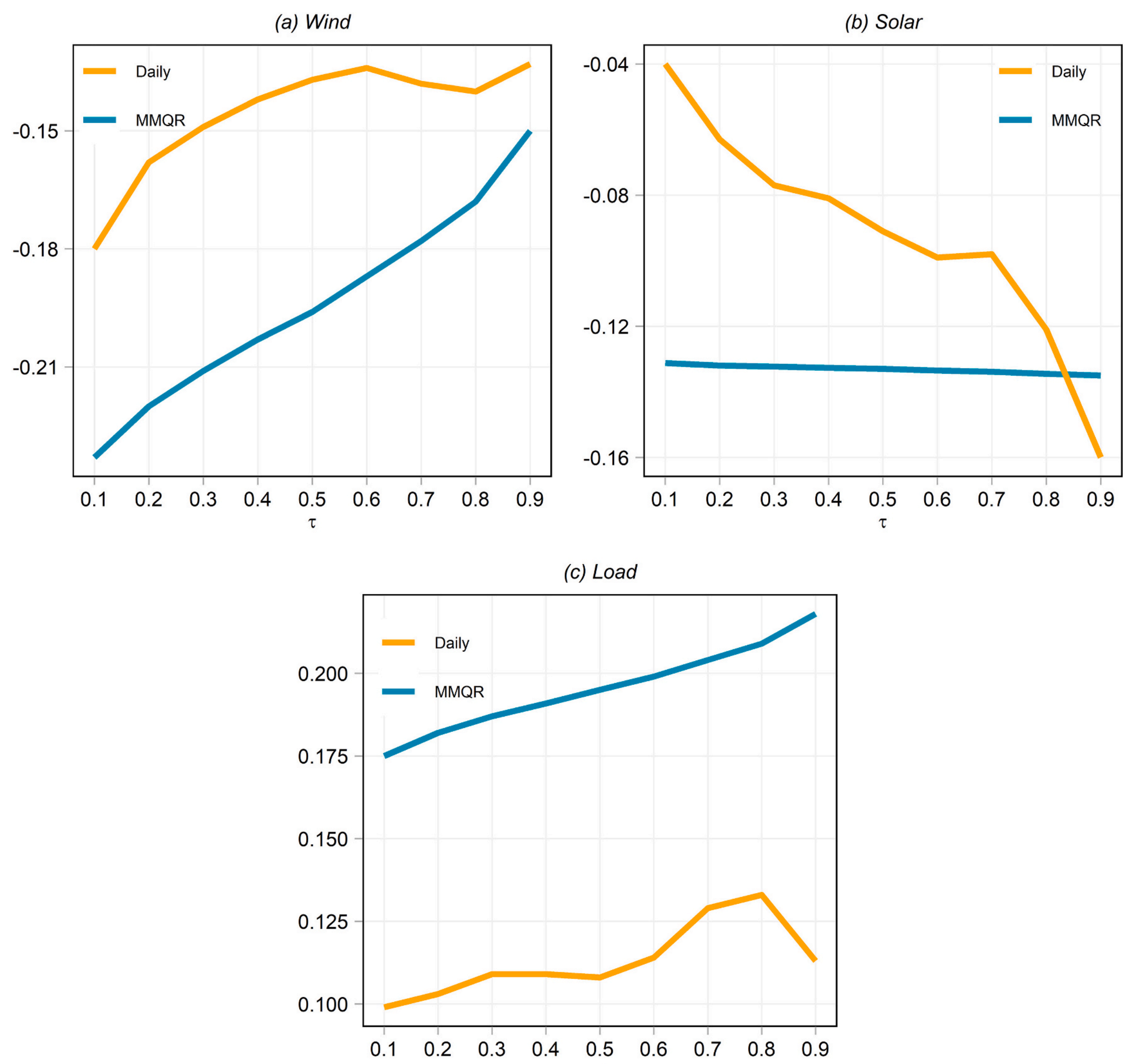

Fig. 5. Baseline model 1 daily vs MMQR estimates in DE.

Fig. 6. Model 2 – conditional on demand daily vs MMQR estimates 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. Fig. 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. 6 demonstrates the non-linear MMQR model and daily time-series 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 (Fig. 7) is explored, it is observed that for low demand the two

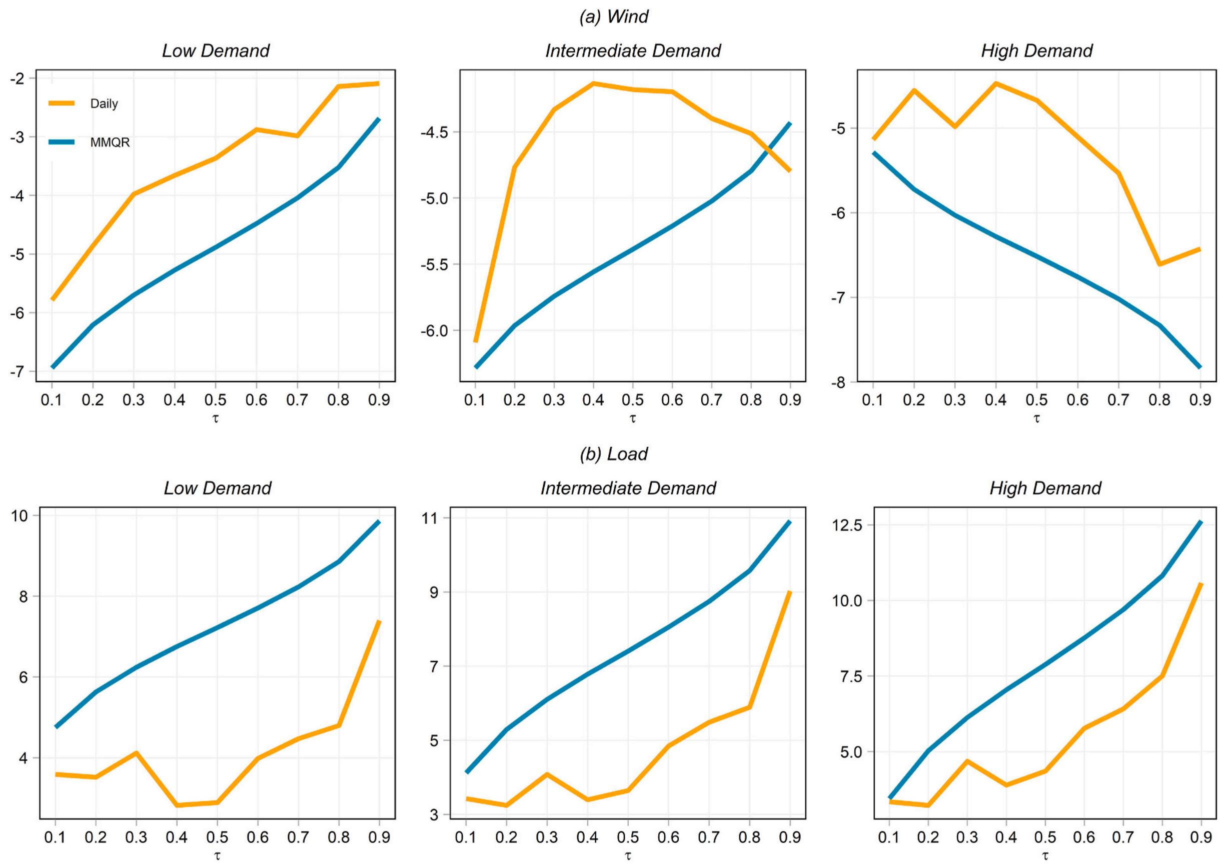

Fig. 7. Model 2 – conditional on demand daily vs MMQR estimates in Denmark.

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.

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.

Since it is well-known that higher data resolution could provide more accurate estimates, we used the hourly data in a time-series setting,[5] without aggregating them, and estimated the same models as in the aggregated case[6](see Appendix E). The hourly time-series results appear to be similar to the aggregated findings, but they suggest a smoother effect of RES across the price quantiles. Thus, using the hourly-data in a time-series setting would still yield underestimated RES impacts on the electricity price quantiles. This prompts us to believe that the difference between the aggregated and hourly results originates from the chosen methodology and the inclusion of the hour-specific characteristics in the panel approach, and not from the higher data resolution. Hence, we believe that future research should account for the cross-sectional dimension in the data and use a panel approach to investigate the RES influence on electricity prices.

After analyzing the time-series (aggregated and hourly) results and the panel outcomes, we believe that our chosen method offers many benefits in comparison to time-series (aggregated or not). Firstly, using the hourly data resolution provides a higher informative setting, than time-series data, that results in improved efficiency of the econometric estimates. Renewable energy production can strongly diversify among hours, thus including this hourly variation offers valuable information in the analysis. Thus, through the panel approach we can identify and measure impacts that are not detectable in pure time-series data. Secondly, electricity price formation and risk vary highly during the day, for instance extremely low or high prices. Electricity is a unique commodity that needs to be produced and consumed simultaneously, and that does not have high storage capacity. Therefore, the field should be investigated through a dynamic approach that utilizes all the information that is disclosed in the data. The panel approach allows us to control for time-invariant characteristics that exist between hour groups while time-series focus only on the time dimension and do not recognize this cross-sectional dimension. The panel approach and its higher prediction accuracy can offer wider and more precise information about the dynamics in power markets. In this way, market participants such as producers, regulators, etc., can use this methodological tool to efficiently adjust to existing risks and recognize future profit opportunities.

[5] We thank an anonymous reviewer for the recommendation. The insightful comment made the section more interesting and strengthened our claims for choosing this methodological approach.

[6] In the introduction and the methodological part, we argue that using the hourly data in a time-series setting could provide inaccurate estimates since the method does not account for the cross-sectional dimension between the variables. Thus, we are using the time-series to illustrate that our results do not originate from the higher data resolution but the inclusion of the hourly-specific effect.

7. 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 F.

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 F 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.

8. 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.

Previous research has used electricity prices in daily resolution or investigated individual hours of the day. In our paper, we argue that group hours are heterogeneous (Huisman et al., 2007), and we should choose a methodology that can account for this heterogeneity. The main contribution of our research is the use of the hourly resolution electricity data in a panel approach, considering the cross-sectional dimension of the data. The panel approach, using hourly electricity prices and RES, can give more informative data and include the dynamic characteristics of power markets. Furthermore, it allows for the control of time-invariant (group hour) characteristics that are embedded in the cross-sectional dimension of electricity prices. Therefore, we believe that the panel setting provides better predictions which is of high value since electricity is considered as a unique commodity since supply and demand needs to be continuously balanced. Thus, through this novel methodological approach we attempt to provide important insights of the power market and improve the operations and decisions made by market participants. The additional information revealed by the panel approach, compared to traditional time-series, can support future investments in flexible system assets such as demand-response technologies, and ensure that long-term sustainability goals in the energy sector can be reached.

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.

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; Rintamäki et al., 2017), it comes as a surprise in Denmark. Rintamäki 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. In order to verify that the differences between the aggregated time-series and the hourly panel results are not driven by the higher frequency data resolution, we also use the hourly data in a time-series setting and estimate the same models as in the aggregated-daily case. The results show that using hourly data in a time series manner would still yield underestimated RES effects on the electricity price distribution (as in the aggregated-daily case). Therefore, these findings prompt us to believe that the time-invariant (hourly-specific) effect plays an important role in the market and support our claims that it 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.

CRediT authorship contribution statement

Kyriaki Tselika: Conceptualization, Methodology, Software, Data curation, Visualization, Investigation, Writing – original draft, Writing – review & editing.

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Appendix A

The electricity markets in Europe.

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 h 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 price through a marginal price setting procedure (Huisman et al., 2014). Electricity prices can be affected by generation capacity, transmission constraints and meteorological factors (Nord Pool, 2021). 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.

Appendix B

Table B1
Diagnostic tests for Denmark and Germany.

Variable	*Denmark*			*Germany*			
	Price	Wind	Load	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 (2005)	−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 C

Table C1
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									
	−6.159***	−5.935***	−5.782***	−5.653***	−5.534***	−5.409***	−5.273***	−5.110***	−4.848***
Wind	(0.093)	(0.086)	(0.094)	(0.107)	(0.124)	(0.143)	(0.165)	(0.194)	(0.243)
	3.756***	4.971***	5.803***	6.506***	7.154***	7.833***	8.571***	9.458***	10.88***
Load	(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									
	−0.233***	−0.22***	−0.211***	−0.203***	−0.196***	−0.187***	−0.178***	−0.168***	−0.15***
Wind	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
	−0.131***	−0.132***	−0.132***	−0.133***	−0.133***	−0.1335***	−0.134***	−0.1345***	−0.135***
Solar	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
	0.175***	0.182***	0.187***	0.19***	0.195***	0.199***	0.204***	0.209***	0.218***
Load	(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 C2
Model 2 estimates in Denmark with standard errors.

τ	Wind			Load		
	$\beta^{w}_{1,L}$	$\beta^{w}_{2,M}$	$\beta^{w}_{3,H}$	$\beta^{L}_{1,L}$	$\beta^{L}_{2,M}$	$\beta^{L}_{3,H}$
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 C3
Model 2 estimates in Germany with standard errors.

τ	Wind			Solar			Load		
	$\beta^{w}_{1,L}$	$\beta^{w}_{2,M}$	$\beta^{w}_{3,H}$	$\beta^{S}_{1,L}$	$\beta^{S}_{2,M}$	$\beta^{S}_{3,H}$	$\beta^{L}_{1,L}$	$\beta^{L}_{2,M}$	$\beta^{L}_{3,H}$
0.1	−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 C4
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
	−5.641***	−4.770***	−4.302***	−4.177***	−4.092***	−4.215***	−4.433***	−4.452***	−4.676***
Wind	(0.364)	(0.264)	(0.222)	(0.204)	(0.198)	(0.242)	(0.230)	(0.231)	(0.337)
	4.067***	3.465***	3.959***	4.603***	4.602***	6.153***	6.093***	6.404***	9.683***
Load	(1.092)	(0.790)	(0.856)	(0.776)	(0.797)	(0.699)	(0.731)	(0.959)	(1.423)
	−1.607	−0.521	−0.750	−0.504	0.615	−1.183	1.083	2.722	−1.449
Constant	(2.578)	(1.722)	(1.893)	(1.817)	(1.748)	(1.619)	(1.815)	(2.172)	(3.504)
Observations	2154	2154	2154	2154	2154	2154	2154	2154	2154

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 C5
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	2149	2149	2149	2149	2149	2149	2149	2149	2149

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 C6
Daily estimates of model 2 in Denmark.

τ	Wind			Load		
	$\beta^{w}_{1,L}$	$\beta^{w}_{2,M}$	$\beta^{w}_{3,H}$	$\beta^{L}_{1,L}$	$\beta^{L}_{2,M}$	$\beta^{L}_{3,H}$
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.	2154	2154	2154	2154	2154	2154

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 C7
Daily estimates of model 2 in Germany.

τ	Wind			Solar			Load		
	$\beta^{w}_{1,L}$	$\beta^{w}_{2,M}$	$\beta^{w}_{3,H}$	$\beta^{S}_{1,L}$	$\beta^{S}_{2,M}$	$\beta^{S}_{3,H}$	$\beta^{L}_{1,L}$	$\beta^{L}_{2,M}$	$\beta^{L}_{3,H}$
0.1	−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.	2149	2149	2149	2149	2149	2149	2149	2149	2149

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 D

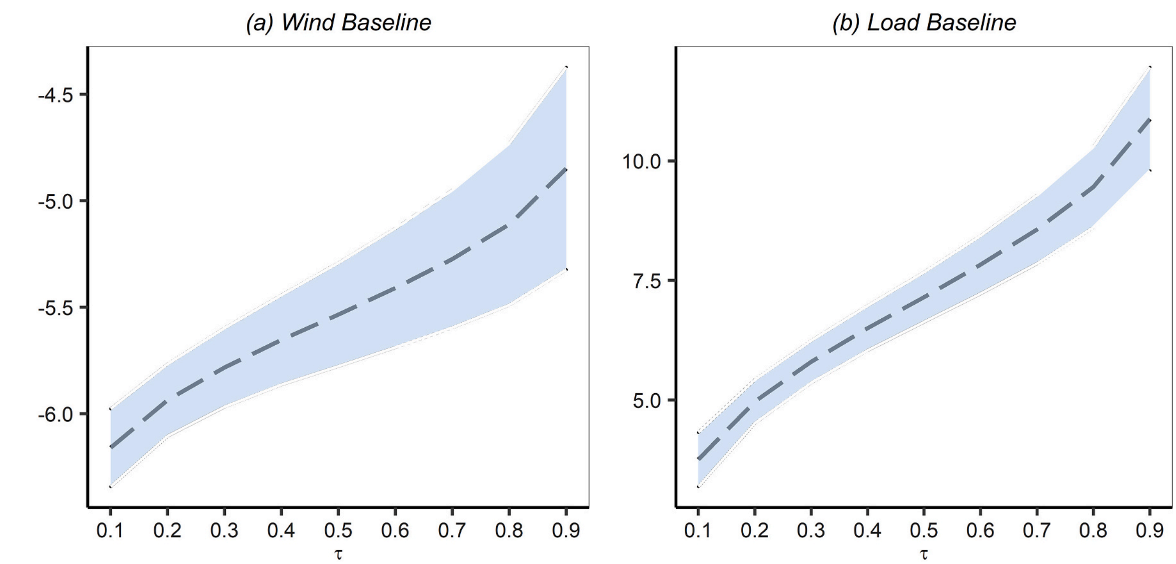

Fig. D1. Baseline model estimates in Denmark. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

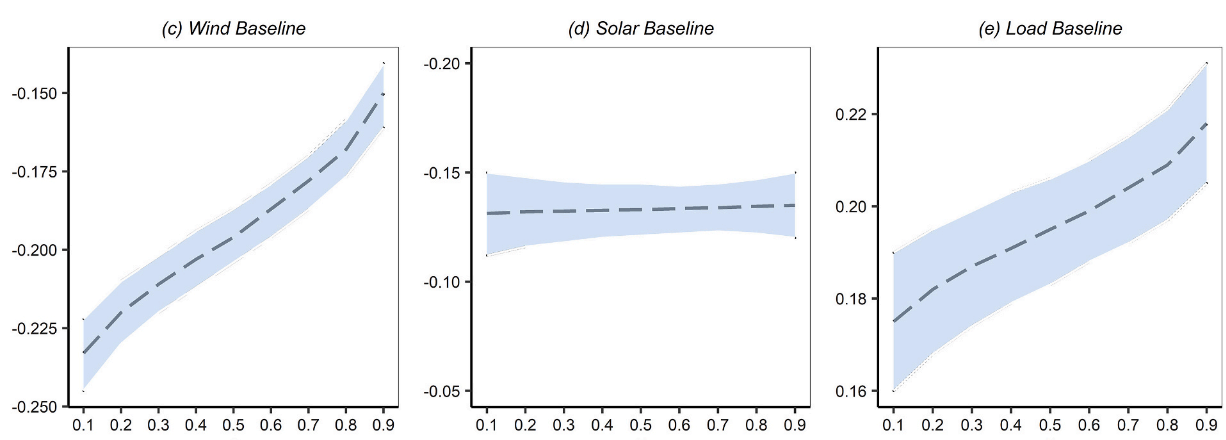

Fig. D2. Baseline model estimates in Germany. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

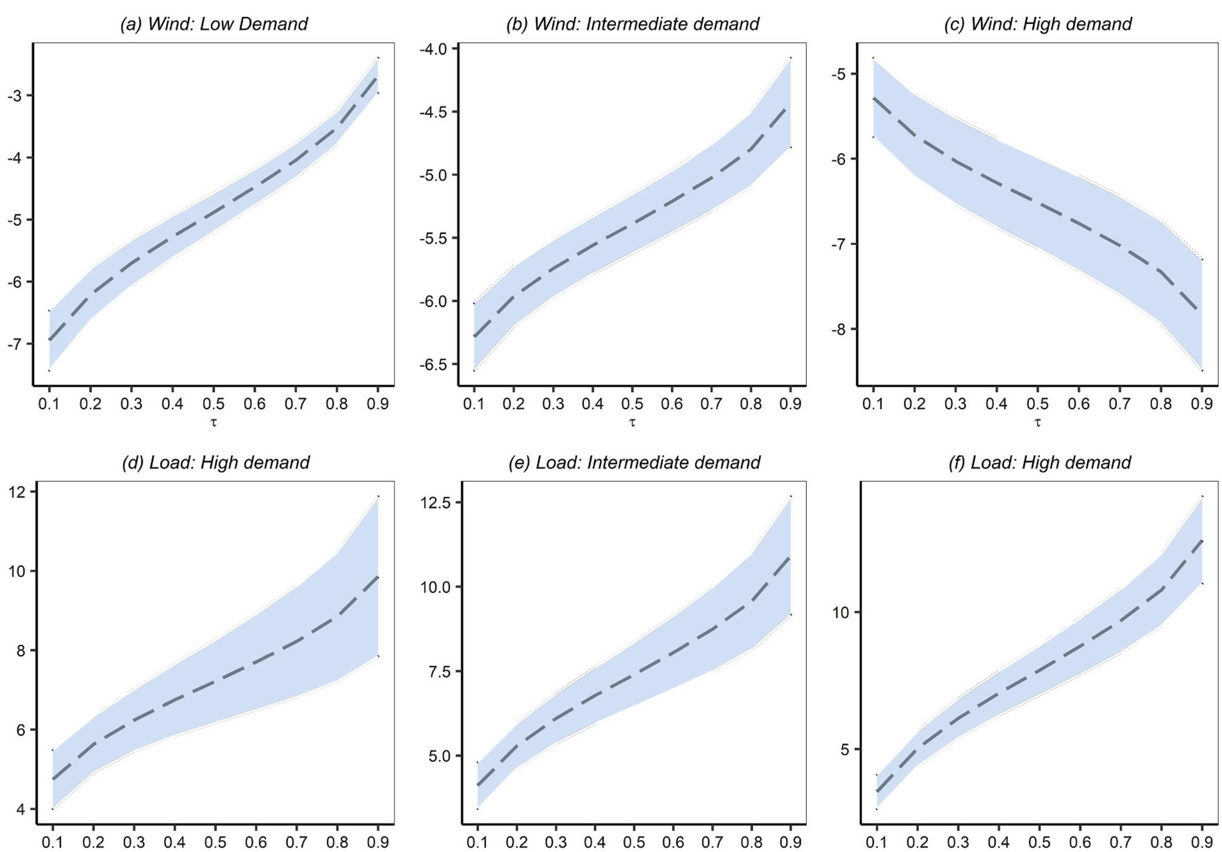

Fig. D3. Conditional on demand estimates-model 2 in Denmark. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

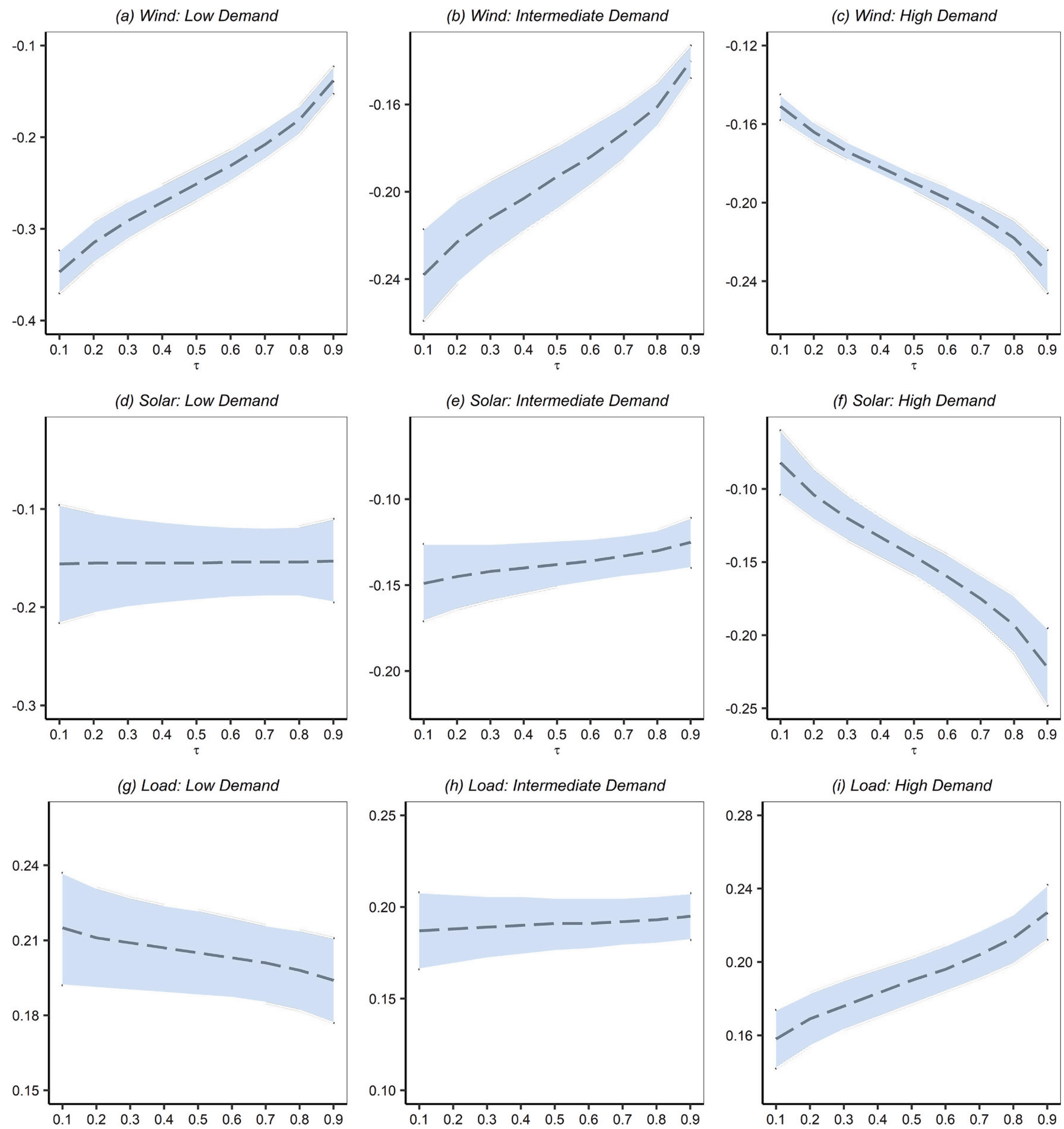

Fig. D4. Conditional on demand estimates-model 2 in Germany. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

Appendix E

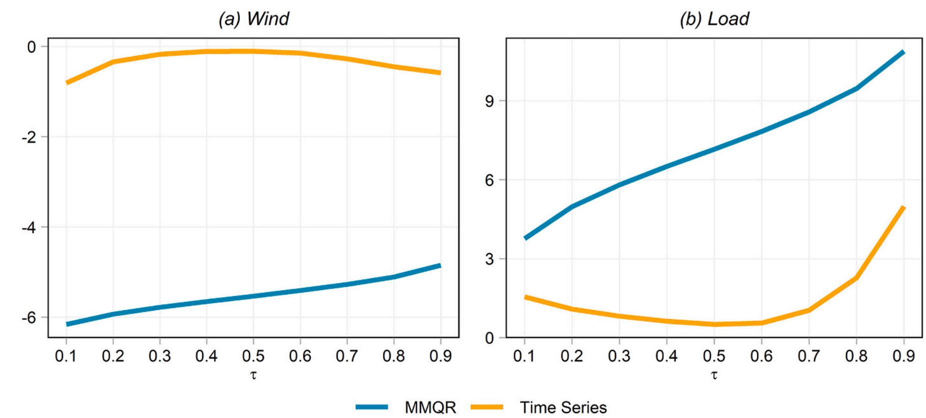

Fig. E1. Model 1 estimates in Denmark using the hourly data in a time-series setting. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

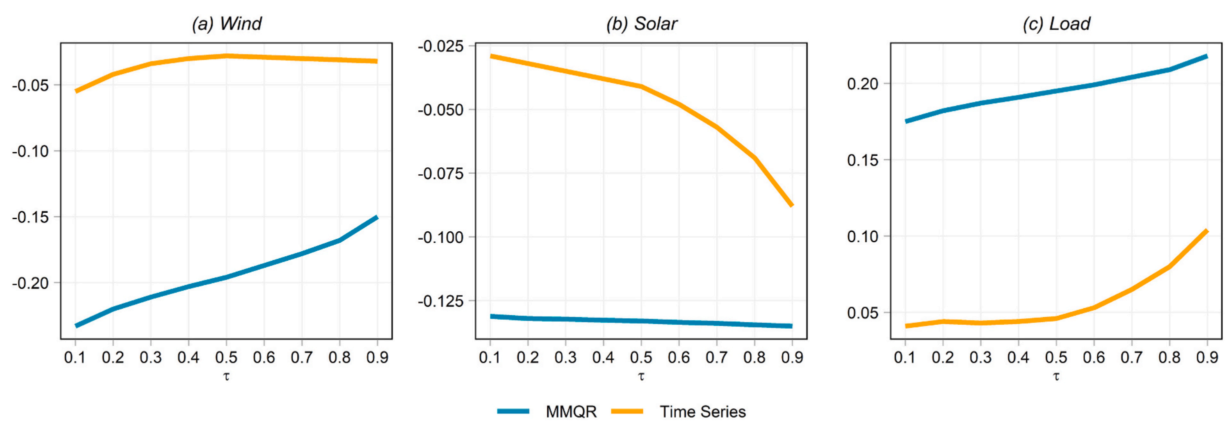

Fig. E2. Model 1 estimates in Germany using the hourly data in a time-series setting. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

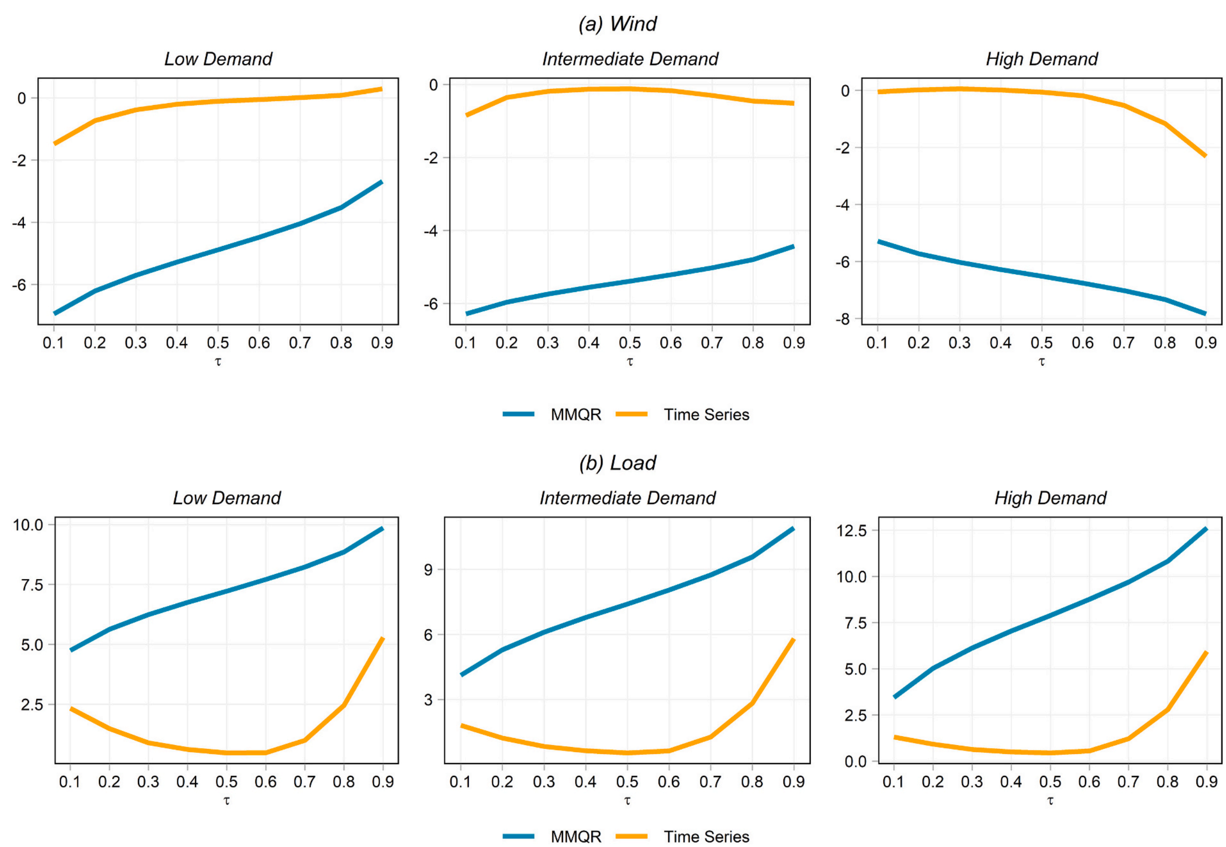

Fig. E3. Model 2 estimates in Denmark using the hourly data in a time-series setting. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

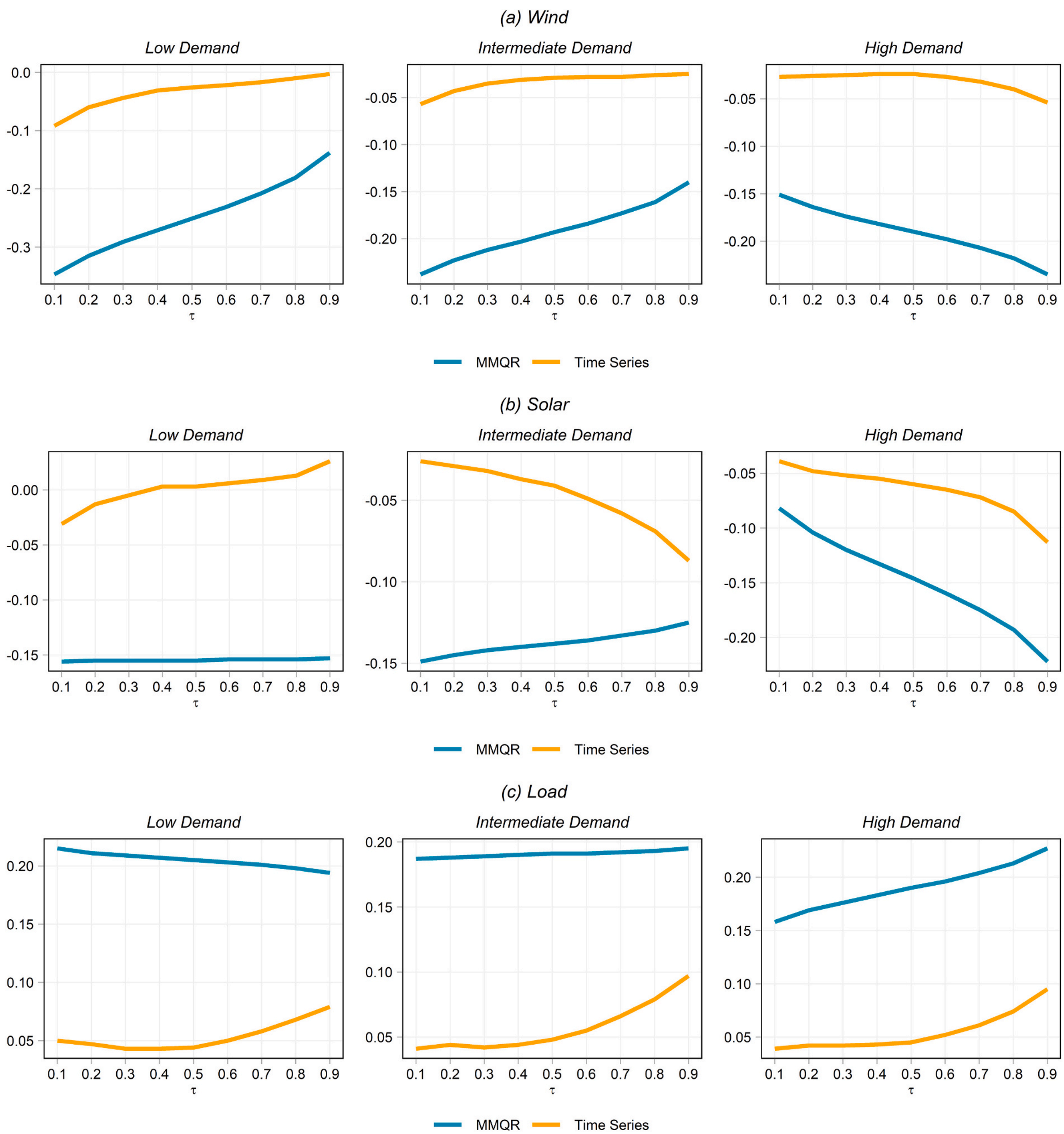

Fig. E4. Model 2 estimates in Germany using the hourly data in a time-series setting. $\tau = 0.1, 0.2, \ldots, 0.9$ with 95% confidence intervals.

Appendix F

Table F1
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)
	−6.287***	−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***
0.2	(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)
	−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***
0.3	(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)
	−5.359***	−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***
0.4	(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)
	−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***
0.5	(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)
	−4.569***	−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***
0.6	(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)
	−4.133***	−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***
0.7	(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)
	−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***
0.8	(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)
	−2.783***	−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***
0.9	(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.

Appendix G. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106194.

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