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REVISITING SHORT-TERM PRICE AND VOLATILITY DYNAMICS IN DAY-AHEAD ELECTRICITY MARKETS WITH RISING WIND POWER

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REVISITING SHORT-TERM PRICE AND VOLATILITY DYNAMICS IN DAY-AHEAD ELECTRICITY MARKETS WITH RISING WIND POWER

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ABSTRACT

This paper revisits the short-term price and volatility dynamics in day-ahead electricity markets in consideration of an increasing share of wind power, using an example of the Nord Pool day-ahead market and the Danish wind generation. To do so, a GARCH process is applied, and market coupling and the counterbalance effect of hydropower in the Scandinavian countries are additionally accounted for. As results, we found that wind generation weakly dampens spot prices with an elasticity of 0.008 and also reduces price volatility with an elasticity of 0.02 in the Nordic day-ahead market. The results shed lights on the importance of market coupling and interactions between wind power and hydropower in the Nordic system through cross-border exchanges, which play an essential role in price stabilization. Additionally, an EGARCH specification confirms an asymmetric influence of the price innovations, whereby negative shocks produce larger volatility in the Nordic spot market. While considering heavy tails in error distributions can improve model fits significantly, the EGARCH model outperforms the GARCH model on forecast evaluations.

Keywords: Wind power, day-ahead price, volatility, GARCH

JEL: C32, L94, L52

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1. INTRODUCTION

Since the last decade, the share of wind power in electricity generation has been rapidly increasing and foreseen to continuously increase due to its positive environmental and economic externalities. For instance in Europe, in order to ensure the transition from fossil fuel-based power generation to renewable energy sources (RES), the European Commission aims at raising the share of RES in final energy consumption to 20% by 2020 (EC, 2009) and to at least 27% by 2030 (EC, 2014). Consequently, the rise of wind energy supply brings various challenges to current energy systems since wind power generation is highly variable and poorly predictable, and these characteristics have great influences on the evolution of electricity day-ahead markets (i.e. spot markets). Therefore, to understand these new aspects of price and volatility dynamics calls for a reexamination of electricity day-ahead markets in consideration of high penetration of wind power in generation mix.

Among numerous countries with well-developed wind power, early deregulation and investments have contributed to today's considerable share of wind power in Denmark (IRENA, 2013). The Nordic wholesale electricity market, namely Nord Pool Spot, has been a liberalized system with relatively long history. For these reasons, Denmark and the Nord Pool day-ahead market appear to be an ideal case to study the dynamics of the wholesale electricity market under the impacts of wind generation. Using hourly data from Denmark and Nord Pool Spot, the present paper has two purposes. First, it examines the impacts of wind power generation and electricity cross-border exchanges on price and volatility dynamics in the Nordic electricity day-ahead market. Purposely, a generalized conditional heteroscedasticity (GARCH) process is applied to analyze price volatility with exogenous market drivers. One of the novelties of this paper is that as a particular fundamental of the Nord Pool market, cross-border exchanges are further distinguished into market coupling flows between Nord Pool and other spot markets, and net import flows to Denmark from Sweden and Norway. The latter term is of importance to capture the technical substitution between wind power and hydropower in the abovementioned Nordic countries. Second, it models electricity prices and concentrates on price and volatility evolutions driven by both market-specific fundamentals and electricity price series' specific characteristics. As many scholars have pointed out that modeling electricity prices and volatility is not a trivial task due to electricity's idiosyncrasies such as non-storability and constrained transmission capacities, the resulting electricity prices often show pronounced seasonality at multiple levels, high and asymmetric time-varying volatility and short-lived jumps and spikes (Knittel and Roberts, 2005; Mugele et al., 2005; Liu and Shi, 2013). The forecasting performance of purely statistical models is inadequate, partially due to the occurrences of abrupt price fluctuations that can only be pre-indicated by relevant exogenous variables rather than historical price patterns (Karakatsani and Bunn, 2008). Given the intermittent nature of wind power, these fluctuations can be especially related to or exaggerated by the variations of wind power generation. Therefore, an adequate prediction model should take account all together of seasonality, market-fundamental drivers and proper statistical distributions of the price series.

The contributions of the present paper are at least trifold. First, the paper explores the specific characteristics of the Nord Pool market and gives an insight into the impacts of wind power, cross-border coupling and internal power exchanges on the day-ahead market. In this regard, it accentuates the roles of market fundamentals in price and volatility determination, suggesting that the analysis of price evolutions should be hence market-specific. Particularly for the first time in econometric literature, the Nordic-specific balancing effect between the Danish wind export and the Norwegian and Swedish hydro import is modeled. As will be shown later, the interactions between these two generating technologies result in stabilizing the day-ahead prices, proving the importance of this specific market driver to Nord Pool. Regarding the impact of wind penetration on spot prices in an economic sense, high level of wind supply in the system is expected to dampen wholesale prices on average in electricity spot markets. This phenomenon is commonly recognized as a merit order effect. It occurs when high penetration of wind power pushes some conventional plants with high marginal costs out of generating profile and thus depresses market prices, as wind power is dispatched prior to other technologies when it is at disposal given its advantages from nearly zero marginal costs and subsidy programs. Furthermore, there may be congestions in transmission system, especially during the periods when wind penetration is high. This will lead to a separation of different areas in one single market, additionally lowering spot prices in congested regions (EWEA, 2010). In contrast to the impacts on wholesale prices, the influences of the development of wind generation on price volatility have received less attention. As the amount of electricity generated from wind power is highly dependent on meteorological conditions, wind power can be considered as exogenous shocks to electricity supply. For periods when wind power output is large, wholesale prices will be low, even negative for some extreme cases.[2] However, for periods when wind output is low, flexible plants must be activated to satisfy end-users' demand. [3] Associated high ramping and marginal costs as well as exercise of market power may create price spikes that may reach a higher level than the price level without wind power fed in the system at all. In other words, peak load plants are usually preferred when production from intermittent power is low given the advantage of flexibility comparing to mid-merit plants.[4] However, this case is reversed in the Nordic system because of the abundant hydro resource, which grants Denmark a natural tool to cope with undirected variations of wind output. Owing to this fact, price and volatility dynamics in Nord Pool needs to be examined under the influence of wind power while bearing in mind the interactions of generating technologies in adjacent countries. These specificities are reflected in our price and volatility models in order to obtain accurate market inferences and price forecasts.

Second, besides the consideration of price and volatility drivers, the paper applies deasonalization and various GARCH processes in order to define an accurate model to predict means and volatility of electricity prices. More precisely, we explore the asymmetric impacts of price shocks and price series' heavy-tail distributional property on time-varying conditional volatility, and suggest that there is a tradeoff between considering extreme prices as a fundamental-driven phenomenon and as a stochastic behavior of the price series itself.

Third, in contrast to the studies using daily-frequency data of wholesale prices or wind output, which conceal diurnal profiles, the current paper applies hourly data and this is especially important referring to wind power. In the Nord Pool day-ahead market, electricity is traded hourly. Therefore, using the data at the availably highest frequency can help us to better understand the particularities of wind power. The nature of intermittent energy displays distinct patterns of output each hour and thus the intraday variations of output can be large, compared with power demand for example, whose intraday patterns are more predictable. To this end in order to investigate the instantaneous impact of wind power and obtain meaningful short-term predictions of the day-ahead market, one cannot overstate the importance of using data with hourly frequency, whereas seldom econometric studies have explored this facet of the story regarding to wind power generation.

The rest of the paper is organized as follows. Section 2 summarizes the literature on price forecasts and impacts of intermittent energy on electricity spot markets. Section 3 introduces Nord Pool Power Exchange and wind power in Denmark, and then describes the dataset to be used. Section 4 provides frameworks of deseasonalization and estimation models employed in this study. Empirical results and discussions are presented in Section 5 and finally Section 6 concludes.

2. LITERATURE REVIEW

The complexity of electricity price has motivated many scholars to carry out a number of studies on price forecasts. Since electricity cannot be economically stored and demand is almost inelastic,

[2] Negative spot prices are observed infrequently in European Energy Exchange (EEX), mainly covering the French and German markets, as a result of the growth of electricity production from RES generators, whose revenues are ensured by fixed tariffs. For more details, see Fanone et al. (2013).

[3] See for example, Delarue et al. (2011) apply a portfolio theory model to show that deployment of wind power requires the need for sufficiently flexible technologies to deal with the fluctuation of wind power output. Bushnell (2010) argues that increasing reliance on intermittent resources causes firms to turn to more flexible and more expensive plants. Meanwhile, he also points out that the added costs associated with fluctuating end-use demand can be greatly mitigated if consumers can be more responsive to prices.

[4] Generally, base load plants include hydro, nuclear and lignite power plants; mid-merit plants are coal-fired and combined-cycle combustion gas turbines (CCGT); peak load plants consist of open-cycle gas turbines, oil or gas plants. For details on cost classification of different types of technologies, see IEA (2010).

electricity spot prices often exhibit seasonality, serial correlations, mean reverting, spikes, skewness and heavy tails (Jónsson et al., 2010). The rich econometric literature on price forecasts includes mean-reverting models (Huisman et al., 2007), regime-switching models (Huisman, 2003, 2008; Janczura and Weron, 2010; Bordignon et al., 2013), nonlinear least square models (Lucia and Schwartz, 2002) as well as time-varying parameter regression models (Karakatsani and Bunn, 2008). Furthermore given the background in which electricity spot markets have shown extensive volatility since the deregulation of electricity markets, autoregressive conditional heteroskedastic (ARCH) (Engle, 1982) or GARCH (Bollerslev, 1986) processes become commonly used to model the volatility of electricity prices (e.g. Worthington et al., 2005; Sadorsky, 2012). Despite different types of GARCH models have been exploited, there is no consensus on the most suitable GARCH specification for modeling electricity price volatility (Thomas and Mitchell, 2005; Liu and Shi, 2013). On the contrary to the differed choices of GARCH specifications, the properties of time-evolving heteroskedasticity and volatility clustering of electricity prices have been validated by several scholars (Knittel and Roberts, 2005; Garcia et al., 2005; Higgs, 2009), suggesting that a GARCH process is adequate and appropriate to model electricity price volatility in day-ahead markets. As spot prices often demonstrate heavy tails, non-Gaussian distributions were also proposed to capture this aspect (Mugele et al., 2005). However the common goal of the price forecasting literature is to merely show that the employed models yield satisfying predictive performance for electricity spot prices without tracing the influences of specific market fundamentals such as renewable generation and cross-border trades.

On top of price forecasts, as wind power becomes increasingly competitive and raises more and more challenges to the electricity system, effort has also been made on modeling the displacement of generating technologies brought by merit order effect and the incentives to invest in different generation technologies, ranging from gas to thermal, under the envisaged growth of RES use. For example, Forrest and MacGill (2013) show that wind penetration in the Australian electricity market is negatively correlated with the wholesale price and has greater effects at high levels of demand. This point of view is shared with Ciarreta et al. (2014) for the case of Spain, as well as with Traber and Kenfert (2011) for the case of Germany, although the main technologies to be replaced considered in these studies are different. Related to price volatility, some scholars have explored the impact on wholesale price stability caused by wind deployment and found increased price variations when electricity markets rely on a large share of intermittent generation (Green and Vasilakos, 2010; Steggals et al., 2011; Woo et al., 2011; Jacobsen and Zvingilaite, 2010; Twomey and Neuhoff, 2010). Their results are interpreted as a threat to the reliability of overall electricity supply resulting from fluctuations of wind output. Consistent with former evidence, Ketterer (2014) illustrates very recently that the growth of wind power in Germany reduces the mean of day-ahead prices but raises the volatility in the EEX spot market. However the study is carried out with daily average data and thus blocks out the possibility of intraday variations of spot prices and wind output, despite that accounting for these could be influential given the nature of wind feed-in. On the contrary to the results of the abovementioned studies, Jónsson et al. (2010) claim for the case of Denmark West bidding area, through a non-parametric method, diminishing intraday price variations caused by wind penetration. Regarding Denmark and the Nord Pool system, some additional work has also been dedicated to the implementation and the integration of wind power, from the perspectives of macroeconomics (Sperling et al., 2010), geographical aggregation (Østergaard, 2008) and end-user demand responsiveness (Grohnheit et al., 2011). Munksgaard and Morthorst (2008) recognized that facing higher volatility risk-averse investors would be reluctant to invest in wind installation in Denmark after a high feed-in tariff scheme was replaced by a new tariff scheme aiming at a smooth transition from a guaranteed price to a market price for wind producers. However none of these studies has explicitly quantified the impacts of large wind penetration on the day-ahead market or examined the variations of market signals facing wind intermittency.

The lack of evidence on the short-run links between wind power and wholesale electricity markets calls for a reexamination of their relationships with intraday data. The present paper differs from all previous studies and fills the gap on seeking this link between day-ahead market performance and wind generation by reflecting on the specific market design of Nord Pool and its particularities on generation mix where cross-border transmissions and strategic hydro storage are essential for system stabilization. Additionally as mentioned in Section 1, most up-to-date econometric work that involves electricity price forecasts or impacts of intermittent technologies has used the average of daily wholesale prices or daily-frequency data. By doing so, such specifications tend to conceal intraday patterns of spot prices and especially the ones of wind output. Therefore, the current paper contributes to literature by predicting electricity prices and volatility with high-frequency data in relation with wind deployment and also examining other influential factors in the determination of their relationships.

3. MARKET SETTINGS AND FUNDAMENTALS

In this section, we describe the market settings of the Nord Pool Spot electricity market and the development of wind power in Denmark, which inspire us on choosing the most representative market fundamentals to analyze the short-run dynamics of the Nord Pool day-ahead market. Besides fluctuations in wind power output, we show that net coupling inflows to Nord Pool from other markets and net power exchange flows to Denmark from other Scandinavian countries are the two fundamental drivers of the Nordic day-ahead market. In the end, the dataset used for this study is introduced and various properties of the price series and wind output are analyzed.

3.1. The Nord Pool Spot and system price

Nord Pool Spot operates the Elspot day-ahead market, along with the Elbas intraday market and N2EX financial market[5] in the Nordic (Denmark, Finland, Norway and Sweden) and Baltic (Estonia, Latvia and Lithuania) regions. [6] At Elspot, the hourly system price is calculated on the basis of equalizing aggregate supply and demand represented by bids and offers for the entire trading region. Gate closes at 12:00 CET, which is the deadline for submitting bids for power that will be delivered in the following day for the period of midnight to midnight. Because of transmission constraints, the Nordic market is divided into various bidding areas with mostly area prices being different from system prices to reflect transmission scarcities. Therefore, the system price denotes an unconstrained market-clearing price since the trading capacities between the bidding areas have not been taken into account in finding this price. Although the system price does not depend on the internal transmission scarcity of Nord Pool, it is certainly influenced by external market coupling flows from other European spot markets, i.e. Germany and the Netherlands[7]. Therefore, the analyses carried out in the present paper are based on the Nord Pool system price accounting for net market coupling flows between Nord Pool and other spot markets in order to examine the overall impacts of wind power on the wholesale system.

3.2. Wind power in Denmark

By the end of 2013, Denmark had achieved 4792MW of wind power capacity with an annual average rate of 33.2% of wind power in final consumption, by far the largest share of any country in the world. The rest of the electricity generation almost all comes from Combined Heat and Power (CHP) plants. By 2003, all wind generators were connected to the grid. The remuneration was made up of the market price plus a premium. After the booming of wind generation installation in the 1990s, the wind power development stagnated once the feed-in-tariff was abandoned in 2004. According to the data from the Global Wind Energy Council (GWEC, 2014) between 2004 and 2008 the Danish wind capacity was only added by 129MW. In 2009, there was a significant increase in new installation of wind power capacity as a combined result from the development of offshore wind power and

[5] N2EX was formerly based in the UK and is wholly owned by Nord Pool Spot since October 2014. For more details on Elbas and N2EX, see http://www.nordpoolspot.com.

[6] The Elspot bidding areas are opened in Estonia in 2010 and in Latvia in 2013. Elbas is introduced in both Latvia and Lithuania in 2013.

[7] The Netherlands is connected to Norway.

reinforced supports for new wind turbines (DEA, 2010).[8] In 2011, the Danish government set an ambitious target of 50% wind energy in electricity consumption by 2020 as part of its long-term strategy to achieve 100% independence from fossil fuels in the national energy mix by 2050 (DEA, 2014). Fig. 1 demonstrates the annual development of the national production, gross consumption as well as the shares of wind power in Denmark between 2009 and 2013. The proportions of wind generation in gross consumption and total production have been steadily growing since 2009. While the annual gross consumption stays relatively stable, the total power production in Denmark varies each year. As the rationale will be explained later in section 3.3, for example, a lower total production in 2012 corresponds to a rather wet year with respect to other years in Scandinavia, which allows Denmark to import more electricity produced by hydropower from Sweden and Norway in order to lower its domestic production from fossil fuels.

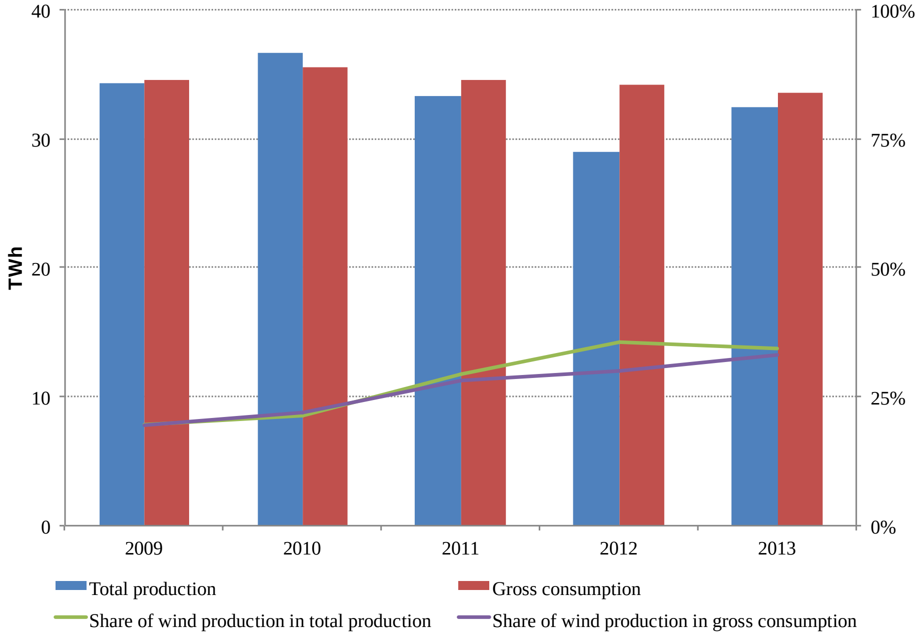


Fig. 1: Evolutions of total production, gross consumption and wind power generation in Denmark. Data source: Author's calculation based on energinet.dk (2015).

3.3. Substitution between wind power and hydropower

In Elspot, Denmark is divided into two bidding areas: Denmark West (DK1) and Denmark East (DK2). The two areas have extensive connections with neighboring countries but had little exchange between them until 2010 (Østergaard, 2008). Fig. 2 illustrates the international connections and transmission capacities between Denmark and other neighboring countries. By 2014, both DK1 and DK2 have built up a prominent level of transmission capacities to the north with the Scandinavian countries as to the south with Germany. The only connection between western and eastern Denmark is the Great Belt Power Link, commissioned in 2010 with a transmission capacity of 600MW. The inauguration of the Great Belt Link also signified the end of era of complete separation between the two Danish bidding regions.

[8] According to the Danish Promotion of Renewable Energy Act that came into force in 2009, electricity produced by onshore wind turbines that connected to the grid on or after 21 February 2008 is paid a supplement of DKK 0.25 per KWh additional to market prices. As for the supplement paid to electricity produced by offshore wind power, a process of government tender determines the amount.

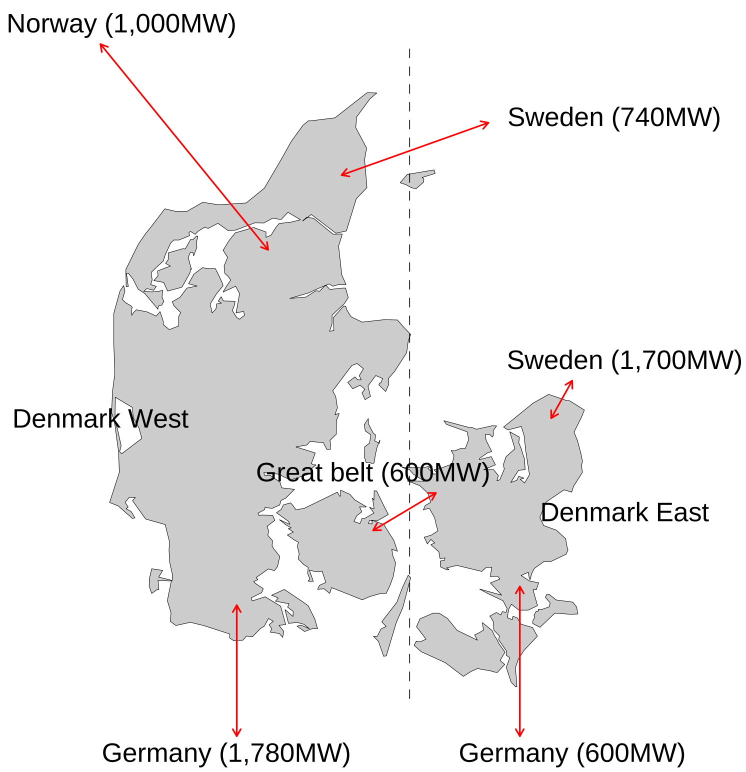


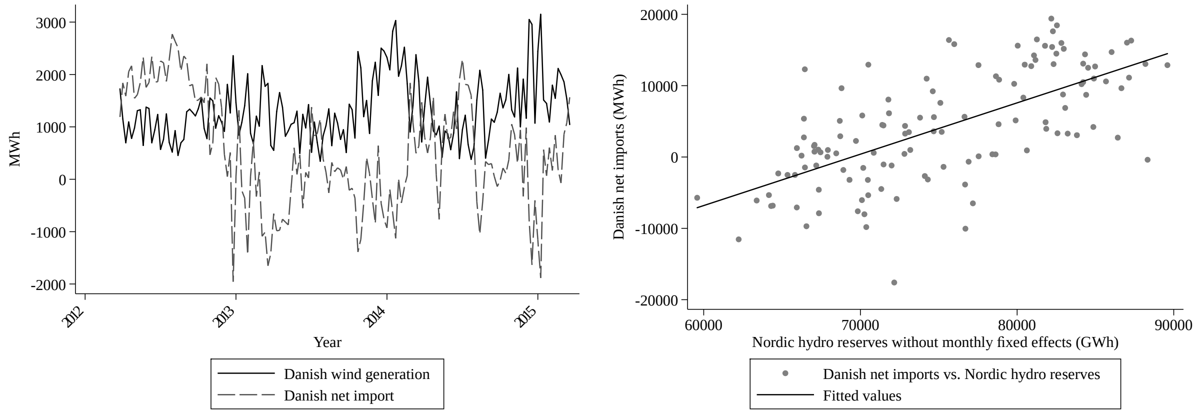
Fig. 2: Cross-border connections and transmission capacities between Denmark and neighboring countries. Data source: Author's realization based on energinet.dk (2015).

As seen in Fig. 2, Denmark is well connected to its neighboring countries—Germany, Norway and Sweden—and the latter two have a high proportion of hydro generation.[9] The Danish strategy to handle the varying wind output is to coordinate with available hydropower in Norway and Sweden through its imports and exports (Green, 2012). By exchanging power produced by wind farms with hydro, the opportunity cost foregone is the expected cost of hydro generation, while the quantity of water stored in hydro reservoir changes from a rainy season to a dry season on a yearly basis. Therefore, stable hydro storage in Norway and Sweden has a buffering effect on the uncontrollable output of wind power in Denmark. When the Danish wind generation is high, Denmark can export surpluses to neighboring countries and make savings on the value of hydropower. The interest on exporting wind output is especially greater if hydro storage is low. In the opposite case however, a lack of wind power calls in an increase in imports or domestic thermal generation. In this case, import is particularly favorable to Denmark when the storage of water reservoir in Norway and Sweden is high, making import less costly compared with the cost of launching domestic CHP plants. In fact according to Green and Vasilakos (2012), Denmark adjusts variations in its net exports exactly in this way. Fig. 3 presents the relationships among net power imports, wind generation in Denmark and (fitted) storage of hydro reservoir in Norway and Sweden.[10] Fig. 3 (left) clearly demonstrates a negative correlation between the Danish wind generation and its net imports, which indicates that Denmark exports its surplus of wind production to its neighboring countries. The figure on the right shows that the net quantity of electricity imported in Denmark and the level of hydro storage in Norway and Sweden are positively correlated. That is to say, Denmark tends to import electricity when its wind production is low and foreign hydro storages are high. As a consequence, the market-

[9] Hydropower represents virtually all of installed capacity (95%) in Norway and nearly half of the Swedish generation capacity (Nordic Energy Regulator, 2014).

[10] As the hydro reservoir displays strong seasonal and annual pattern, a fitted curve is obtained by removing monthly fixed effects.

specific substitution of generating technologies in the Nordic electricity market can be justified and captured by the variable of net electricity imports in Denmark.



Hourly averages of Danish wind generation and net imports per week

Hourly averages of Danish net imports and Nordic hydro storage per week

Fig. 3: Correlations between Danish wind generation, Danish net imports and Nordic hydro storage. Data source: Author's realization based on energinet.dk and Nord Pool Spot (2015).

Accordingly, having demonstrated the importance of the market exchange flows between the Nordic market and other countries in Section 3.1 as well as the substitution of hydropower to wind power in Denmark's strategy to handle wind intermittency through net imports, we expect that these two factors would have significant impacts on the determination of the price level and volatility in the day-ahead market. These considerations along with wind penetration are brought forward in our model specifications.

3.4. The data

The time series data of system prices in each trading hour measured in euro per megawatt hour (€/MWh) in the Nord Pool Spot are retrieved from the Danish Transmission System Operator Energinet.dk (2015). Since we focus on Elspot, at the point of one day prior to the physical delivery of electricity, the available and appropriate information to be used would be the forecasts on wind production in Denmark and total demand in all Nord Pool areas. These two forecasts are obtained from the website of Nord Pool Spot (2015). Furthermore, also sourced from Nord Pool Spot, the data on market coupling flows and Danish net power imports are calculated by aggregating the net flows of various bidding areas or neighboring countries.[11] All quantity variables are measured in megawatt hour (MWh). Finally, the dataset covers the period from March 25, 2012 to March 24, 2015, including 26,280 observations with hourly frequency. Each day has a length of 24 hours. Table 1 provides a summary of statistics of the system price series, according to which positive skewness and excess kurtosis of the spot prices can be detected. Furthermore, it is worth noting that negative system prices have not been present in our dataset.[12] One of the idiosyncrasies of wholesale electricity prices is seasonality, which presents hourly, daily, weekly and monthly. As shown in Figs. A.1 and A.2 in Appendix A, electricity prices exhibit distinguished multiple levels of seasonality depending on hours of day, days of week and months of year. As will be discussed in Section 4, price variations as a result of seasonality are not caused by market conditions or by intermittent generation and thus should be treated before applying econometric techniques.

Table 1 Summary of statistics of the system price series (€/MWh)

Mean	Median	S. D.	Max.	Min.	Skew.	Kurt.

[11] The original data are obtained for each bidding area in the Nordic market.

[12] In contrast to system prices, we do observe negative area prices due to high penetration of renewable generation, low demand and transmission congestion. For example, they are detected for 143 hours in Denmark West and 98 hours in Denmark East during the same period, among which a lot of them happen around the time of the Christmas and the New Year.

32.64	32.17	9.94	224.97	1.38	3.47	48.51

Notes: S. D., Max., Min., Skew. and Kurt. are standard deviation, maximal value, minimal value, skewness and kurtosis of the electricity price series for the period of March 25, 2012 to March 24, 2015.

Unlike the day-ahead electricity price, wind generation does not exert a specific hourly regularity although the output level can be largely and continuously volatile. The peculiarity of intermittent technology results in stable means and substantial variances in wind output. This characteristic is demonstrated by Fig. B.1 in Appendix B, in which the average hourly wind production only slightly peaks in the afternoon hours during spring and summer seasons while it stays relatively flat during autumn and winter. While the average hourly wind generation varies from 750MWh to 1700MWh over the year, the standard deviations of the hourly wind production are almost unvarying and as large as around 1000MWh for all four seasons. Hence in contrast to the studies that treat the price series in each hour separately (e.g. Bordignon et al., 2013) or as panel data (e.g. Huisman et al., 2007), we treat our time series data continuously on the account of the continuity and short-term variations of wind generation.

4. METHODOLOGY

4.1. Long-term and short-term seasonal components

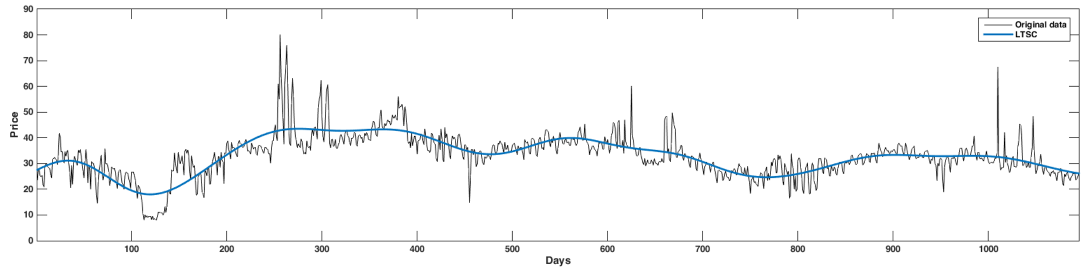
The electricity price series under study is high frequency and characterized by monthly, day-of-week and hourly seasonality. Carefully treating long- and short-term seasonality can produce superior estimation and prediction results (Janczura et al., 2013). Given that intermittent wind output is substantially influential on intraday price patterns, we need to keep the hourly price patterns as well as abrupt variations to the largest extent while removing monthly and weekly seasonality. There are different treatments in econometric literature for dealing with seasonal components in electricity price dynamics.[13] Following Weron (2009) and Janzura and Weron (2010)'s suggestion of a three-step deseasonalization approach, we represent the spot price P_t by a sum of two independent parts: a seasonal part f_t describing the predictable behavior of electricity prices and a residual stochastic part p_t, i.e. $P_t = f_t + p_t$.[14] Additionally, the deterministic part f_t is further decomposed into a long-term seasonal component (LTSC) L_t and a weekly short-term seasonal component (STSC) S_t. Then for the price series in each hour, the first step consists of applying wavelet decomposition and smoothing techniques to estimate L_t. Wavelet decomposition is more robust to price spikes and jumps and less strictly periodic alternative to Fourier analysis (Janczura et al., 2013; Stevenson et al., 2006). Here a continuous function (i.e. electricity price series) can be approximated by a set of orthogonal signal components that include one father wavelet function and a sequence of mother wavelet functions:

$$f(t) = \sum_{k=-\infty}^{\infty} \alpha_{J,k}\phi_{J,k}(t) + \sum_{k=-\infty}^{\infty} \beta_{J.k}\psi_{J,k}(t) + \sum_{k=-\infty}^{\infty} \beta_{J-1.k}\psi_{J-1,k}(t) + \cdots + \sum_{k=-\infty}^{\infty} \beta_j\psi_{j,k}(t) + \cdots + \sum_{k=-\infty}^{\infty} \beta_1\psi_{2,k}(t) \quad (1)$$

[13] Other suggestions in the literature of energy economics are for instance, adding seasonal dummies, sinusoidal functions and exponentially weighted moving average. For more details, see Trück et al. (2007) and Janczura et al. (2013).

[14] For a robustness check, a linear deseasonalization process with seasonal dummies in combined with an ARMA-GARCH model leads to roughly similar estimation results but worse performance in model fits. See Appendix C.

where J is a positive integer representing the coarsest level of resolution, k is the translation parameter associated with a shift in the time t, $\alpha_{J,k}$ and $\beta_{j,k}$ are the wavelet transform coefficients, $\phi_{j_0,k}(t)$ and $\psi_{j,k}(t)$ are the father and mother wavelet functions, respectively. Therefore, by properly choosing the maximum scale sustainable by the number of observations 2^J, the father wavelet can serve as estimation for a long-term trend of the signal, while adding a mother wavelet at each step can improve the estimation of the original signal until the complete reconstruction of the original signal. As in Janczura et al. (2013), we choose the parameter $J = 6$, which approximately corresponds to bimonthly ($2^6 = 64$) smoothing. Therefore, we obtain the price series without the LTSC by removing the wavelet filters from P_t. Taking the seventh and 16th hour of a day for an illustration, the results of the LTSC estimation are shown in Fig. 4.



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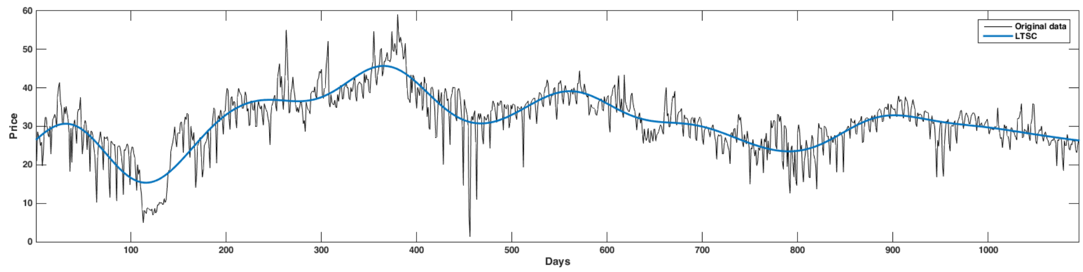
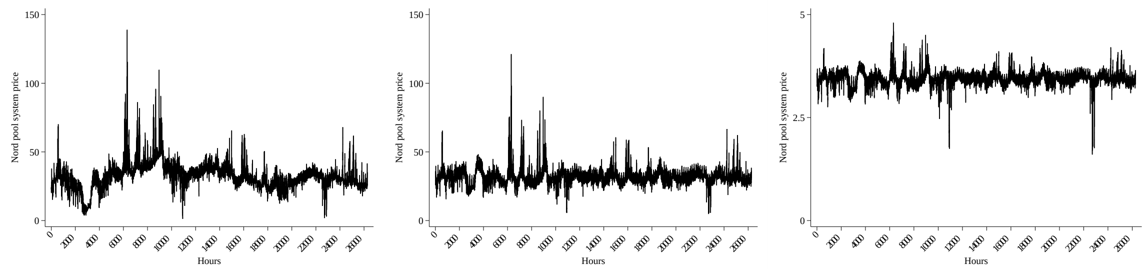


3pm-4pm

Fig. 4: Estimation of the long-term seasonal components (LTSC) of the day-ahead prices

Second, the price series without the SRSC is obtained by removing a weekly periodic pattern to account for the day-of-week fixed effects (Janczura and Weron, 2010; Weron, 2006). To avoid the influence of short-lived price spikes and jumps, we subtract weekly medians instead of weekly means from the obtained price series above. Finally for each hour, the deseasonalized prices $p_t = P_t - L_t - S_t$ are scaled up with their hourly means, so that log-prices can be used for this analysis. The patterns of hourly prices in Elspot are shown in Fig. 5, reflecting that the removal of seasonality is effective. The deseasonalized hourly spot prices and their logarithmic forms are relatively smoother.



Original price Deseasonalized price Log-deseasonalized price

Fig. 5: Hourly day-ahead spot price and deseasonalized price in Elspot from March 25, 2012 to March 24, 2015 (€/MWh). Data source: Author's realization based on energinet.dk (2015).

As a pre-examination of the suitability of a GARCH model, we conduct Ljung-box test (Ljung and Box, 1978) and Engle (1982)'s Lagrange multiplier test (ARCH-LM) for the residuals of deseasonalized prices. The results reported in Table 2 strongly reject their null hypotheses, indicating that price residuals display temporal autocorrelations and the error terms exhibit time-varying volatility clustering. In order to model the volatility of the day-ahead prices, a GARCH process is in consequence needed.[15]

Table 2: Results of Ljung-Box and ARCH-LM tests

	LB test	ARCH test
Price	3.376e+05 (0.00)	21200.15 (0.00)

Notes: p-values between parentheses. Ljung-Box statistics correspond to a test of the null of no autocorrelation with the number of lags equal to 40. ARCH Lagrange multiplier statistics correspond to a test of the null of no ARCH effect.

Finally, we plot partial autocorrelation functions (PACF) of the day-ahead prices in Fig. 6 in order to grab the gist of appropriate autoregressive orders. PACF shows great intraday temporal correlations, which shrink to a relatively insignificant level after 25 hours. Therefore, autoregressive terms are included in order to capture intraday partial autocorrelations.

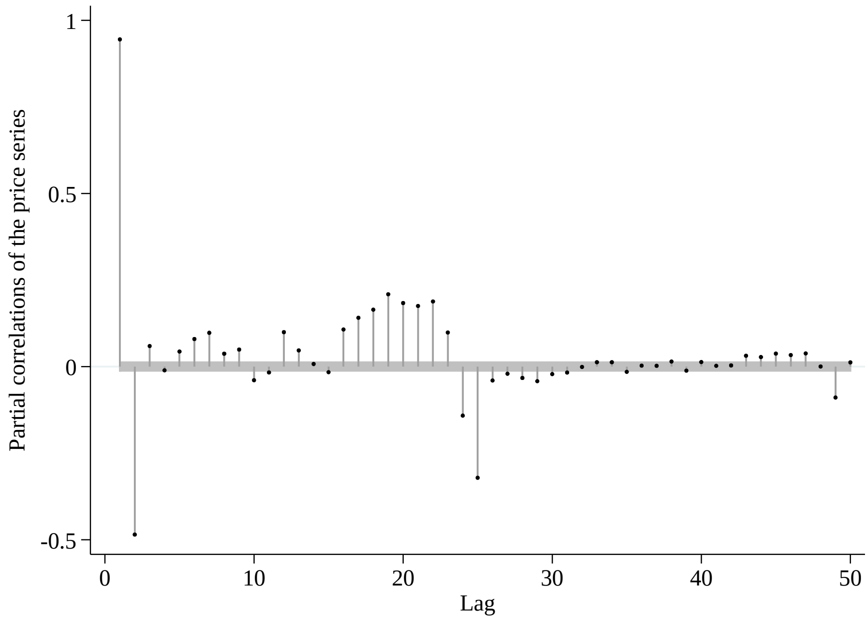


Fig. 6: Partial autocorrelation function (PACF) of the Nord Pool system prices. Data source: Author's calculation based on energinet.dk (2014).

4.2. Model specifications

In order to model price and volatility dynamics under the influence of wind power, net market coupling and power import, we need to specify a mean and a volatility equation respectively. For the mean equation, denoting by y_t the deseasonalized electricity price in logarithmic form at time *t*, the proposed AR(*P*) model fits the equation of the price level as follows:

$$y_t = \delta + X_t{}'\theta + \sum_{i=1}^{P} \rho_i \, y_{t-i} + \varepsilon_t \quad (2)$$

where δ is the constant, θ is the coefficient vector associated with exogenous variables, ρ_i is the autoregressive coefficient of the price series, *P* is the lag parameters of the dependent variable, ε_t is the error term which follows Gaussian distribution conditional on past history, X'_t is a set of exogenous variables, as indicated in the previous section, that may be expressed as $X'_t = (Wind_t, Coupling_t, Import_t, Load_t)$, where $Wind_t$ stands for the hourly prognosis of wind generation; $Coupling_t$ represents the net coupling flows into Elspot from other European spot

[15] Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips and Perron (PP) (1988) tests are carried out for all variables used in this study, indicating that all series are stationary. Therefore a GARCH process can be applied without the concern of spurious regression.

markets; $Import_t$ represents the net import flows into Denmark from Norway and Sweden; $Load_t$ is the demand prognosis for the Nord Pool day-ahead market included as a control variable. Among the above four explanatory variables, $Wind_t$ and $Load_t$ are in logarithmic form. [16]

In an integrated framework, the conditional price variance defined by a GARCH(1, 1) process with exogenous variables added in the specification is as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + Z'_t\pi \qquad (3)$$

where ω is a constant term, α and β are the coefficients of the ARCH term ε_{t-1}^2 and GARCH term σ_{t-1}^2 respectively, Z'_t is a set of exogenous variables included in the variance equation and π is the associated coefficient vector. A fact that should be borne in mind is that the non-negative constraint on σ_t^2 should be checked jointly with the values of all regressors. It is also important to notice that a conventional GARCH specification as Eq. (2) implies that the impacts of ε_{t-1}^2 is symmetric, meaning that positive and negative shocks to spot prices influence the volatility to the same extent. For the above two reasons, we further explore an exponential GARCH (EGARCH) developed by Nelson (1991) in order to relieve the non-negativity constraint on conditional variances and capture the asymmetric impacts of innovation terms on volatility. In an EGARCH(1,1) framework, the specification for the conditional variance is:

$$\log(\sigma_t^2) = \omega + \alpha\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - E\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|\right) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\log(\sigma_{t-1}^2) + Z'_t\pi \qquad (4)$$

Therefore for $\gamma > 0$, positive shocks will produce a bigger impact on price volatility than negative shocks and vice versa. By taking the logarithm of the conditional variance, the EGARCH model ensures the process to be positive by construction and this is especially meaningful given the inclusion of explanatory variables.

Finally to further capture the heavy-tail property of electricity prices, a Student's *t* distribution replacing the Gaussian error distribution is used to fit the above two GARCH models. The mean and variance equations are estimated by maximum likelihood, and the orders of autoregressive terms are chosen in consistency with the orders indicated in the partial autocorrelation functions.

4.3. Model evaluation and forecast accuracy

In order to evaluate the performance of the different GARCH models, we provide Akaike's Information Criterion (AIC) and Schewarz's Bayesian Information Criterion (BIC) to compare the in sample goodness-of-fit. For the performance of out-of-sample forecasts, root-mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Theil's inequality coefficient (TIC) are generally used as forecast error statistics. They are computed as follows:

$$\text{RMSE} = \sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}(\hat{y}_t - y_t)^2} \qquad (7)$$

$$\text{MAE} = \frac{1}{h}\sum_{t=T+1}^{T+h}|\hat{y}_t - y_t| \qquad (8)$$

$$\text{MAPE} = \frac{100}{h}\sum_{t=T+1}^{T+h}\left|\frac{\hat{y}_t - y_t}{y_t}\right| \qquad (9)$$

$$\text{TIC} = \frac{\sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}(\hat{y}_t - y_t)^2}}{\sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}\hat{y}_t{}^2} + \sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}y_t{}^2}} \qquad (10)$$

where $\hat{y}_t$ and y_t are the predicted value and true observed value respectively, and *h* is the forecast horizon. Smaller forecast error statistics are usually preferred while choosing the best model, and among them RMSE and MAE depend on the scale of the variable while MAPE and TIC do not.

5. EMPIRICAL RESULTS AND ANALYSES

[16] Since net coupling flows and net import flows contain both positive and negative values, they are not in logarithmic form. For a robustness check, scaling up the minimal values of these two variables to zero and then taking the log do not alter the main results, but for the sake of price and volatility interpretation and prediction, we prefer to use the original values of the variables.

5.1. Estimation results of a conventional GARCH model

The estimated results of the above-mentioned AR-GARCH process based on Eqs. (2) and (3) are summarized in Table 3. The first column presents the results of the specification only controlling for demand. Columns (2) – (4) present the estimation results by adding wind power generation, net coupling flows between Nord Pool and external markets as well as the Danish net imports from Norway and Sweden in the mean equation, while columns (5) – (7) report the estimation results by adding the same exogenous variables in the variance equation. At the first glance, almost all coefficients are highly significant. Adding net coupling and net import flows does not alter the significance levels either the signs of the coefficients of wind and consumption forecasts, suggesting the robustness of the model and the importance of cross-border electricity exchanges in determining the day-ahead prices and volatility. The gradually lowered values of AIC and BIC signify improvements on model fits from more thorough consideration of market fundamentals in price and volatility dynamics. As shown in Table 3 in the mean equation across all specifications, all estimates for wind power and net coupling flows with other wholesale markets are negative, whereas the estimates for the Danish net electricity imports are positive. Consistent with our expectation from the merit order effect, an increase in wind output leads to a decrease in electricity price in the Nordic market as RES crowds out conventional plants with higher marginal costs out of generating profile. In the case of Nord Pool, more expensive thermal plants are substituted by wind power to produce electricity when wind penetration is high, bringing down the average electricity spot price. In the variance equation, the negative impact of wind power on the conditional variance may seem surprising in the first place, but this has to be analyzed jointly with internal and external electricity exchange flows. This point will be discussed later on in section 5.3.

Table 3: Estimation results for the price and variance equations with market fundamentals

	AR specifications				GARCH specifications		
Mean equation	(1)	(2)	(3)	(4)	(5)	(6)	(7)
δ	-0.423***	0.042	0.884***	0.970***	-1.139***	-1.146***	3.116***
Wind		-0.015***	-0.013***	-0.010***	-0.002***	-0.002***	-0.010***
Coupling			-1.19e-05***	-8.80e-06***	-8.13e-06***	-8.05e-06***	-7.69e-06***
Import				4.44e-06***	2.28e-06***	2.39e-06***	2.63e-06***
Load	0.362***	0.328***	0.248***	0.238***	0.426***	0.427***	0.036***
AR(1)	1.206***	1.190***	1.195***	1.194***	1.261***	1.260***	1.206***
AR(2)	-0.419***	-0.411***	-0.419***	-0.418***	-0.488***	-0.487***	-0.480***
AR(3)	0.059***	0.054***	0.059***	0.059***	0.089***	0.088***	0.072***
AR(6)	-0.051***	-0.053***	-0.060***	-0.060***	-0.001	-0.000	-0.039***
AR(7)	0.072***	0.072***	0.080***	0.080***	0.066***	0.066***	0.087***
AR(8)	-0.044***	-0.046***	-0.050***	-0.050***	-0.087***	-0.085***	-0.120***
AR(9)	0.050***	0.050***	0.048***	0.048***	0.105***	0.103***	0.104***
AR(12)	-0.038***	-0.037***	-0.044***	-0.043***	-0.064***	-0.064***	-0.067***
AR(14)	0.053***	0.053***	0.059***	0.059***	0.034***	0.035***	0.047***
AR(16)	-0.048***	-0.047***	-0.048***	-0.048***	0.012***	0.012***	-0.027***
AR(19)	0.018***	0.021***	0.023***	0.023***	-0.029***	-0.029***	0.008***
AR(23)	0.255***	0.256***	0.261***	0.260***	0.099***	0.096***	0.120***
AR(24)	-0.127***	-0.115***	-0.118***	-0.117***	-0.010***	-0.006***	-0.011***
Variance equation							
ω					-0.001***	-0.001***	-0.000
α					0.850***	0.855***	0.696***
β					0.219***	0.217***	0.302***
Wind					-2.98e-05***	-2.43e-05***	-6.37e-05***
Coupling						-1.91e-08***	-5.76e-08***

Import							-5.14e-08***
Load					1.59e-04***	1.18e-04***	7.57e-05***
R2	0.94	0.94	0.94	0.94	0.93	0.93	0.94
Adj. R2	0.94	0.94	0.94	0.94	0.93	0.93	0.94
LL	46890	46987	47276	47284	53737	53753	54330
AIC	-3.57	-3.58	-3.60	-3.60	-4.09	-4.09	-4.14
BIC	-3.57	-3.57	-3.59	-3.59	-4.08	-4.09	-4.13

Notes: Wind is the log hourly wind generation forecasts for Denmark. Coupling is the net flow of electricity from Germany and the Netherlands to Nord Pool Spot. Import is the net flow of electricity from Norway and Sweden to Denmark. Load is the log consumption forecasts in Nord Pool. Asterisks indicate significance at *** p<0.01, ** p<0.05, * p<0.1. LL, AIC and BIC are log likelihood, Akaike Information and Bayesian Information Criteria respectively.

5.2. Asymmetric GARCH and heavy-tail error distribution

We now incorporate the asymmetric impacts of innovations on conditional variances based on the aforementioned EGARCH process. Since electricity day-ahead prices often show more extreme values, the assumption on a Gaussian error distribution may not be appropriate. For this reason, we further fit the errors with a Student's *t* distribution in order to accommodate fatter tails of the spot prices.[17] The estimation results of the asymmetric GARCH with Gaussian or Student's *t* distributions are described in Table 4.[18] While the estimates of coefficients of the mean equations remain stable in asymmetric GARCH models compared with the conventional GARCH, the estimates of the variance equations vary in scales and this is due to different function forms in GARCH and EGARCH. Under Gaussian assumption according to the AIC and BIC criterion, there is a slight gain in model fits when moving from GARCH to EGARCH. The parameter γ measuring asymmetric effects is significant and positive in the EGARCH models. As a consequence, the asymmetric influences of innovations on conditional variances found here is a "standard leverage effect". Knittel and Robert (2005) and Liu and Shi (2012) have defined an inverse leverage effect as one of the particularities of electricity spot prices, which means that positive shocks to electricity prices would influence price volatility to a greater extent compared with negative shocks. This is the inverse case to the leverage effect in financial markets in which bad news often has a larger influence on volatility. However contrary to their findings, here the significant positive sign of the parameter γ contests the finding of inverse leverage effect by evincing resulted larger volatility from negative price shocks in the case of the Elspot electricity market. That is, after controlling for the market fundamentals, this price series' particularity is not valid anymore. Consequently, the reliability of the asymmetric impacts of innovations may largely depend on the accountability of market fundamentals as well as the stochastic properties of price series in a specific market.

Table 4: Estimation results of asymmetric GARCH compared with conventional GARCH

	Gaussian		Student's *t*	
Mean Equation	**GARCH**	**EGARCH**	**GARCH**	**EGARCH**
δ	3.116***	3.575***	1.208***	1.159***
Wind	-0.010***	-0.010***	-0.008***	-0.008***
Coupling	-7.69e-06***	-7.07e-06***	-9.95e-06***	-9.76e-06***
Import	2.63e-06***	3.44e-06***	3.45e-06***	3.66e-06***
Load	0.036***	0.009	0.203***	0.207***
AR(1)	1.206***	1.254***	1.295***	1.295***

[17] The estimation and forecast results with a generalized error distribution (GED), which can also capture heavy tails, are reported in Appendix D, showing similar estimation and forecast performance as the one of a Student's *t* distribution.

[18] To conserve space, only AR order 1 is reported in Table 4.

Variance Equation				
ω	-0.000	-0.776***	0.003***	-0.248
α	0.696***	0.415***	1.056***	0.903***
β	0.302***	0.930***	0.182***	0.613***
γ		-0.042***		-0.024*
v			2.692***	2.667***
Wind	-6.37e-05***	-0.046***	-2.65e-06	-0.021**
Coupling	-5.76e-08***	-4.56e-05***	-2.87e-08***	-4.04e-05***
Import	-5.14e-08***	-4.96e-05***	-3.88e-08**	-5.85e-05***
Load	7.57e-05***	0.028***	-2.41e-04***	-0.256***
R2	0.94	0.94	0.94	0.94
Adj. R2	0.94	0.94	0.94	0.94
LL	54330	54484	59085	58979
AIC	-4.14	-4.15	-4.50	-4.49
BIC	-4.13	-4.14	-4.49	-4.48
ARCH test	0.16	0.00	0.91	0.96

Notes: γ is the estimated asymmetric parameter in EGARCH model. *v* is the *t* distribution parameter. Wind is the log hourly wind generation forecasts for Denmark. Coupling is the net flow of electricity from Germany and the Netherlands to Nord Pool Spot. Import is the net flow of electricity from Norway and Sweden to Denmark. Load is the log consumption forecasts in Nord Pool. Asterisks indicate significance at *** p<0.01, ** p<0.05, * p<0.1. LL, AIC and BIC are log likelihood, Akaike Information and Bayesian Information Criteria respectively. ARCH test reports the P-value by testing the null hypothesis of no ARCH effects.

Considering the Student's *t* error distribution, the estimate of the *t* distribution parameter *v* >2, is highly significant in both GARCH and EGARCH specifications, effectively controlling for errors' fat tails. It is also clear that Student's *t* distributional errors fit the electricity prices much more accurately according to the significantly improved AIC and BIC compared with the results in the second and the third columns. Especially, the ARCH tests for GARCH and EGARCH with *t* distribution suggest that the null hypothesis of no ARCH effects is not rejected, meaning that serial correlations are sufficiently captured by these models. Finally, it is noticeable that under *t* distribution the coefficients of wind power generation lose significance to some extent in the variance equation. This is understandable in the sense that extreme prices can be seen as a result of wind fluctuations or a stochastic behavior of price series itself. Accordingly, a choice needs to be made in order to precisely predict spot prices between modeling price variations as fundamental-driven and incorporating large fluctuations into a heavy-tail distribution. Finally, analogous rationale could be applied to explain the alleviated effect from the demand side when price spike and jumps are captured by a heavy-tail distribution rather than load fluctuations.

5.3. Discussions of estimation results

To further interpret our results, we concentrate on the EGARCH specification in Table 4 given the advantages that EGARCH satisfies the non-negativity constraint on the conditional variance by construction and a log-form specification of the conditional variance provides a convenient way to interpret variance elasticity. In the mean equation, the model specification includes the Danish wind forecasts and the Nordic consumption forecasts in logarithmic forms. As a consequence, the values of coefficients of the wind generation and the Nordic consumption forecasts could be interpreted as elasticities of price and demand. That is to say, an increase of 1% in wind generation would lead to, on average, a decrease of 0.008% in the Nord Pool day-ahead price. More concretely, a 10% increase of intermittent wind generation only reduces the average day-ahead price by approximately 0.03 euros (32.64 times 0.08%). The resulted merit order effect is hence very small in Nord Pool Spot. In contrast, the load forecasts for the next day presents a positive effect on the wholesale price on average. The estimated coefficient implies that if the load forecast is 1% higher then the spot price will raise as large as 0.20%, meaning that an increase in demand will be passed through disproportionately as one fifth on the spot price in the day-ahead market. Moreover, an increase in external supply from Germany and the Netherlands to Nord Pool could also reduce the Nordic system electricity price level as electricity supply is backed up by outside sources. Comparing with other electricity wholesale markets, higher proportion of hydropower and cross-border transmissions are well established in the Nordic system, which take part in determining the day-ahead prices in reaction to wind generation. More precisely, the positive sign of the Danish net imports signifies that imports relating to Denmark's scarcity in wind power generation will result in an increase in price levels and this reflects, at least to some extent, the opportunity costs of hydro usage in the other Scandinavian countries. The opposite case is true when Denmark exports under high wind penetration: the decrease in prices should reflect savings on opportunity costs of hydropower. In other words, the internal flows between Denmark, Norway and Sweden postulate a substitution between wind power and hydropower to counterbalance the intermittency of wind, preventing system prices from large fluctuations. Hence, having more hydro storage in Norway and Sweden as well as market coupling with external markets tends to ensure a stable system price level. The way that renewables interact in the Scandinavian countries renders Nord Pool systematically steadier, while the surge of electricity prices is predominantly driven by the demand.

Turning our attention to the results of the variance equation, the day-ahead price is stabilized jointly by wind generation net coupling and net imports as they all present negative effects on price variances. In Elspot, a negative relationship between wind power and price volatility is found and a 1% increase in wind penetration reduces intraday price volatility by 0.02%. That is to say, in Elspot wind penetration not only limits the spot price from increase but also reduces associated price risks. This result may seem surprising at first and it is in contradiction to the results of some other studies (Jacobsen and Zvingilaite, 2010; Woo et al., 2011; Ketterer, 2014), but it is consistent with Jónsson et al. (2010) for the case of Denmark. This discrepancy in results concerning price volatility can be explained for the following reasons. First, this result should be analyzed together with the negative impacts of internal and external exchange flows on volatility. The well-established connections in the Scandinavian region, which at the same time enable cross-border electricity trading and balance supply between hydro and wind power generation, play a role in smoothing the pattern of hourly prices by diminishing their variances. The Danish wind power facilitates both internal and external Elspot trades of electricity, in the way that it interacts with the coupling flows between Nord Pool and other markets as well as with imported electricity generated by hydropower from Norway and Sweden. Contrarily when its wind production is low, the resulting price variations may reveal the values of different sources to fill the gap of wind power generation and these values mirrored in price fluctuations may vary largely depending on whether the replacement resource is hydropower, fossil fuel or other more expensive reserves. Consequently, intraday spot prices are more oscillating during low-wind periods. This conforms to our initial suggestion that the Danish bidding zones benefit from the hydro generation in neighboring countries through power imports and exports as a means to cope with wind intermittency. Second, another potential reason to explain the difference between our results and former studies could be the use of hourly time series, which allows us to capture the finest variations in prices and the property of intermittency of wind power. It also should be claimed that the volatility in the long run might be different from the one in the short run. Therefore wind power could possibly have distinct impacts on price volatility depending on the time horizon considered. Third, it should be noted that in this study the system price of the Nord Pool Spot is used in order that interactions between wind power and hydropower come into play. The area prices in DK1 and DK2 are with no doubt more volatile than the system price due to constraints on transmission capacities.[19] Although examining volatility of area prices is clearly out of the scope of this paper, it would be interesting to see if the impacts of wind power on system price volatility and area price volatility are different. These results would signal potentially how the system is constrained by transmission capacities.

[19] A comparison between the Danish area prices and the system price is described in Appendix E.

5.4. Forecast performance

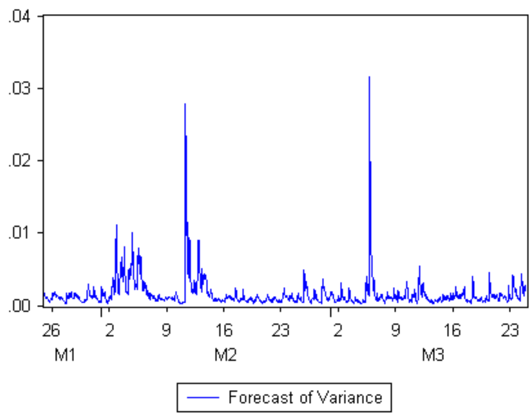
In order to provide a guidance on the accuracy of price forecasts, we split the dataset into two periods: the first period dated from March 25, 2012 to January 24, 2015 for the use of in-sample estimation and the second period starting from January 25, 2015 to March 24, 2015 for out-of-sample forecasts.[20] Table 5 displays the forecast performances of GARCH specifications under the assumptions of Gaussian and Student's *t* error distributions. Overall, EGARCH model under the Gaussian and *t* distributions have very similar statistics and outperform conventional GARCH models. Furthermore for the selected two months' period, EGARCH model with a Gaussian error distribution is sufficient to serve as a prediction model as it slightly outperforms EGARCH with a Student's *t* error distribution and has the best out-of-sample prediction accuracy.

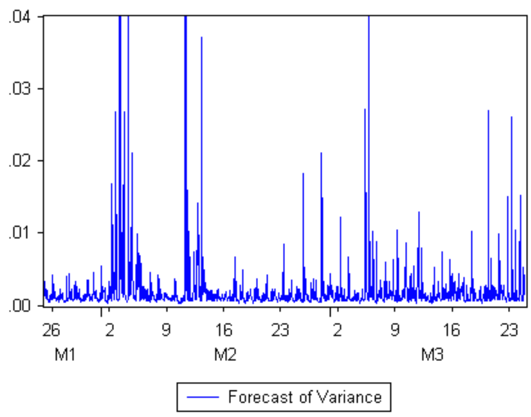
Table 5: Forecast evaluation of GARCH specifications under a Student's *t* distribution

	Gaussian		Student's t	
	GARCH	EGARCH	GARCH	EGARCH
RMSE	0.0979	0.0378	0.0645	0.0391
MAE	0.0805	0.0244	0.0478	0.0246
MAPE	2.3406	0.7036	1.3798	0.7076
TI	0.0141	0.0055	0.0094	0.0057

Notes: out-of-sample forecast period January 25, 2012 – March 24, 2015. RMSE, MAE, MAPE and TIC are root-mean squared error, mean absolute error, mean absolute percentage error, and Theil's inequality coefficient respectively.

We plot the out-of-sample predictions of the price variance offered by the above EGARCH models with the two error distributions in Fig. 7, which shows that *t* distribution would generally produce larger predictions for volatility since price series are considered to have heavy tails. The results of static forecasts for the study period under the two EGARCH specifications are plotted in Fig. 8. Both forecasted series yield very similar patterns compared with the original price series. They not only follow the general price trends but also track the evolutions of the price variations for the whole forecast period when both market fundamentals and stochastic properties of the spot prices are appropriately accounted for.

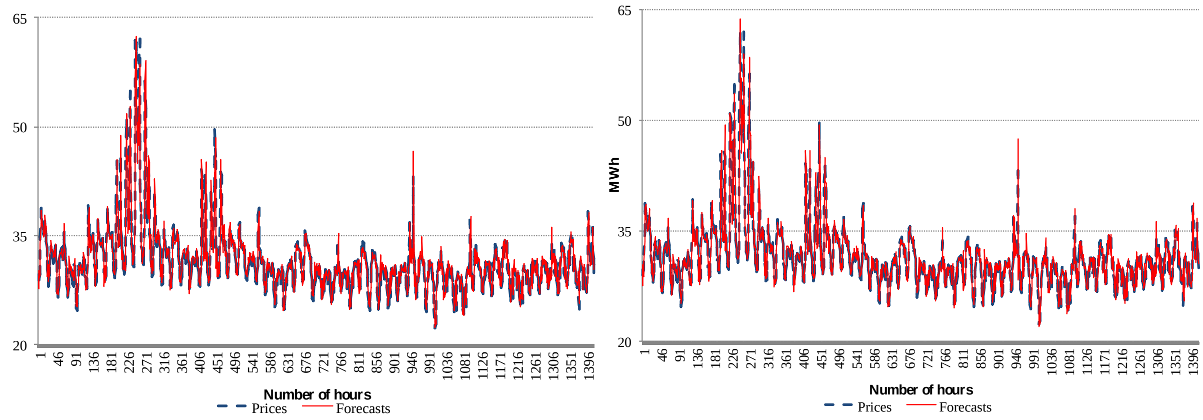




EGARCH-Gaussian EGARCH-Student's *t*

Fig. 7: Out-of-sample forecasts of volatility January 25, 2012 – March 24, 2015

[20] The model is stable when choosing different periods for the forecasts.



EGARCH-Gaussian EGARCH-Student's *t*

Fig. 8: One-step ahead forecasts of the price series January 25, 2012 – March 24, 2015

6. CONCLUSION

In this paper, we revisit the short-term price and volatility dynamics in day-ahead electricity markets with a consideration of an increasing share of wind power generation, using the Nord Pool day-ahead market and the Danish wind generation as an example. We inspect the impacts of wind power generation and electricity cross-border exchanges on price and volatility dynamics in the Elspot electricity market by applying a GARCH process with exogenous market drivers. Cross-border exchanges are further distinguished between market coupling flows between Nord Pool and other spot markets, and import flows to Denmark from Sweden and Norway. The latter term is of importance to capture the substitution effect between wind power and hydropower in the above Nordic countries. Furthermore, we model electricity prices driven by both market-specific fundamentals and electricity price series' statistical properties in order to obtain accurate forecasts and market inferences.

As results, the price reduction effect resulted from wind penetration for the sake of merit order is very weak and the price elasticity estimated with respect to wind generation is 0.008. Meanwhile, we found evidence on that wind penetration affects negatively the diurnal price volatility in Nord Pool with an estimated elasticity of 0.02. Particularly, the price and volatility stabilization are also contributed by the coupling flows between Nord Pool and neighboring countries as well as the interexchange of hydro and wind power among Denmark, Norway and Sweden. After controlling for market fundamental drivers, an asymmetric impact of price shocks on price volatility can be found, that is, negative innovations have a larger impact on conditional variances of spot prices. Considering the fat-tail error distributional property of electricity prices can significantly increase model fits. In terms of forecasting performance, EGARCH models outperform conventional GARCH models and yield satisfying forecasts.

The centerpiece of the paper highlights that the current infrastructure and market organization in Nord Pool Spot is able to handle the challenge of intermittency arose from the current amount of wind power in Denmark. The key features of Elspot to manage wind variability and uncontrollability of the wind output in the Nordic region are the reliable hydro storage accompanied with relatively flexible CHP systems and the international transmission lines within the region. The key issue here seems to be developing market integration and this casts light on the prevailing electricity market design for Nord Pool and also for other electricity systems. First, through extensive grid connections, the market effects of renewables' intermittency and variability are reduced and benefits can be created for efficient uses of other power plants (Schaber et al., 2012), namely hydro and CHP plants in the case of Nord Pool and Denmark. Moreover, market integration can effectively improve competition (Mulder and Schoonbeek, 2013) through enlarged market size and number of competitors, and thus limit generators' ability to exercise market power especially when systems face ramping and flexibility constraints during low wind periods. Finally, geographic diversification brings in an amount of other generating capacities in other areas or regions such that security of supply can be further ensured.

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Appendices

Appendix A. Seasonality of the Elspot electricity price

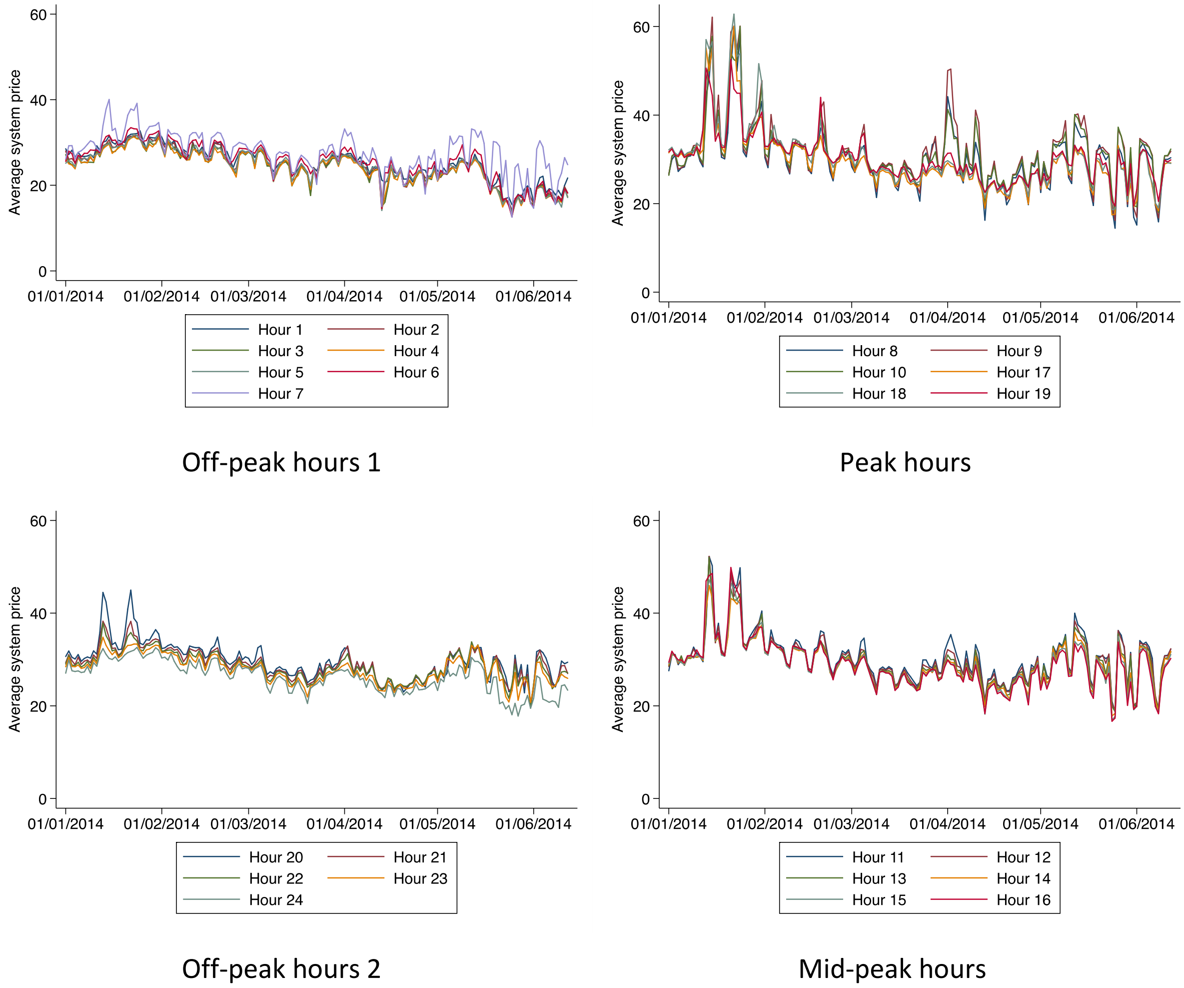


Figure A.1: Hourly patterns of the Nord Pool system prices from January 1, 2014 to June 30, 2014 (€/MWh). Data source: Author's realization based on energinet.dk (2015).

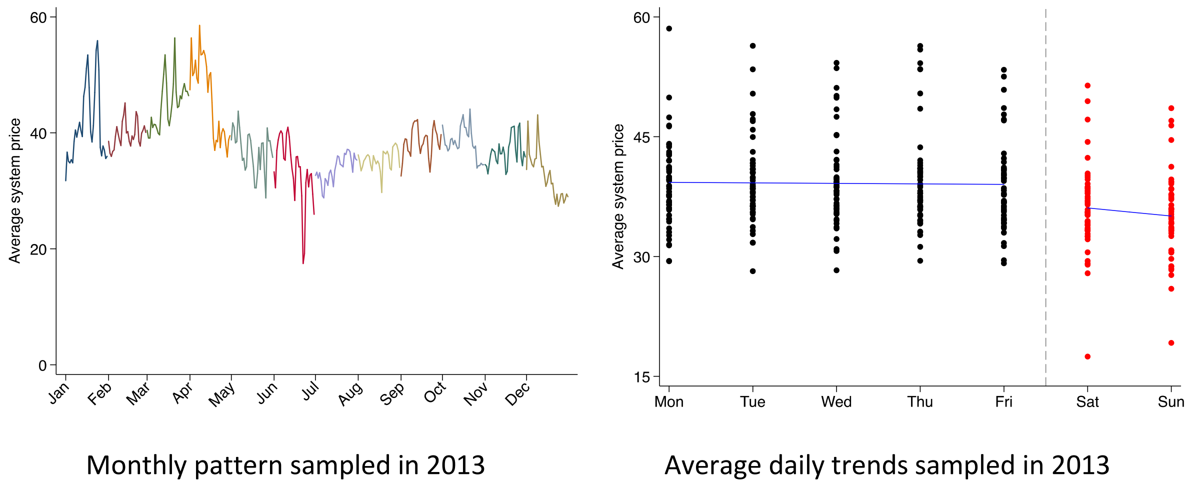


Figure A.2: Monthly and weekday/weekend patterns of average daily prices (€/MWh). Data source: Author's realization based on energinet.dk (2015).

Appendix B. Seasonal and hourly variations of wind power prognosis

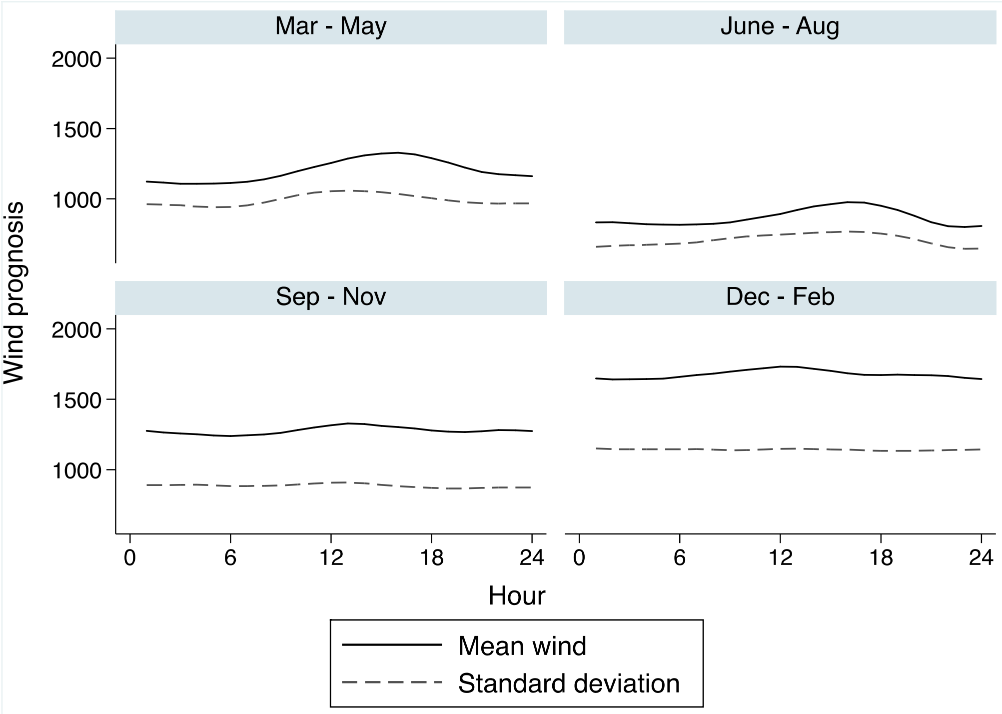


Figure B.1. Seasonal and hourly profiles of wind generation prognosis.

Data source: Author's calculation based on Nord Pool Spot (2015).

Appendix C. Estimation results with a linear deseasonalization process

Since a linear deseasonalization process is very sensitive to extreme values, we define outliers as price levels exceeding the range of 5-100€/MWh. The range considered largely surpasses three times of standard deviation relative to the average.[21] After all, there are 77 observations are detected as extreme events, whose number is very small compared to the total number of observations. Thus the price values identified as outliers are replaced by the mean prices averaged over 24 and 48 hours before and 24 and 48 hours after in order to smooth the overall price series.

The fitted spot prices at time t are derived by taking out the seasonal fixed effects in the following form:

$$P_t = \beta_0 + \sum_{i=2}^{24} \beta_{1,i} H_{i,t} + \sum_{j=1}^{6} \beta_{2,j} D_{j,t} + \sum_{l=2}^{12} \beta_{3,l} M_{l,t} + \sum_{p=2013}^{2014} \beta_{4,p} Y_{p,t} + \beta_5 Hol_t + \varepsilon_t \quad \text{(B.1)}$$

where H_t, D_t, M_t, Y_t and Hol_t are dummy variables for hours of day, days of week, months, years and national holidays in Denmark. The estimated results are shown in Table C.1.

Table C.1: Estimated coefficients for removing seasonality

[21] As electricity price is specifically more volatile than other commodities' prices and price spikes happen often to reflect generation scarcity relative to demand, we did not apply the outlier filter as 3 times of standard deviation (Ketterer, 2014) in order to allow for more variations of the spot price. This process is applied another time to the fitted value of electricity spot prices later.

Var.	Coef.		Var.	Coef.		Var.	Coef.		Var.	Coef.	
Hour 2	-1.027***	(0.330)	Mon	4.157***	(0.178)	Feb	1.173***	(0.214)	2013	7.206***	(0.105)
Hour 3	-1.645***	(0.330)	Tue	4.379***	(0.178)	Mar	-3.622***	(0.209)	2014	-5.498***	(0.145)
Hour 4	-1.899***	(0.330)	Wed	4.683***	(0.178)	Apr	-2.718***	(0.212)	Holiday	-3.522***	(0.268)
Hour 5	-1.523***	(0.330)	Thu	4.445***	(0.178)	May	-6.607***	(0.210)	Constant	30.65***	(0.304)
Hour 6	-0.145	(0.330)	Fri	3.628***	(0.179)	Jun	-10.22***	(0.225)			
Hour 7	2.057***	(0.330)	Sat	0.871***	(0.179)	Jul	-16.74***	(0.238)			
Hour 8	5.479***	(0.330)				Aug	-11.02***	(0.238)			
Hour 9	7.064***	(0.330)				Sep	-8.439***	(0.240)			
Hour 10	6.509***	(0.330)				Oct	-4.043***	(0.238)			
Hour 11	5.973***	(0.330)				Nov	-5.010***	(0.240)			
Hour 12	5.484***	(0.330)				Dec	-2.486***	(0.238)			
Hour 13	4.828***	(0.330)									
Hour 14	4.286***	(0.330)									
Hour 15	3.927***	(0.330)									
Hour 16	3.795***	(0.330)									
Hour 17	4.385***	(0.330)									
Hour 18	5.828***	(0.330)									
Hour 19	5.632***	(0.330)									
Hour 20	4.703***	(0.330)									
Hour 21	3.691***	(0.330)									

Hour 22	3.007***	(0.330)
Hour 23	2.188***	(0.330)
Hour 24	0.627*	(0.330)
R-squared	0.502	

Notes: OLS regression with seasonal dummies. Standard errors in parentheses. Asterisks indicate significance at *** p<0.01, ** p<0.05, * p<0.1. Hour 1 (00:00-01:00), Sunday, January, the year 2012 and non-holiday days are set as references.

The estimated results of an ARMA-GARCH process are summarized in Table C.2,[22] where the first column presents the results of the specification with only wind and consumption forecasts included. The second and the third columns represent the estimation results by adding the net coupling between Nord Pool and other spot markets as well as the Danish net import from Norway and Sweden. Column (4) presents the results of the overall impact in Elspot of the wind to load ratio. Compared with the estimation results obtained after applying wavelet decomposition and smoothing, most of estimates remain robust except for the variable net import in the mean equation.

Table C. 2: Estimated coefficients for hourly price equation and variance equation

		Model specification			
		(1)	(2)	(3)	(4)
Mean equation	Wind	-0.02401***	-0.02327***	-0.03410***	
		(0.00)	(0.00)	(0.00)	
	Load	0.14141***	0.02265***	0.20320***	
		(0.00)	(0.00)	(0.00)	
	Coupling		-0.00002***	-0.00003***	-0.00003***
			(0.00)	(0.00)	(0.00)
	Import			-0.00001***	-0.00001***
				(0.00)	(0.00)
	Wind share				-1.54232***
					(0.00)
	Constant	2.04030***	3.24865***	1.30770***	3.34985***
		(0.00)	(0.00)	(0.00)	(0.00)
	AR(1)	0.95370***	0.97383***	0.51089***	0.97564***
		(0.00)	(0.00)	(0.00)	(0.00)
	MA(1)	0.21165***	0.18986***	0.51972***	0.19191***
		(0.00)	(0.00)	(0.00)	(0.00)
Variance equation	Wind	-0.00002***	-0.00002***	-0.00090***	
		(0.00)	(0.00)	(0.00)	
	Load	0.00024***	0.00026***	-0.00153***	
		(0.00)	(0.00)	(0.00)	

[22] To conserve space, only AR and MA order 1 are reported in Table 4. The orders included in the regression of Column (3) are AR(1), AR(2), AR(5), AR(16), AR(17), AR(24), AR(25), MA(1), MA(2), MA(3), MA(24), MA(25), MA(49), MA(73), MA(167), MA(168) and MA(169).

Coupling		-2.95E-08***	-3.40E-07***	-1.63E-07***
		(0.00)	(0.00)	(0.00)
Import			-4.18E-07***	-1.65E-07***
			(0.00)	(0.00)
Wind share				-0.00531***
				(0.00)
Constant	-0.00199***	-0.00222***	0.02384***	0.00054***
	(0.00)	(0.00)	(0.00)	(0.00)
ARCH(1)	0.80671***	0.97593***	0.44023***	0.84283***
	(0.00)	(0.00)	(0.00)	(0.00)
GARCH(1)	0.23163***	0.20622***	0.15419***	0.24943***
	(0.00)	(0.00)	(0.00)	(0.00)
Adjusted R2	0.95	0.95	0.95	0.95
AIC	-3.70	-3.80	-3.53	-3.83
BIC	-3.69	-3.79	-3.52	-3.82
ARCH test	0.03	0.16	0.24	0.13

Notes: Wind share is the ration of wind prognosis in load.

Appendix D. TGARCH, GJRGARCH and GARCH specifications with a Generalized Error Distribution (GED)

To test the robustness of the asymmetric impacts of innovation terms on volatility, a threshold GARCH (TGARCH) (Zakoian, 1994), and a Glosten-Jagannathan-Runkle GARCH (GJRGARCH) (Glosten et al., 1993) processes are also applied. TGARCH and GJRGARCH are close ideas to allow the conditional standard deviation and variance to depend upon the sign of the lagged innovations. Specifically, a TGARCH(1, 1) specification is expressed as follows:

$$\sigma_t = \omega + \alpha|\varepsilon_{t-1}| + \gamma|\varepsilon_{t-1}|I(\varepsilon_{t-1} < 0) + \beta\sigma_{t-1} + Z'_t\pi \qquad (5)$$

Similarly a GJRGARCH(1, 1) may be expressed as:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) + \beta\sigma_{t-1}^2 + Z'_t\pi \qquad (6)$$

where $I = 1$ if $\varepsilon_{t-1} < 0$ and 0 otherwise. Therefore, in these two specifications, the parameter γ also captures the asymmetric aspect of innovations. However in the contrary to the EGARCH model in order to produce larger impacts with negative innovations, γ needs to be positive. As seen in Table D.1, GJRGARCH performs relatively poorly compared with other GARCH models while TGARCH provides good model fits. As a result, the parameter γ measuring asymmetric effects is indeed negative in these specifications.

Table D.1: Estimation results with TGARCH and GJRGARCH

	Gaussian		Student's *t*	
Mean Equation	**TGARCH**	**GJRGARCH**	**TGARCH**	**GJRGARCH**
δ	3.432***	-0.012	1.138***	-0.002
Wind	-0.010***	-0.011***	-0.008***	-0.014***
Coupling	-7.11e-06***	7.16e-06***	-9.84e-06***	-4.94e-06***
Import	3.25e-06***	2.27e-05***	3.62e-06***	9.33e-06***
Load	0.023***	0.339***	0.209***	0.330***
AR(1)	1.247***	0.521***	1.290***	0.352***
Variance Equation				
ω	0.005***	0.004***	0.056***	0.011***
α	0.233***	0.275***	0.645***	0.239***
β	0.782***	0.641***	0.271***	0.510***
γ	0.098***	0.164***	0.044**	0.105***
v			2.671***	20.000***

Wind	-0.001***	-1.27e-04***	-1.58e-04	-2.53e-04***
Coupling	-5.92e-07***	-9.93e-08***	-6.04e-07***	-1.54e-07***
Import	-6.23e-07***	-9.91e-08***	-8.40e-07***	-1.69e-07***
Load	8.62e-05	-2.51e-04***	-0.004***	-8.38e-04***
R2	0.94	0.90	0.94	0.88
Adjusted R2	0.94	0.90	0.94	0.88
LL	54401	47800	59076	48115
AIC	-4.14	-3.64	-4.50	-3.66
BIC	-4.13	-3.63	-4.49	-3.65
ARCH test	0.00	0.00	0.99	0.00

Notes: Wind is the log hourly wind generation forecasts for Denmark. Coupling is the net flow of electricity from Germany to Nord Pool Spot. Import is the net flow of electricity from Norway and Sweden to Denmark. Load is log the consumption forecasts in Nord Pool. Asterisks indicate significance at *** p<0.01, ** p<0.05, * p<0.1. LL, AIC and BIC are log likelihood, Akaike Information and Bayesian Information Criteria respectively. ARCH test reports the P-value by testing the null hypothesis of no ARCH effects.

Finally, a Generalized Error Distribution can serve as an alternative to model fat tails of the price series. The estimation and prediction results are presented in Table D.2 and Table D.3, respectively.

Table D.2: Estimation results with a GED

Mean Equation	GARCH	EGARCH	TGARCH	GJRGARCH
C	1.473***	1.470***	1.373***	0.002
Wind	-0.008***	-0.008***	-0.007***	-0.010***
Coupling	-9.71e-06***	-9.24e-06***	-9.30e-06***	1.49e-05***
Import	4.01e-06***	4.33e-06***	4.29e-06***	3.09e-05***
Load	0.177***	0.176***	0.185***	0.329***
AR(1)	1.295***	1.290***	1.282***	0.119***
Variance Equation				
ω	0.001***	-2.007***	0.023***	0.014***
α	0.763***	0.766***	0.536***	0.206***
β	0.189***	0.625***	0.291***	0.590***
γ		-0.025**	-0.031*	0.082***
GED dist.	0.873***	0.867***	0.871***	1.984***
Wind	-2.04e-05***	-0.046**	-5.49e-04***	-0.001***
Coupling	-2.67e-08***	-4.93e-05***	-6.54e-07***	-2.86e-07***
Import	-2.85e-08**	-6.27e-05***	-7.78e-07***	-3.46e-07
Load	-4.45e-05	-0.080**	-8.15e-04	-0.001***
R2	0.94	0.94	0.94	0.72
Adj. R2	0.94	0.94	0.94	0.72
LL	58699	58592	58690	36320
AIC	-4.47	-4.46	-4.47	-2.76
BIC	-4.46	-4.45	-4.46	-2.76
ARCH test	0.79	0.88	0.99	0.00

Notes: Wind is the log hourly wind generation forecasts for Denmark. Coupling is the net flow of electricity from Germany to Nord Pool Spot. Import is the net flow of electricity from Norway and Sweden to Denmark. Load is the log consumption forecasts in Nord Pool. Asterisks indicate significance at *** p<0.01, ** p<0.05, * p<0.1. LL, AIC and BIC are log likelihood, Akaike Information and Bayesian Information Criteria respectively. ARCH test reports the P-value by testing the null hypothesis of no ARCH effects.

Table D.3: Forecast evaluation of GARCH specifications with a GED

	GARCH	EGARCH	TGARCH	GJRGARCH
RMSE	0.0619	0.0391	0.0391	0.1188
MAE	0.0450	0.0245	0.0245	0.0981
MAPE	1.2968	0.7058	0.7054	2.8558
TI	0.0090	0.0057	0.0057	0.0171

Notes: out-of-sample forecast period January 25, 2012 – March 24, 2015. RMSE, MAE, MAPE and TIC are root-mean squared error, mean absolute error, mean absolute percentage error, and Theil's inequality coefficient respectively.

Appendix E. Comparisons between the Danish area prices and the system price

Table E.1: Area prices in DK1 in comparison with the system prices

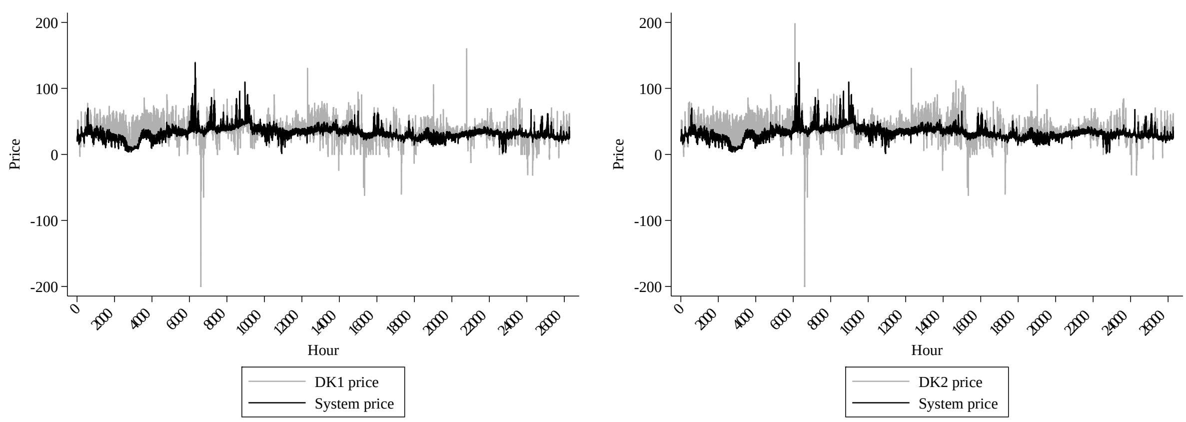
Price DK1	Frequence	%
Equal	5,630	21.42
Lower	9,835	37.42
Higher	10,815	41.15

Notes: Area prices of DK1 are assumed to be different from the system price when their differences exceed 0.1€/MWh.

Table E.2: Area prices in DK2 in comparison with the system prices

Price DK2	Frequence	%
Equal	6,280	23.9
Lower	6,208	23.62
Higher	13,792	52.48

Notes: Area prices of DK2 are assumed to be different from the system price when their differences exceed 0.1€/MWh.



DK1 DK2

Figure E.1: Comparisons between Danish area prices and the system price

Data source: Author’s calculation based on Nord Pool Spot (2015).

Appendix F. Unit root tests for stationarity of the variables

Table F.1: Results of unit root tests for included variables

Variables	ADF	PP
Price	-27.34	-28.17
Wind	-14.95	-19.63
Load	-14.01	-19.37
Coupling	-31.04	-29.57
Import	-25.22	-24.80

Notes: ADF and PP stand for the augmented Dickey-Fuller test and Phillips-Perron test, respectively. The null hypothesis is that the variable contains a unit root. The critical values for 1%, 5% and 10% quantiles are -3.43, -2.86 and -2.57, respectively.