Modelling and Forecasting the Volatility of the Nordic Power Market: An Application of the GARCH-Jump Process

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Abstract

Although the presence of extreme jumps in electricity prices is a common phenomenon, investigating the jump behavior in the power market does not receive significant attention in earlier studies. The present study aims to conceal this void in the existing literature. To do so, we employ the autoregressive conditional jump intensity (ARJI) model, combining with the GRACH method, to describe the volatility process and the jump behavior in Nordic electricity prices. The empirical findings reveal that the Nordic power market is highly volatile and time-varying jumps do exist in the electricity prices. In addition, the GARCH-jump models produce more accurate out-of-sample volatility forecasts than do the GARCH and EGARCH models. In summary, the results demonstrate that energy economists, energy policymakers and market analysts should consider the existence of time-varying jumps in the Nordic power market, because the GARCH-jump model provides the best forecasts for electricity prices.

Key words: Nordic power market; GARCH-jump model; Time-varying jumps; Outliers; Volatility forecasts

1. Introduction

Over the last few decades, electricity price forecasting has received much attention in the literature. This is because an accurate price forecasting is crucial for bidding strategies, making proper investment decisions and hedging against risks (Zhang and Tan, 2013). Besides, consumers can also utilize the price forecasting to develop appropriate power purchasing schemes for utility maximization (Pindoriya et al., 2008). Therefore, a large number of studies have employed several alternative approaches to forecasting electricity price in a more precise manner.

Notably, modeling volatility of electricity prices has recently received particular attention among the academics given that understanding the volatility of power market plays a crucial role in policymaking. Kostrzewski and Kostrzewska (2019) adopt a Bayesian process to model the volatility of PJM electricity markets. The study shows that the employed approach is a promising tool of modelling and forecasting electricity prices. A recent study by Ciarreta et al. (2020) conduct an empirical analysis of Spanish electricity price volatility. The authors detect two important structural breaks linked to key measures related to renewable electricity: (i) the abolishment of the feed-in tariff scheme; and (ii) the establishment of a more market-oriented regulation based on investment and operating costs. Do et al. (2020) explore the volatility linksge between the Irish and Great Britain electricity markets and how it is driven by changes in energy policy, institutional structures and political ideologies. The study concludes that magnitude of the good volatility connectedness is marginally larger than that of the bad volatility connectedness. In addition, Han et al. (2020) investigate the volatility connectedness across different regions in the Australian National Electricity Market, in order to shed light on the transmission of risks in a multiregional context. The authors document that volatility spillovers are typically more pronounced between physically interconnected markets.

It is worth mentioning that recent studies on the volatility of electricity price have been dominated by time series models and artificial neural networks (ANNs) (Shrivastava and Panigrahi, 2014). Although these models provide accurate predictions for short-term electricity price forecasting, they cannot capture extreme jumps that frequently occur in electricity prices (Cifter, 2013).

Due to the large price jumps detected in electricity markets, several researchers consider jump components in electricity price models. Notable contributions include Kaminski(1997), Clewlow and Strickland (2000), Deng (2000), Huisman and Mahieu (2003), Knittel et al. (2005), Seifert and Uhrig-Homburg (2007), Chan et al. (2008), Ullrich (2012) and Cifter (2013). These studies, in general, recommend the application of jump approaches while modeling and forecasting the volatility of electricity markets. For example, Huisman and Mahieu (2003) claim that employing such models not characterizes the frequent extreme jumps in electricity prices, but also outperforms the standard time series or ANN models. Moreover, while analyzing and predicting the German electricity price index, Seifert and Uhrig-Homburg (2007) discuss why jumps are observed in the power market. The authors argue that power plant or supply line outages can lead to short or long price impacts, depending on the severity and length of the outage. In addition, unexpected strong changes in weather can cause price spikes, while extreme weather situations can result in very volatile and jumpy price periods due to a high load level. It is therefore crucial to use a model that can capture both volatility dynamics and jump behavior of electricity prices so that the future volatility can be measured more closely.

Note that a number of recent studies (Daskalakis and Markellos, 2009; Wimschulte, 2010; Nomikos and Soldatos, 2010a, 2010b; Cifter, 2013; Dong et al. 2019) have focused on the price and volatility dynamics of Nordic power market. This market has received ample attention over the past decades as Nord Pool is one of the most successful deregulated power markets in the world. It has a very liquid derivatives market as well. Studies including Nomikos and Soldatos (2010a) and Vaissalo (2021) claim that the Nordic electricity market is considered to be among the most efficient regional electricity markets in the world. Since establishment of the Nord Pool market in the early 1990s, security of supply has been at a very high level and electricity prices in the Nordic wholesale market have been historically among the lowest in Europe. In terms of power generation capacity, there is no lack of electricity supply in the Nordic market[1]. We thus study this market considering it as one of the leading electrical power suppliers in Europe.

Importantly, many recent papers shed light on the importance of detecting jumps in power markets. Nomikos and Soldatos (2010b), for instance, argue that electricity prices exhibit very high volatility and large jumps represent the main feature of power markets. Such jumps and spikes are extreme short-lived price movements in the spot market which is due to extreme load fluctuations, combined with generating outages or transmission failures. Therefore, it is essential to use a volatility model that can capture jumps as well. Cifter (2013) also shows that Markov-switching GARCH model, which also takes jumps into account, performs better than the traditional GARCH models. More recently, Dong et al. (2019) employ a non-parametric model to study the volatility and jump dynamics of electricity prices in Denmark and Sweden. The findings indicate that

[1] The information is sourced from Fortum Energy Review, November 2016

electricity prices are more stable in Swedish price areas as hydropower is a more stable energy source.

It is also noteworthy that Nordic countries usually have longer winters and relatively colder summers, which leads to different demand side patterns (Dong et al., 2019). Besides, the substantial use of renewable energy in electricity generation process tends to have a significant impact on the variation of electricity prices. These characteristics of price movements may introduce large jumps in Nordic power prices, which need to be captured for managing risk more precisely so that future electricity prices can be predicted correctly.

In this study, unlike the earlier researchers, we, therefore, employ the autoregressive conditional jump intensity (ARJI) model, combining with the GRACH method, to simultaneously capture the volatility process and the jump behavior in Nordic electric power market prices. The GARCH-jump approach, proposed by Chan and Maheu (2002), is considered advantageous, since contrasting the traditional GARCH models, it can capture the impact of extreme news or abnormal information emerging from crashes, terrorist attacks and similar other events (Fowowe, 2013). Moreover, in addition to accounting for smooth persistent changes in volatility, the model also captures the discrete jumps in the underlying price series. Since modeling jumps in electricity prices is crucial to understand the future price risks, our study contributes to the scarce literature by further unfolding the jump behavior in power market.

The rest of the study will proceed as follows. The next section provides a brief overview of the Nordic electricity markets. Section 3 describes the data considered in our empirical analysis. Section 4 outlines the GARCH-jump models. Results are discussed in Section 5. Section 6 concludes the paper.

2. Nordic electricity markets

Nordic power markets have one dominating exchange for energy, which is called Nord Pool. Nord Pool is one of the oldest marketplaces for electricity in the world. The market covers most of the Europe as market operators from 20 different countries participate in it.

The Nordic power system appears to be a mixture of generation sources. In this market, electricity is mainly produced from hydro, nuclear and wind power. The Nordic region has a number of energy intensive industries and a large share of electricity heated houses. Accordingly, the electricity consumption in this part of the world is higher than in the rest of the EU. Growth in electricity consumption greatly depends on the weather condition. For instance, lower electricity demand is observed during the summer, while demand grows significantly in wintertime. The Nordic countries have a higher share of clean energy production compared to the rest of EU. Hydropower accounts for more than 50% of the electricity production in this region. The Nordic power industry contains several markets that are “time windows” for physical trading in electricity: the day-ahead market, the intra-day market and the balancing market. In this zone, trading is performed mainly on the day-ahead market (spot market), and the “system price”, which is the common Nordic price for all hours of the next following 24-hour period, is crucial for price formation within the other time windows (the intra-day and balancing markets and the financial market for long-term contracts). The intra-day market is primarily a correction market, where actors have the opportunity to trade into balance, including adjusting any earlier trading if the forecasts turn out to be wrong. The intra-day market closes one hour before the delivery hour. The balancing market is trading in automatic and manual reserves used by the Nordic transmission system operators (TSOs) in order to maintain power balance during the hour of operation. Nord

Pool Spot is responsible for the day-ahead market and the intra-day market, while the TSOs are responsible for the balancing market[2].

The Nordic countries deregulated their power markets in the early 1990s and brought their individual markets together into a common Nordic market[3]. Estonia, Latvia and Lithuania deregulated their power markets, and joined the Nord Pool market in 2010-2013. Since the deregulation, the Nordic electricity market has continued to inflate and today it is the main marketplace of electricity in 13 countries. Moreover, Nord Pool also provides electricity for Belgium, Germany, the Netherlands, Luxemburg, France and the United Kingdom. Altogether, trading in Nord Pool region includes 360 companies in 20 countries. The overall volume electricity being traded in the exchange was 494 TWh during year 2019 (Nord Pool, 2021). Integration of the Nordic market to other European markets continues via new grid investments and improved congestion management. The Emissions Trading System also contributes to such integration. European level market liberalisation and integration continues.

Nordic countries, including Finland, Sweden, Norway and Denmark, accounted for total generation of 401 TWh out of the total 494 TWh traded in the Nord Pool power exchange during the year 2019. Figure 1 illustrates how the power production mixes in these countries are constructed in corresponding year. In this region, hydro power appears to be the dominant method of energy production. In Norway, for instance, hydro generation accounts for 93% of all electricity. Wind power is the other popular method of production which contributes to 35% of power

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[2] The information is sourced from **www.nordicenergyregulators.org**.

[3] The term 'deregulation' means that the state is no longer running the power market, and instead that free competition is introduced. Deregulation was undertaken to create a more efficient market, with exchange of power between countries and increased security of supply. Available power capacity can be used more efficiently in a large region compared to a small one, and integrated markets enhance productivity and improve efficiency (see for more details **www.nordpoolgroup.com**)

production in Finland and 40% in Sweden. The volume of wind power has grown substantially over the recent years and currently, it is used to generate a significant proportion to match the energy demand in Nordic region. As evident from the figure, countries in Nord Pool already rely on production methods that are capable of generating electricity without or with only low carbon emissions (Vaissalo, 2021).

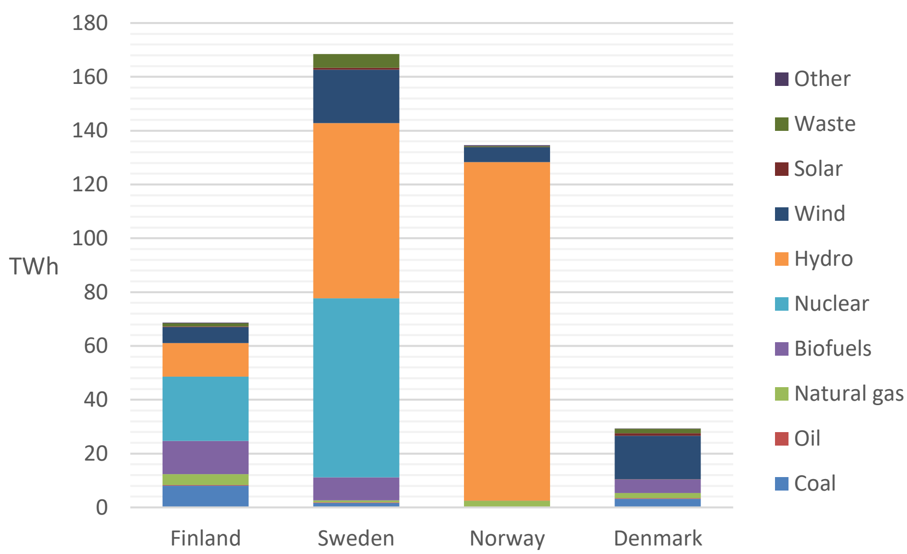

Figure 1. Electricity production mix in Nordic countries (Vaissalo, 2021)

It is noteworthy that Nordic power industry uses financial contracts for price hedging and risk management. These contracts have a time horizon up to ten years and cover daily, weekly, monthly, quarterly and annual contracts. The system price calculated by Nord Pool is considered as the reference price for the financial market in the Nordic region. There is no physical delivery for financial power market contracts. Cash settlement takes place throughout trading – and/or the delivery period, starting at the due date of each contract, depending on whether the product is a future.

3. Data

The data used in this study have been sourced from the website of Nordic power market[4]. In this database, intraday, daily, quarterly, and annual power prices are reported. We consider daily spot prices since the GARCH-type models are mostly appropriate for daily frequency (Cifter, 2013). Our sample period starts in 1 January, 2013 and ends in 31 December, 2020. The beginning of our sample period depends on the availability of the data.

Table 1 displays the descriptive statistics and unit root test results for the return series. The findings show that the data are positively skewed and leptokurtic. The Jarque-Bera test further confirms that the electricity prices do not follow the normal distribution and hence the volatility models should be estimated with non-normal distributions (e.g., *t*-distribution). While assessing the stationary property of the data used, the augmented Dickey–Fuller (ADF) and the Philips–Perron (PP) tests suggest that the return series does not contain unit root.

4. Methodology

The GARCH-jump model has recently received ample attentions from academics across the globe. Some fresh evidence includes Dutta et al. (2017), Xiao and Zhou (2018), Zhang et al. (2018), Zhou et al. (2019), Chiang et al. (2019), Gronwald (2019) and Dutta et al. (2020). While all these studies

[4] The data are retrieved from http://www.nordpoolspot.com/PowerMaket/

mainly investigate the occurrence of jumps in stock and commodity prices, this paper examines such events in electricity prices. This process takes the following form[5]:

$$R_t = \pi + \mu_1 R_{t-1} + \mu_2 R_{t-2} + \epsilon_t \qquad (1)$$

where R_t is the log return of electricity prices at time *t* and ϵ_t refers to the error term at time *t* which has two components as follows:

$$\epsilon_t = \epsilon_{1t} + \epsilon_{2t} \qquad (2)$$

The first component ϵ_{1t} is a mean-zero innovation with normal stochastic process assuming the following form:

$$\epsilon_{1t} = \sqrt{h_t} z_t, \quad z_t \sim NID(0,1)$$

$$h_t = \omega + \alpha\epsilon_{1t-1}^2 + \beta h_{t-1} \qquad (3)$$

The second component ϵ_{2t} is a jump innovation which consists of abnormal price movements with $E(\epsilon_{2t}|I_{t-1}) = 0$, where I_{t-1} designates the information set. Now ϵ_{2t} is defined as the discrepancy between the jump component and the expected total jump size between *t*-1 and *t*:

$$\epsilon_{2t} = \sum_{l=1}^{n_t} U_{tl} - \theta\lambda_t \qquad (4)$$

[5] Selection of the mean and variance equations is based on the Akaike Information criterion (AIC) and Bayesian Information criterion (BIC). We first estimate the AR(1)-GARCH(1,1) model. In addition, several alternative models are also considered. These include AR(2)-GARCH(1,1), AR(3)-GARCH(1,1), AR(2)-GARCH(2,1), AR(2)-GARCH(2,2) amongst others. But, on the basis of AIC and BIC statistics, we finally choose the AR(2)-GARCH(1,1) model as it produces the lowest values for AIC and BIC. Once the appropriate lags have been identified, we test for the autocorrelation amongst the residuals to verify whether the selected model is correctly fitted.

where U_{tl} denotes to the jump size and is assumed to be normally distributed with mean θ and variance d^2, $\sum_{l=1}^{n_t} U_{tl}$ is the jump component and n_t defines the number of jumps. It is assumed that n_t is distributed as a Poisson variable with an autoregressive conditional jump intensity (ARJI) given by

$$\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \gamma\xi_{t-1} \tag{5}$$

where λ_t is the time-varying conditional jump intensity parameter and $\lambda_t > 0$, $\lambda_0 > 0$, $\rho > 0$ and $\gamma > 0$.

Now the log-likelihood function can be expressed as:

$$L(\Omega) = \sum_{t=1}^{T} \log f(R_t | I_{t-1}; \Omega)$$

where $\Omega = (\pi, \mu_1, \mu_2, \delta, \omega, \alpha, \beta, \theta, d, \lambda_0, \rho, \gamma)$.

Moreover, for the purpose of robustness checking, the constant jump intensity model (Jorion, 1988) has also been estimated in addition to the ARJI approach. The constant jump intensity model simply assumes that $\lambda_t = \lambda_0$.

5. Empirical Results

5.1. Results of the GARCH-jump models

Table 2 exhibits the results of the constant along with the autoregressive conditional jump intensity models. These findings indicate that the GARCH parameters are statistically significant at 1%

level suggesting the existence of strong ARCH and GARCH effects. The sum of α and β also reveals high degree of persistence in the price fluctuations.

It is also evident from Table 2 that the jump parameters are all significant implying that jumps do exist in the Nordic electricity market returns and they are time-varying. The positive coefficient of the jump mean indicates that the jump behavior driven by the abnormal information has a positive impact on returns, while the negative coefficient of the jump variance infers that volatility driven by abnormal information has a negative effect on volatility of returns (Fowowe, 2013, Dutta et al., 2017). The results further document that all the jump intensity parameters $(\lambda_0, \rho, \gamma)$ are also statistically significant suggesting that the jump intensity varies over time. For instance, the ρ parameter, which provides a measure of persistence in the conditional jump intensity, is estimated to be 0.7154 implying that a high probability of many (few) jumps today tends to be followed by a high probability of many (few) jumps tomorrow, as documented by Chan and Maheu (2002). In addition, the γ parameter, which measures the sensitivity of λ_t to the past shock, ξ_{t-1}, appears to be 0.1448 indicating a unit increase in ξ_{t-1} results in a dampened effect (0.14) on the next period's jump intensity (Chan and Maheu, 2002).

Additionally, these parameters satisfy the constraints that $\lambda_0 > 0$, $\rho > 0$ and $\gamma > 0$ and hence we can infer that the GARCH-ARJI model is a proper choice for describing the jump behavior in the electricity market returns. Furthermore, the positive ρ and γ indicate that the current jump intensity (λ_t) is affected by the most recent jump intensity (λ_{t-1}) and intensity residuals (ξ_{t-1}). We also report that the high values of ρ and γ suggest a high degree of persistence in the jump intensity.

Moreover, the supremacy of the jump models is also evidenced by both the standard information criteria and the likelihood ratio test (see Table 3). The findings confirm that each of the jump models outperforms the traditional GARCH models which are estimated as benchmarks[6]. Further, the ARJI model surpasses the constant intensity jump model which, in turn, implies that the jump intensity is time-dependent. To sum up, the ARJI- GARCH model provides the best fit to the electricity price series under investigation.

5.2. Out-of-sample forecast results

We now evaluate the forecast performance of various models considered in our empirical analysis. We choose the in-sample estimation period from 1 January, 2013 to December 31, 2019 and the out-of-sample forecast period from January 1, 2020 to December 31, 2020.The following loss functions are used in our investigations:

$$\text{Mean Square Error: } MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\sigma_{a,t}^{2} - \sigma_{f,t}^{2}\right)^{2}$$

$$\text{Mean Absolute Error: } MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\sigma_{a,t}^{2} - \sigma_{f,t}^{2}\right|$$

where, *n* indicates the number of forecast data points, $\sigma_{a,t}^{2}$ signifies the actual volatility on day *t* and $\sigma_{f,t}^{2}$ denotes the volatility forecast for day t. The actual volatility is defined as the squared daily returns.

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[6] We consider the GARCH (1,1) and EGARCH (1,1) approaches in our analysis as the benchmark models. These models are defined as follows:
GARCH (1,1): $h_t = \omega + \alpha\varepsilon_{t-1}^{2} + \beta h_{t-1}$, where $\omega > 0, \alpha \geq 0, \beta \geq 0$ and $\gamma \geq 0$ to guarantee the positivity of h_t.
EGARCH (1,1): $\ln(h_t) = c + \frac{a|\varepsilon_{t-1}| + v\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + b\ln(h_{t-1})$

Table 4 exhibits the one-day ahead forecasting performance of different models. These outcomes support that in each case, the ARJI-GARCH model evidences a superior volatility forecasting ability by producing the lowest values for both MSE and MAE statistics. It is also noteworthy that the constant jump model has emerged as the second best model confirming that while predicting the Nordic power market price series, all the employed jump approaches outperform the standard GARCH models. The Diebold and Mariano test (1995) further confirms that the ARJI model performs better than others.

5.3. Additional tests

In this section, we conduct some additional tests to examine further if the ARJI model produces better volatility forecasts compared to other approaches. In particular, we estimate the Mincer and Zarnowitz (MZ, 1969) regression model to serve our purpose. The MZ regression is specified as

$$Vol_t = \varphi_0 + \varphi_1 \widehat{Vol_t} + \epsilon_t \tag{6}$$

where, Vol_t and $\widehat{Vol_t}$ indicate the true volatility and volatility forecast for day *t*, respectively. Our objective is to compute the coefficient of determination (i.e., R^2) in order to find the best forecast model.

We present these R^2 (%) values in Table 5. We find that the ARJI model (26%) generates the highest R^2 values with the CJI process (22%) being the second best model. Moreover, of the traditional GARCH models, the asymmetric GARCH or EGARCH process excels its symmetric counterpart. In sum, we document that the ARJI model appears to be the best forecast model followed by the CJI process. We, therefore, conclude that the information content of time-varying jumps is important for forecasting the volatility of Nordic power markets.

5.4. Jumps and outliers

It is important to note that several studies have investigated the volatility dynamics of the Nordic electricity market using GARCH-type models without correcting for potential outliers. However, several researchers argue that outliers can affect identification and estimation of the GARCH-type models and they can wrongly suggest conditional heteroscedasticity or hide true heteroscedasticity (Charles and Darné, 2005; Carnero et al., 2007; Catalán and Trívez, 2007; Charles, 2008; Carnero et al., 2012). Therefore, it is of paramount importance for practitioners to use outlier-free data to estimate the volatility of financial markets (Dutta, 2018a). In addition, it is also stimulating to examine if time-dependent jumps exist even after correcting for outliers. Given that the significance of outliers and time-varying jumps in Nordic power market does not receive considerable attention in earlier studies, this empirical research seems to add a new dimension to the standing literature.

In this study, we follow Ané et al. (2008) in detecting the presence of outliers. Let R_t be the log return on the electricity price index on day *t*, which follows an AR(2)-GARCH(1,1) model:

$$R_t = b_0 + b_1 R_{t-1} + b_1 R_{t-2} + \varepsilon_t \tag{7}$$

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \sigma_{t-1}^2 \tag{8}$$

where $\varepsilon_t = \sigma_t z_t$ with z_t being an i.i.d. process such as $z_t / I_{t-1} \sim IIN(0,1)$; I_{t-1} refers to the filtration of information at time $t-1$.

R_{t+1} is considered an outlier if it does not belong to the following interval:

$$R_{t+1} \in [R_{t,t+1} \pm F(1-\frac{\alpha}{2})\sigma_{t,t+1}]$$

where, $R_{t,t+1}$ is the one-step ahead return forecast given by:

$$R_{t,t+1} = E(R_{t+1}/I_t) = b_0 + b_1 R_t + b_2 R_{t-1}$$

and $\sigma_{t,t+1}^2$ denotes the one-step ahead variance forecast defined as:

$$\sigma_{t,t+1}^2 = \mathrm{var}(R_{t+1}/I_t) = a_0 + (a_1 + a_2)\sigma_t^2$$

Furthermore, $F\left(1-\frac{\alpha}{2}\right) = P(z_t \le 1 - {}^{\alpha}/_{2})$ is a fractile of the assumed conditional distribution. The above detection procedure is rolled-over until the end of the sample period. Notably, the detection procedure is robust to any model misspecifications (Ané et al., 2008). It is worth mentioning that a number of recent studies have employed this process to identify outliers in different financial markets. Dutta (2018a), for example, documents that outliers play a crucial role in modelling the volatility of the EU emission market. Another study by Dutta (2018b) obtains similar results for various precious and industrial metal markets. Other important studies include Chen et al. (2010), Dai et al. (2012), Behmiri and Manera (2015), Chatzikonstanti (2017), Chatzikonstanti and Karoglou (2020). All these papers find this approach, developed by Ané et al. (2008), suitable while identifying possible outliers or extreme observations in stock and commodity markets.

The findings from the outlier detection process suggest that extreme observations occur in the Nordic electricity prices. Overall, we have found 11 outliers during the sample period. We also document that these outliers are mainly present after the soar.

Next, Table 6 presents the results of GARCH-jump models after correcting for outliers. Both the constant jump intensity and ARJI models have been considered in our analysis. The findings show that most of these jump parameters appear to be significant even after utilizing the outlier-free data. These findings clearly evidence that outliers and time-varying jumps play a key role in modeling the volatility or risk of the Nordic electricity price index. Nevertheless, assessing the significance of outliers and time-varying jumps in this power market has received little or no attention in prior research. Our empirical analysis aims to fill this void in the existing literature.

6. Conclusion

Although the presence of extreme jumps in electricity prices is a common phenomenon, investigating the jump behavior in the power market does not receive significant attention in the earlier studies. The aim of this study is to conceal this void in the existing literature. To serve our purpose, we consider using the autoregressive conditional jump intensity (ARJI) model, combining with the GRACH method, to describe the volatility process and jump behavior in Nordic electricity prices.

The key findings of our research are the following. First, the GARCH parameters are found to be statistically significant at 1% level indicating that the Nordic power market is highly volatile. Second, Jumps do exist in the electricity prices and they are time-varying. Third, both the standard information criteria and the likelihood ratio test confirm that the jump models outperform the traditional GARCH models. Finally, the GARCH-jump models generate more accurate out-of-sample volatility forecasts than do the GARCH and EGARCH models. It is also important to note that we find outliers in electricity prices and more importantly, the jumps occur even after correcting for such outliers. These findings thus suggest Nordic power market is not only characterized by time-varying volatility, but also by extreme price movements, which exceed the current respective market volatility. Such jump behavior points towards an instable condition in the market and hence the information on electricity prices could mislead the investment decisions On the whole, our findings suggest that energy economists, energy policymakers and market analysts should consider the presence of time-varying jumps in the Nordic power market given that the GARCH-jump approach provides the best forecasts for electricity prices.

Note that the stable price of electricity in Nordic region could be attributed to the fact that these markets make a significant use of renewable energies for producing electricity. The really high percentage of wind power generation, for example, can cover most of the total demand for electricity in this region (Dong et al., 2019). However, as the production of wind power may vary second by second depending on the meteorological conditions, electricity prices tend to experience hourly jumps. It is thus important to use of the appropriate econometric models for capturing such jumps in Nordic electricity markets. Besides, proper choice of econometric models will also allow policymakers to comprehend the dynamics of the risk premium. Such knowledge is essential given that understanding the frequent changes in the risk premium behavior plays a major role for designing the optimal hedging strategies for investors and policymakers, since the cost of hedging is substantially affected by the time when the hedge is created (Gudkov and Ignatieva, 2021). The precise use of derivatives, depending on the complexity of the contracts and the adopted hedging strategy, would also help market participants hedge the potential risk significantly.

Moreover, few earlier works (Schlueter, 2010; Cifter, 2013) document that electricity prices also exhibit asymmetric characteristics. Further research may include the application of asymmetric GARCH-jump models to forecast the electricity price volatility more accurately. In addition, future studies could also examine whether key relevant factors such as crude oil prices, emission allowances or prices of renewables can predict these time-varying jumps.

References

Ané, T., Loredana, U.R., Gambet, J.B., Bouverot, J. (2008). Robust outlier detection for Asia-Pacific stock index returns. Journal of International Financial Markets, Institutions & Money, 18, 326–343.

Behmiri, Niaz B., Manera, Matteo, 2015. The role of outliers and oil price shocks on volatility of metal prices. Resour. Policy 46, 139–150Byers, J. W., Ivilina T Popova, and Betty Simkins. (2021). "Robust Estimation of Conditional Risk Measures Using Machine Learning Algorithm for Commodity Futures Prices in the Presence of Outliers". Journal of Commodity Markets (Forthcoming). (24), 18. 2405-8513.

Carnero, M., Peña, D., Ruiz, E.: Effects of outliers on the identification and estimation of GARCH models. J. Time Ser. Anal. 28.4, 471–497 (2007)

Carnero, M.A., Pena, D., Ruiz, E., 2012. Estimating GARCH volatility in the presence ~ of outliers. Econ. Lett. 114, 86-90.

Catalán, B, Trívez, F. J.: Forecasting volatility in GARCH models with additive outliers. Quant. Financ. 7.6, 591–596 (2007)

Chan, K. F., P. Gray, and B. van Campen, "A new approach to characterizing and forecasting electricity price volatility," International Journal of Forecasting, vol. 24, pp. 728-743, 2008.

Chan WH, Maheu JM. Conditional jump dynamics in stock market returns. Journal of Business and Economic Statistics 2002; 20: 377–89.

Charles, A.: Forecasting volatility with outliers in GARCH models. J. Forecast. 27.7, 551–565 (2008)

Charles, A., Darné, O.: Outliers and GARCH models in financial data. Econ. Lett. 86.3, 347–352 (2005)

Chatzikonstanti, V.: Breaks and outliers when modelling the volatility of the US stock market. Appl. Econ 49.46, 4704–4717 (2017).

Chatzikonstanti, V., & Karoglou, M. (2020). Can Black Swans be tamed with a flexible Mean-Variance specification? International Journal of Finance and Economics.

Chen, S.; Härdle, W.K.; Jeong, K. Forecasting volatility with support vector machine-based GARCH model. J. Forecast. 2010, 29, 406–433.

Chiang, S., Chen, C. Huang, Analyzing the impacts of foreign exchange and oil price on biofuel commodity futures, J. Int. Money Finance 96 (2019) 37–48.

Ciarreta A, Pizarro-Irizar C, Zarraga A. Renewable energy regulation and structural breaks: An empirical analysis of spanish electricity price volatility. Energy Econ 2020;104749.

Cifter, A. (2013). Forecasting electricity price volatility with the Markov-switching GARCH model: Evidence from the Nordic electric power market. Electric Power Systems Research, 102(0):61–67.

Clewlow, Les, Chris Strickland (2000): Energy Derivatives: Pricing and Risk Management; London, Lacima Publications.

Dai, W., Wu, J. Y., & Lu, C. J. (2012). Combining nonlinear independent component analysis and neural network for the prediction of Asian stock market indexes. Expert Systems with Applications, 39(4), 4444–4452.

Daskalakis, G. and Markellos, R. N. (2009). Are Electricity Risk Premia Affected by Emission Allowance Prices? Evidence from the EEX, Nord Pool and Powernext. Energy Policy, Vol. 37, No. 7, pp. 2594-2604.

Deng, Shijie (2000): Stochastic Models of Energy Commodity Prices and Their Applications:Mean-Reversion with Jumps and Spikes; Working Paper, PWP-073, Universityof California Energy Institute.

Diebold, F.X., Mariano, R.S., 1995. Comparing predictive accuracy. Journal of Business & Economic Statistics 13, 253–263.

Do, H.X., Nepal, R., Jamasb, T., 2020. Electricity market integration, decarbonisation and security of supply: dynamic volatility connectedness in the Irish and Great Britain markets. Energy Econ. 92, 104947.

Dong S, Li H, Wallin F, Avelin A, Zhang Q, Yu Z. Volatility of electricity price in Denmark and Sweden. Energy Procedia 2019;158:4331–7.

Dutta, A. (2018a). Modeling and Forecasting the Volatility of Carbon Emission Market: The Role of Outliers, Time-varying Jumps and Oil Price Risk. Journal of Cleaner Production, 172: 2773-2781.

Dutta, A. (2018b). Impacts of Oil Volatility Shocks on Metal Markets: A Research Note. Resources Policy, 55: 9-19.

Dutta, A., Bouri, E. and Roubaud, D. (2020). Modelling the volatility of crude oil returns: jumps and volatility forecasts. International Journal of Finance and Economics, Forthcoming.

Dutta, A., Nikkinen, J. and Rothovius,T. (2017). Impact of Oil Price Uncertainty on Middle East and African Stock Markets. Energy, 123: 189-197.

Fowowe B. Jump dynamics in the relationship between oil prices and the stock market: evidence from Nigeria. Energy 2013; 56: 31-8.

Gronwald, M. (2019). Is bitcoin a commodity? On price jumps, demand shocks and certainty of supply. Journal of International Money and Finance, 97: 86-92.

Gudkov, N. and Ignatieva, K. (2021). Electricity price modelling with stochastic volatility and jumps: An empirical investigation. Energy Econ. 98, 105260.

Han, L., Kordzakhia, N., Trück, S., 2020. Volatility spillovers in Australian electricity markets. Energy Econ. 90.

Huisman, R., R. Mahieu (2003): Regime Jumps in Electricity Prices; Energy Economics, 25, 425-434.

Jorion P. On jump processes in the foreign exchange and stock markets. Review of Financial Studies 1988;1:427-45.

Kaminski, Vincent (1997): The Challange of Pricing and Risk Managing Electricity Derivatives; The US power market Risk Publications, London, 149-171.

Knittel, R. C., Michael R. Roberts, "An empirical examination of restructured electricity prices." Energy Economics, vol. 27, pp. 791–817, 2005.

Kostrzewski, M., Kostrzewska, J., 2019. Probabilistic electricity price forecasting with Bayesian stochastic volatility models. Energy Econ. 80, 610–620.

Mincer, J., Zarnowitz, V., 1969. The evaluation of economic forecasts. In: Mincer, J. (Ed.), Economic Forecasts and Expectations. NBER, New York, pp. 3–46.

Nomikos, N.K., Soldatos, O.A., 2010a. Analysis of model implied volatility for jump diffusion models: Empirical evidence from the nordpool market. Energy Econ. 32 (2), 302–312.

Nomikos, N.K., Soldatos, O.A., 2010b. Modelling short and long-term risks in power markets: Empirical evidence from Nord Pool. Energy Policy 38 (10), 5671–5683.

Nord Pool. (2021). About us – History. https://www.nordpoolgroup.com/About-us/History/

Pindoriya NM, Singh SN, Singh SK. An adaptive wavelet neural network based energy price forecasting in electricity markets. IEEE Trans Power Syst 2008;23(3):1423–32.

Schlueter, S.A. A long-term/short-term model for daily electricity prices with dynamic volatility, Energy Economics 32 (2010) 1074–1081.

Seifert, J., Uhrig-Homburg, M. (2007) Modelling jumps in electricity prices: theory and empirical evidence. Review of Derivatives Research 10, 59-85.

Shrivastava, N.A., Panigrahi, B.K., 2014. A hybrid wavelet-ELM based short term price forecasting for electricity markets. Int. J. Electr. Power Energy Syst. 55, 41–50.

Ullrich, Carl J. " Realized volatility and price spikes in electricity markets: The importance of observation frequency." Energy Economics, vol. 34, pp. 1809–1818, 2012.

Vaissalo, J. (2021). Volatility dynamics between EU ETS and Nordic electricity market. University of Vaasa.

Wimschulte, J. (2010). The futures and forward price differential in the Nordic electricity market. Energy Policy, 38, 4731-4733.

Xiao, X., and C. Zhou. 2018. The decomposition of jump risks in individual stock returns. J Empir. Financ, 47, pp. 207–228.

Zhang, C., X. Shi, D. Yu, (2018), The effect of global oil price shocks on China's precious metals market: A comparative analysis of gold and platinum, J. Cleaner Prod. 186, 652–661.

Zhang, J., and Tan, Z. Day-ahead electricity price forecasting using WT, CLSSVM and EGARCH model, Elect. Power Energy Syst., 2013, 45, (1), pp. 362–368.

Zhou, C., Wu, C., Wang, Y. (2019). Dynamic portfolio allocation with time-varying jump risk. J Empir. Financ, 50, pp. 113–124.

Table 1: Descriptive Statistics and unit root tests results

	Logarithmic difference ($R_t = \ln({}^{P_t}/_{P_{t-1}})$)
Mean	0.000051
Standard deviation	0.051467
Skewness	0.655886
Kurtosis	11.890430
Jarque-Bera Test	4912.931***
ADF test	-10.60210***
PP test	-54.17813***

Notes: *** indicates statistical significance at 1% level.

Table 2: Results of GARCH-jump models

Variable	Constant jump intensity model	ARJI
π	-.0007	-.0014**
	(.47)	(.03)
μ_1	.0235	.0276
	(.38)	(.17)
μ_2	-.2714***	-.2669***
	(.00)	(.00)
ω	1.4×10^{-8}	.00001
	(.99)	(.42)
α	.1613***	.1659***
	(.00)	(.00)
β	.7922***	.7931***
	(.00)	(.00)
θ	.0041	.0058***
	(.15)	(.00)
d^2	-.0360***	-.0338***
	(.00)	(.00)
λ_0	.3401**	.1008***
	(.02)	(.00)
ρ		.7154***
		(.00)
γ		.1448***
		(.00)
Log Likelihood	2746.1506	2749.4637

Notes: The values in the parentheses indicate the *p*-values. *** and ** imply significance at 1% and 5% levels respectively.

Table 3: Model performance

Model selection criteria				
Criterion	GARCH	EGARCH	Constant intensity jump (CJI)	ARJI
Log likelihood	2719.08	2722.30	2746.15	2749.46
AIC	-3.7202	-3.7233	-3.7321	-3.7483
BIC	-3.6949	-3.6943	-3.7009	-3.7113
HQ	-3.7108	-3.7124	-3.7200	-3.7216
Likelihood ratio test				
CJI vs GARCH			54.14***	
CJI vs EGARCH			47.70***	
CJI vs ARJI				6.62***
ARJI vs GARCH				60.76***
ARJI vs EGARCH				54.32***

Notes: *** indicates statistical significance at 1% level.

Table 4: Out-of-sample forecasts

	MSE	DM tests	MAE	DM tests
GARCH	0.000063	2.85**	0.003074	4.67**
EGARCH	0.000065	3.09**	0.002983	3.59**
CJI	0.000061	1.79*	0.002768	2.41**
ARJI	0.000059		0.002711	

Notes: ** and * imply significance at 5% and 10% levels respectively. DM indicates the Diebold and Mariano test.

Table 5: The Mincer and Zarnowitz (MZ) regression results

Models →	GARCH	EGARCH	CJI	ARJI
R^2 (%)	16.53%	18.91%	22.38%	26.84%

Notes: The R^2 values are obtained from the Mincer and Zarnowitz (MZ) regression.

Table 6: Results of GARCH-jump models after correcting for outliers

Variable	Constant jump intensity model	ARJI
π	-.0012	-.0006*
	(.35)	(.07)
μ_1	.0469	.0099
	(.13)	(.24)
μ_2	-.2551***	-.2988***
	(.00)	(.00)
ω	.0002	.0007
	(.82)	(.31)
α	.1476***	.1200***
	(.00)	(.00)
β	.7522***	.7765***
	(.00)	(.00)
θ	.0025	.0021
	(.12)	(.11)
d^2	-.0431***	-.0402***
	(.00)	(.00)
λ_0	.3253**	.0962***
	(.03)	(.00)
ρ		.7256***
		(.00)
γ		.1843***
		(.00)
Log Likelihood	2721.2801	2700.7234

Notes: This table presents the results of GARCH-jump models after correcting for outliers. Both the constant jump intensity and ARJI models have been considered in this analysis. The values in the parentheses indicate the *p*-values. *** and ** imply significance at 1% and 5% levels respectively.