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Financial Time Series Modelling on Nordic Pool Electricity Prices

BSC MATHEMATICS WITH FINANCE AND ACCOUNTING: THIRD YEAR PROJECT

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1.0 Introduction

Financial time series are continually brought to our attention (Taylor,2008). Daily news reports through various mass media platforms are common mediums showcasing the latest stock market index value, currency exchange rates, interest rates as well as electricity prices, to name a few. These reports often highlight price changes where the said prices fluctuate up or down by several percentage basis points from their original prices over a certain period of time. Lu, Lee and Chiu (2009) further note that financial time series forecasting has been of growing interest of late as accurate and reliable forecasting of financial prices are becoming vital in investment decision making.

Monitoring price behaviour and attempting to understand the probable and tenable development of prices in the near future is crucial in developing a sound and reliable mechanism that directly feeds into the decision making process of financial decisions. Monitoring prices on a daily basis is beneficial at a consumer level as it helps consumers to make informed decisions and choose the most competitive rates that best suit their individual needs. For example, if you were planning on travelling abroad for leisure, you would need to buy foreign currency. You may look up the latest exchange rates from time to time and attempt to forecast them; the series of prices obtained is thus called a financial time series. This is because a time series is a sequence of observations taken sequentially in time(Box et al., 2015). In addition, suppose you were planning on travelling around the time of the Brexit referendum. Most people would have started buying currency exchange as soon as they could as according to Ben Broadbent, Deputy Governor Monetary Policy who gave a speech in Imperial College London in 2017, the link between currency exchange and the probability of remaining in the EU was evident long before the vote itself, i.e., the pound currency dropped as it became more likely that the United Kingdom would exit the European Union. Broadbent further elaborated that in the months leading up to the actual vote day, June 23 2017, there was a tight correlation between the currency and perceived likelihood of a 'remain' vote as demonstrated in Figure 1 (Broadbent, 2017; Lea, 2006). This further emphasises the practicality and relevance of financial time series in everyday use.

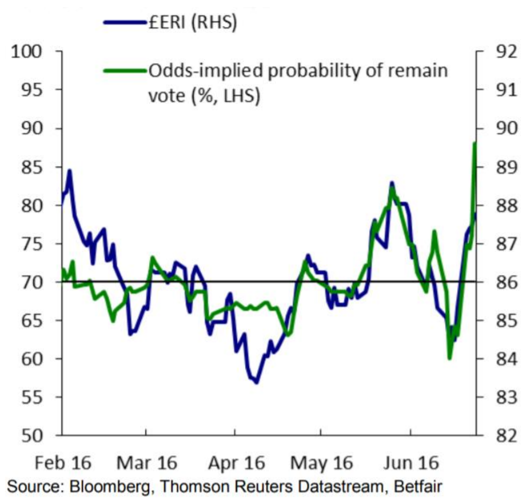


Figure 1: Sterling sensitive to expected result well before the referendum itself (cited in https://www.bis.org/review/r170331a.pdf).

A primary objective of *price studies* is understanding and comprehending how prices behave. Since it is a complex notion, relying solely on theoretical explanations would not be feasible and therefore, the usage of actual prices should be more actively used and considered. Statistical methods are the most intuitive and obvious method to examine and understand prices. Additionally, in this era of technological advancements, we are able to use longer price series with less computing time to help us understand the time series we are modelling. In this thesis, I will attempt to illustrate the electricity spot prices conditioned on a particular hour to gain intuitive insights on the correlation of the hour of the day in relation to the electricity prices. For these reasons, I have used the Nord Pool data set over a range of 7 years to illustrate the time series modelling.

The remainder of this thesis is structured as follows. Section 2 describes the background of the material pertaining to this thesis including the meanings of Financial Time Series, Stationarity, Returns, Nord Pool and Electricity Prices. Section 3 highlights the methodology used in this thesis with Section 4 as the Results and Section 5 the conclusion.

2.0 Background

2.1 Financial Time Series

Arlt (2001) asserts that the supply and demand of money and capital is the foundation deriving the financial market, which is part of the market system. The financial market is defined to be a "complex, evolutionary and non-linear dynamical system" by Yaser and Atiya (1996) (cited by Huang, Nakamori and Wang, 2005). The bond market, stock market, commodity market and exchange market form the four components of the financial market. Credits, loans, bonds, shares, commodities and currency are examples of the different areas that the financial market is comprised of (Arlt, 2001). The basic information that we can extract from a financial market are prices. For example, the prices of its shares, commodities, currency rates and bonds, on a continuous basis. The time series is created based on the prices which are monitored in a certain time frequency. These time series as well as price based and price illustrating time series are known as financial time series.

The financial time series contains distinguished properties pertained by the microstructure of the financial market, as opposed to other economic time series models. The high frequency of individual values is the basic feature of the financial time series. This feature intensifies the influence of non-systematic features to the dynamism of these time series; relatively high volatility of prices which changes throughout time is a consequence of this. While it gives a more complete picture of price movements, the financial time series is inherently noisy, non-stationary and deterministically chaotic for the same reasons that make it dynamic. ((Hall, 1994; Yaser and Atiya, 1996) cited in Tay and Cao, 2003). Lu, Lee and Chiu (2009) describe the financial time series' noise characteristic to be the lack of complete data from financial markets past behaviour to link the correlation between past and future prices. Whilst the financial time series are extremely beneficial to different types of people, from individuals utilising it to make travel decisions for personal use to professionals in the financial industy making decisions on investments, the data set of a financial time series is tricky to model.

In this thesis, the electricity prices data from the Nord Pool was used to elaborate how a time series typically looks like. Prices are represented in thousands of Euros on the y-axis, while the x-axis presents time on an hourly incremental basis, over a period of 7 years. The x–axis range was chosen to be consistent with Taylor's (2008) workings that utilised time taken at equally spaced intervals with time increments ranging from seconds to years. This thesis chose the hourly range as it provided a detailed yet controlled measure for analysis.

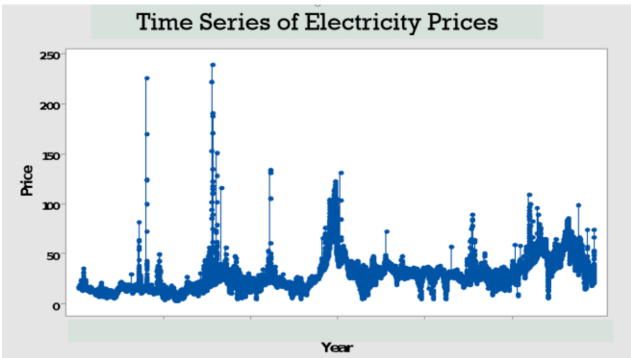


Figure 2: Time series of electricity prices of all Nordic Pool data.

2.2 Stationarity

Time series analysis is used to forecast future outcomes with the given data (Madsen, 2007). Tsay (2005) claims that the stationarity characteristic of the time series is the foundation of time series analysis. We can infer that our time series is non-stationary as the time series has a non-constant mean which changes over time. This can also be inferred from the fact that the time series is seasonal and thus time dependent. This thesis adheres to represent the time series as stationary as we can then assume that the prices in the future would be the same in the past. There are newer methods to analyse non-linear and non-stationary data (Huang et al.). However, as these methods exceed the scope of this paper, Tsay (2005)'s time series analysis approach of stationarising the time series shall be adopted. Tsay (2005) defines a time series $\{r_t\}$ to be strictly stationary if the joint distribution of $(r_{t_1}, \dots, r_{t_k})$ is identical to $(r_{t_1+1}, \dots, r_{t_k+1})$ for all t, where k is an arbitrary positive integer and $(t_1, \dots, t_k)$is a collection of k positive integers which is in line with Palma (2007) and Mills and Markellos (2008). Essentially, strict stationarity requires the invariance of the joint distribution $(r_{t_1}, \dots, r_{t_k})$ to a change of time origin (Mills and Markellos, 2008), in particular, varying about a fixed constant mean level and with constant variance (Box et al., 2015). However, this is an extremely strong condition that is difficult to validate empirically (Tsay, 2005) and therefore, in this paper, we shall adopt the 'weaker' stationary definition as it is more attainable for our data set.

A weaker version of stationarity is often assumed and applied when modelling a time series due to its less stringent and more attainable requirements (Tsay, 2005; Palma,2007; Mills and Markellos, 2008). If the mean of r_t is time invariant, the time series $\{r_t\}$ is defined to be weakly stationary. More precisely, $\{r_t\}$ is weakly stationary if E(r_t)=σ, which is a constant. In practice, assuming that we have observed T data points $\{r_t \mid t = 1, \dots, T\}$; weak stationary implies that the data plot of the stationary series will show the T values fluctuating around a fixed level. We can stationarise the time series by finding their returns and we can directly see the consequence of this which is the data set fluctuating around the fixed point zero in Figure 3 below.

2.3 Returns

In this paper, the focus is concentrated on the electricity returns rather than the analysis of prices. Grianfreda and Grossi (2012) asserts that when the emphasis is on volatility, the analysis of electricity returns play a more vital role compared to the analysis of prices. This is because consecutive prices are highly correlated and the variance of prices increases as time passes, thus making the direct statistical analysis of financial prices challenging (Taylor, 2008). This is due to the fact that the prices are not 'stationary' as described in section 2.2. Moreover, the analysis of returns provides insights concerning the instantaneous growth process of prices due to the fact that they measure time to time variations of prices (Grianfreda and Grossi, 2012). This fact is evident as electricity market investors diligently monitor electricity returns as volatility plays a key role in risk management (Grianfreda and Grossi, 2012). According to Chan, Gray and Campen (2008), there has been an increased need to model dynamics of electricity spot prices due to its extreme jumps of magnitude feature (due to the extreme events) which is rarely observed in financial markets, and occurring at greater frequencies. An understanding of the dynamics of electricity pricing is vital in speculation, derivation of pricing, risk management as well as real option valuation. According to Geman and Roncoroni (2006), spot price risk had been noted to force the energy industry to identify, price and hedge the options granted in energy contracts. Hence, Swinand, Rufin and Sharma (2005); Byström (2005) and Chan and Gray (2006) (cited in Chan, Gray and Camden, 2008) assert that modelling the spot prices accurately is essential in optimising the scheduling of physical assets and valuing real options.

However, according to a research paper by Bask, M and Widerberg (2009), the Nord Pool electricity prices have become more stable during the integration process. The effect of this on the Nordic power market is that is less sensitive to shocks after this process than it was before. Nevertheless, this does not imply that there are no drastic changes from one day to another, but it does imply that the frequency of large price movements is substantially lower.

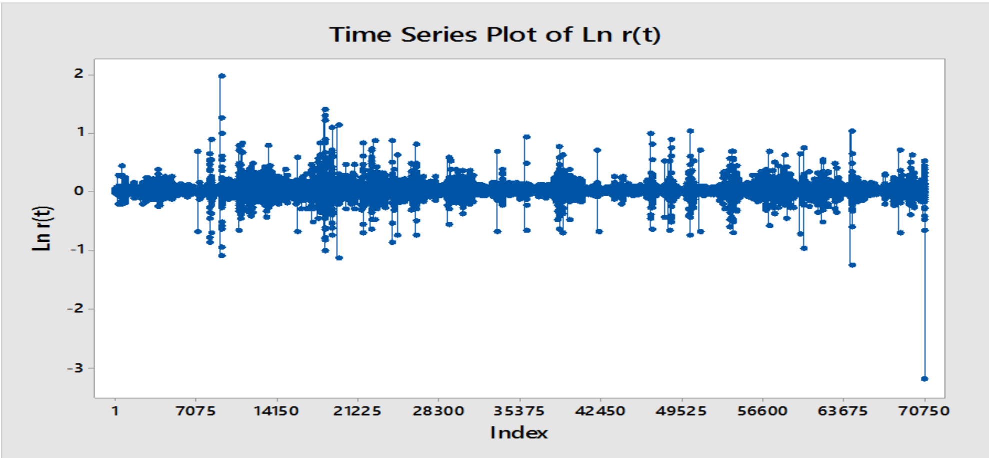


Figure 3: Time Series of Returns.

From Figure 3, we can see extreme peaks which are extreme price fluctuations called extreme events (Gianfreda and Grossi, 2012; Hallerberg, 2008) while the middle parts show slight fluctuations. We want to know where the extreme events come from and check if they happen at a certain hour of the day. According to Hallerberg (2008), common extreme events are natural hazards such as floods, draughts, storms and electricity network crashes. Whilst these examples provide an intuitive understanding of the term extreme events, a precise and general scientific definition has yet to be agreed upon. This is pertaining to the fact that there are different contexts and circumstances in which extreme events are discussed, and as such, it is challenging to provide an exact definition that covers all the potential scenarios. However, to understand the nature of the extreme events, we shall condition the time series at a specific hour.

2.4 Nord Pool

The data set was obtained from The Nord Pool market. According to Bergman (2003), the Nordic electricity market comprises of Norway's, Sweden's, Finland's and Denmark's electricity market which were deregulated and integrated to form a single market for electricity. From an institutional view point, when the border tariffs between countries are eliminated, the creation of a common power exchange is created (Bergman, 2003). Beginning in Norway in the year 1991, regulatory reform progressively spread to Sweden in 1996, Finland in 1997 and in 2002, to Denmark (Von Der Fehr, Amundsen and Bergman, 2005). Denmark, Finland, Sweden, Norway, Estonia and Lithuania however constitutes the Nordic Pool Spot area (Sioshansi and Pfaffenberger, 2006). According to Shuttleworth and McKenzie (2002), the Nord Pool markets' membership is open to any company, regardless of whether they possess any physical assets in the region, as long as they are credit worthy. The creation, regulation and implementation of market rules are still held by each country. This is an important fact as every country has varied motives and rationales as well as schedules for the liberalisation of their markets. As the power of market rules enactment is held by the country itself, these various aspects are able to be incorporated in the rules.

The ability to provide producers as well as consumers of power with price signals which are of use is an invaluable trait of the Nord Pool's market (Mork, 2006). Moreover, Mork (2001) advocates that part of the success of the Nord model is attributed to possessing top notch quality of spot prices which can be applied to benchmarking the prices of financial contracts. The large proportion of hydropower, in which production volumes are able to be adjusted promptly, means that price spikes and outages can be avoided. Apart from being an operationally sound market, the evolution of a power exchange is one of its more prominent features of the Nordic market. Other promising features of the market include:

- Generation and retailing competition which has prompted increased productivity and efficiency levels in the power industry (Bergman, 2005)
- Regulation of transmission and distribution
- Possessing a Transmission System Operator (TSO) accountable for system operations as well as running real-time markets which vary for each individual country
- Point-of-connection transmission tariffs
- "Point-of-connection transmission tariffs"
- "Zonal pricing system of wholesale electricity"
- Consumers provided with the opportunity of choosing their desired supplier
(Sioshansi and Pfaffenberger, 2006)

As the purpose and scope of this dissertation is the modelling of a financial time series; the factors highlighted above all contribute to the decision to use data from the Nord Pool. Additionally, Bergman (2005) insisted that the Nordic market is comparable to the largest national electricity markets in Europe, which makes the findings of this study comparable and vital to large markets.

The Nordic Pool data set comprises of roughly 80 000 data points and the data set contains prices in (EUR/MWh) starting from 00:00 on 1st January 1990 for 7 years with a sampling rate of one hour. Each data point represents an hour in a day and thus, there is an hour's difference between consecutive data points. The advantages of a longitudinal study (over a period of 7 years) are:

- The ability to provide higher accuracy when observing changes
- They are more flexible when dealing with discrepancies
- They are more effective in charting variable patterns over time (Future of working, 2016)

2.5 Electricity Prices

Gianfreda and Grossi (2012) highlights how electricity's risk properties and the features of spot price variability are investors' and operators' main cause of concern. This is attributed to the fact that electricity is deemed a new commodity with unique characteristics. As a result, the volatility structure of electricity prices are analysed and modelled; and forecasting ability examined (Kuo and Huang, 2018). As such, in this dissertation I have analysed and modelled a set of electricity prices from the Nord Pool (in Section 2.4) as Contreras et al. (2003) comments that for electric companies to adjust their daily bids and monthly schedules for contracts appropriately, the prediction of future prices plays a key role.

Due to the fact that electricity cannot be stored (Stoft, 2002; Weron, Bierbrauer and Truck, 2004), the fundamental hypothesis that platforms the modern pricing theory is failed (Aid, 2015). However, this fact is disputed by Ibrahim, llinca and Perron (2008), who argue that electricity can be stored indirectly; this is pertained to the fact that high-performance and economical power electronics are capable of handling extremely high power levels. In this dissertation, we assume that electricity cannot be stored as this better explains the results of the Nord Pool data set. Hence, the occurrence of extreme spikes (Burger et al., 2004) as seen in Figure 3, is the direct outcome of electricity's inability to be stored (Aid, 2015). Of late, Europe's electricity spot prices have recurrently exhibited negative figures (Schneider, 2010) predominantly attributed to the fact the electricity is unable to be stored paired with stringent operational restrictions placed on power plants. (Aid, 2015). However, Schneider (2010) states that while negative prices pose a basic problem to stochastic price modelling, he reassures us that negative prices are a natural occurrence in electricity spot trading (Schneider, 2010; Nicolosi, 2010). He further elaborates that this is due to the fact that plant flexibility is restricted and uneconomical. However, incurring negative prices in terms of electricity is not necessarily a disadvantage (Nicolosi,2010).

According to Kirschen (2003), the primary reason for introducing competitive electricity markets is to reduce the electricity prices paid by consumers. When modelling electricity price time series, one would think that it is to understand the nature of consumer usage and its correlated consumption price. However, the Nord Pool electricity prices are what we call spot prices, which is different from consumer prices. A market equilibrium model where supply and demand curves of market members are matched days ahead are what constitutes the Nordic markets' physical spot prices (Vehvilainen and Pyykkonen, 2005, Weron and Misiorek, 2008). To understand how spot prices work, we need to understand how the spot prices are affected in the Nordic area. According to Vehvilainen and Pyykkonen (2005), winters in the Nord Pool regions are extremely cold with temperatures dipping below freezing point quite frequently. As such, electricity heating is of high demand for household consumers. However, air conditioners are not in high demand during the summers. From this, we can infer that there is a higher electricity demand during winters compared to summers. As our data set starts from 00.00 on 1st January 1990, we can infer that it was winter during those times. This is useful when trying to analyse the data as it would be able to provide us insights on the possible reasons for the price spikes.

3.0 Method

In this section of the dissertation, I shall elaborate how I converted the non-stationary time series formula into a stationary time series formula.

The non-stationary time series is defined as

$$Z_t \sim e^{\sigma t}$$

In order to make the time series stationary, we need to get rid of the exponential and increasing factor t. We can achieve this by taking Z_t and dividing it by Z_{t-1}.

$$r_t = \frac{Z_t}{Z_{t-1}} \sim \frac{e^{\sigma t}}{e^{\sigma(t-1)}} = e^{\sigma}$$

According to Schneider (2010), 'Stochastic modelling of power prices' typically have log transformations.

Thus, by taking the natural logarithm of the function, a constant equation is obtained.

$$\ln r_t \sim \sigma$$

$\ln r_t$ is thus the logarithmic return.

$$\ln r_t = \frac{\ln Z_t}{\ln Z_{t-1}}$$
$$= \ln Z_t - \ln Z_{t-1}$$

We use this formula for the hourly returns time series model. Hourly returns compare the current price with the price from the price before.

Applying a similar approach, we can obtain the daily returns of the time series. The daily returns compare the current price with the price of the same hour the day before.

The formula for the daily returns time series model is

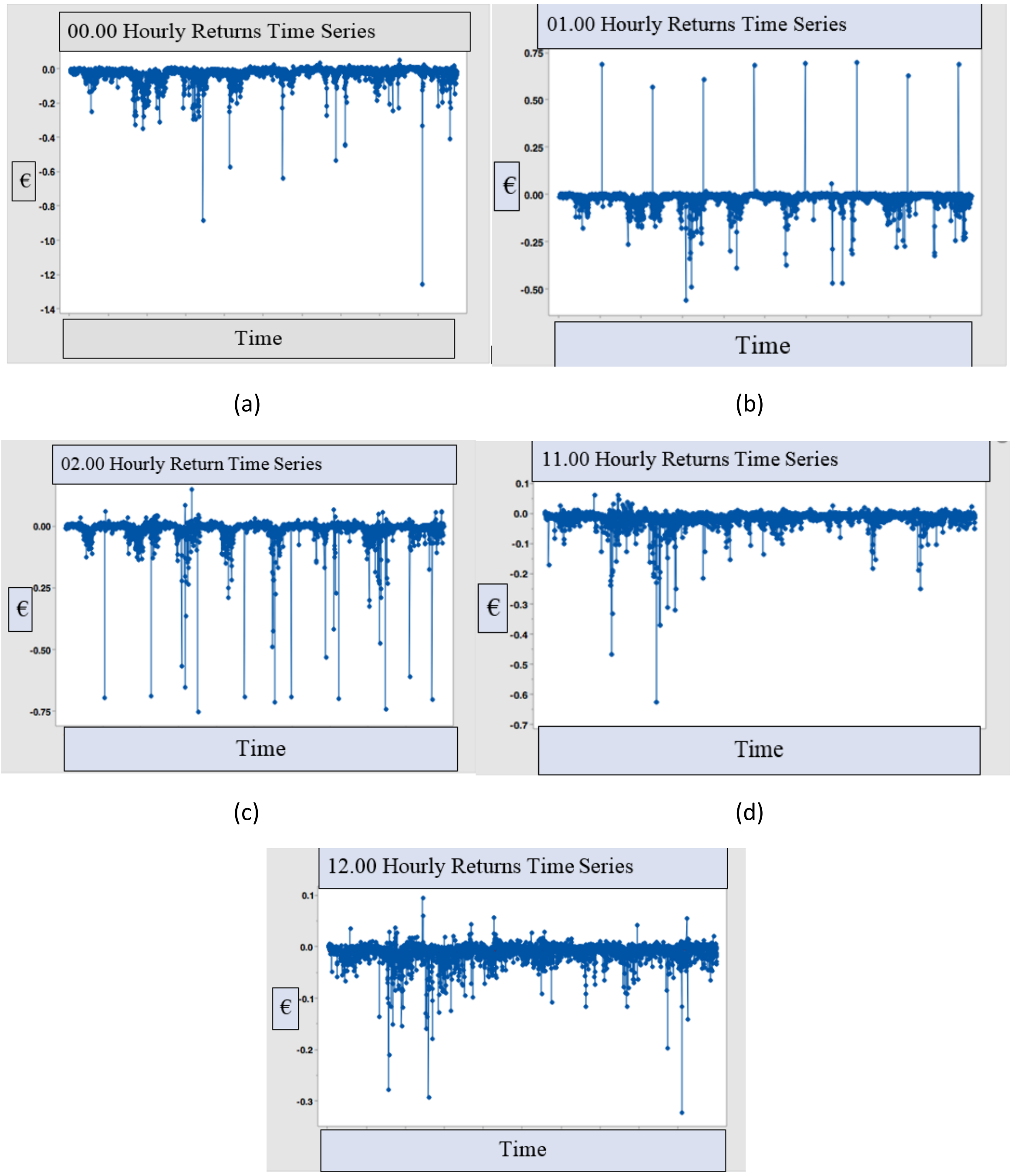
$$\ln r_t = \frac{\ln Z_t}{\ln Z_{t-24}}$$
$$= \ln Z_t - \ln Z_{t-24}$$

3.1 Conditioning

To understand the nature of the extreme events, we can condition the time series at a specific hour and check if they happen at a certain hour of the day. Conditioning is essentially taking a time series and applying a condition such as the time index at a particular hour of the day. So, in our case, the hour of the day is the set condition.

4.0 Results

4.1 Hourly Time Series Results conditioned on the hour



(e)

Figure 4: Time series graphs for (a) 00.00, (b) 01.00, (c) 02.00, (d) 11.00 and (e) 12.00.

Figure 4 are the hourly returns time series condition at 00.00, 01.00, 02.00, 11.00 and 12.00 respectively. These graphs have relatively negative extreme events. The negative extreme events indicate that there is a price decrease from the hour before; from example, 00.00 time series indicated a price decrease from 23.00 to 00.00. There is no specific pattern to the negative extreme events in the graph.

However, the 01.00 time series graph is rather unique as its positive extreme events are rather periodic. This shows us that on a specific day each year, there is a price increase from the hour before. The time scale from one positive event to another is relatively a year. As the price change is from 00.00 to 01.00, we can speculate that the price change may be due to an external factor. Possible explanations away from a change in pricing could be policy changes, updated annual regulation or a mere computer system update.

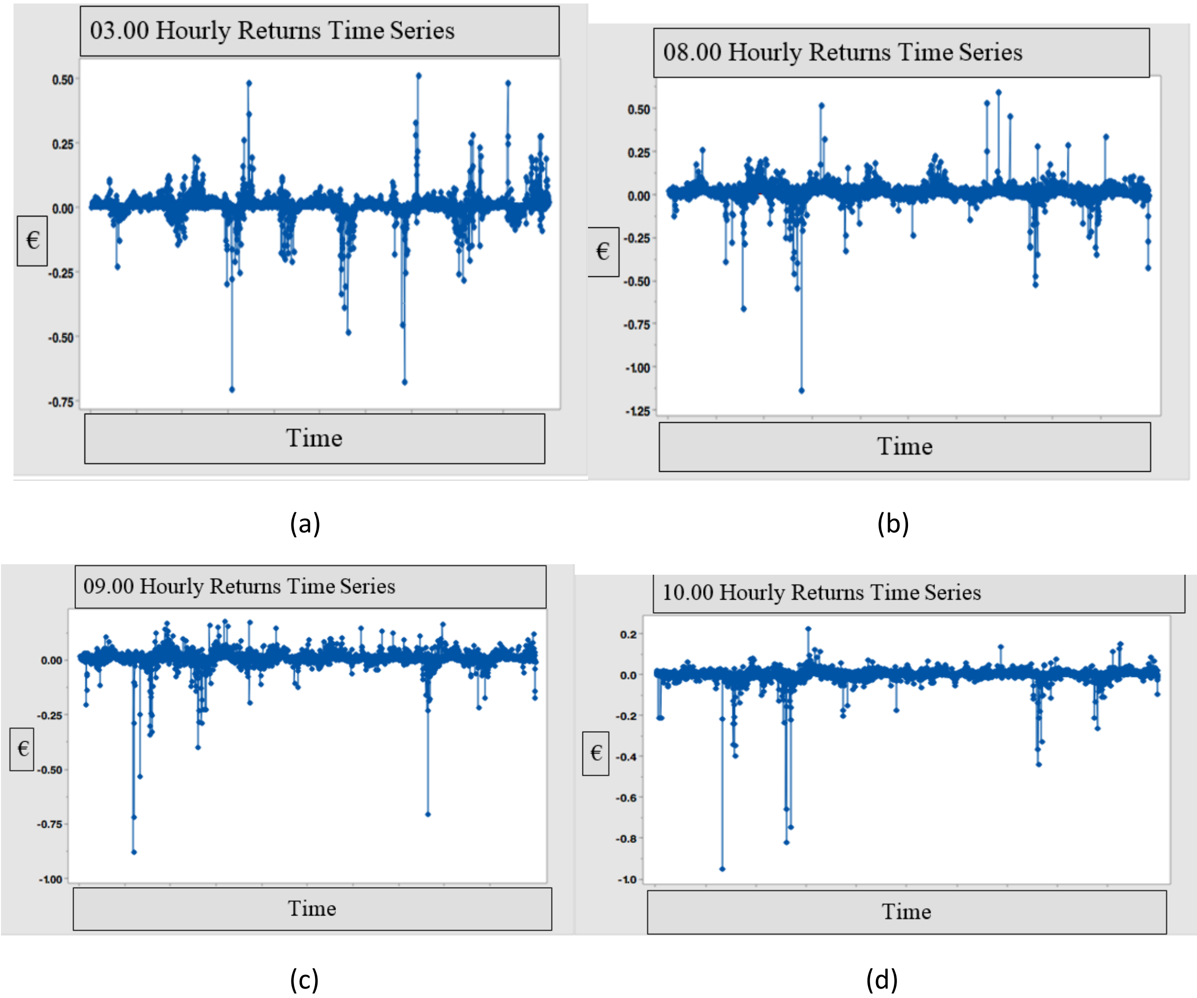


Figure 5: Time series graphs for (a) 03.00, (b) 08.00, (c) 09.00 and (d) 10.00.

For the 03.00, 08.00, 09.00 and 10.00 time series (Figure 5), the price fluctuations are relatively constant, apart from the few positive and negative extreme events that happen sporadically. The relatively constant prices from 02.00 to 03.00 and 07.00 to 08.00, 08.00 to 09.00 and 09.00 to 10.00 could be due to the fact that people are inactive during these times, as 03.00 is the usual time that most people would be asleep. From 08.00 to 10.00, most people would be out of the house and would thus, not require the usage of any of electricity. While the time series are relatively constant, there is a slight periodic pattern in the data set. The data set has slight positive fluctuations and then negative price fluctuations. The positive fluctuations, indicating a price increase from the hour before. One possibility could be that this is during the winter periods and household consumers would require heating as mentioned in the previous section. In contrast, negative price fluctuations could be during the summer period.

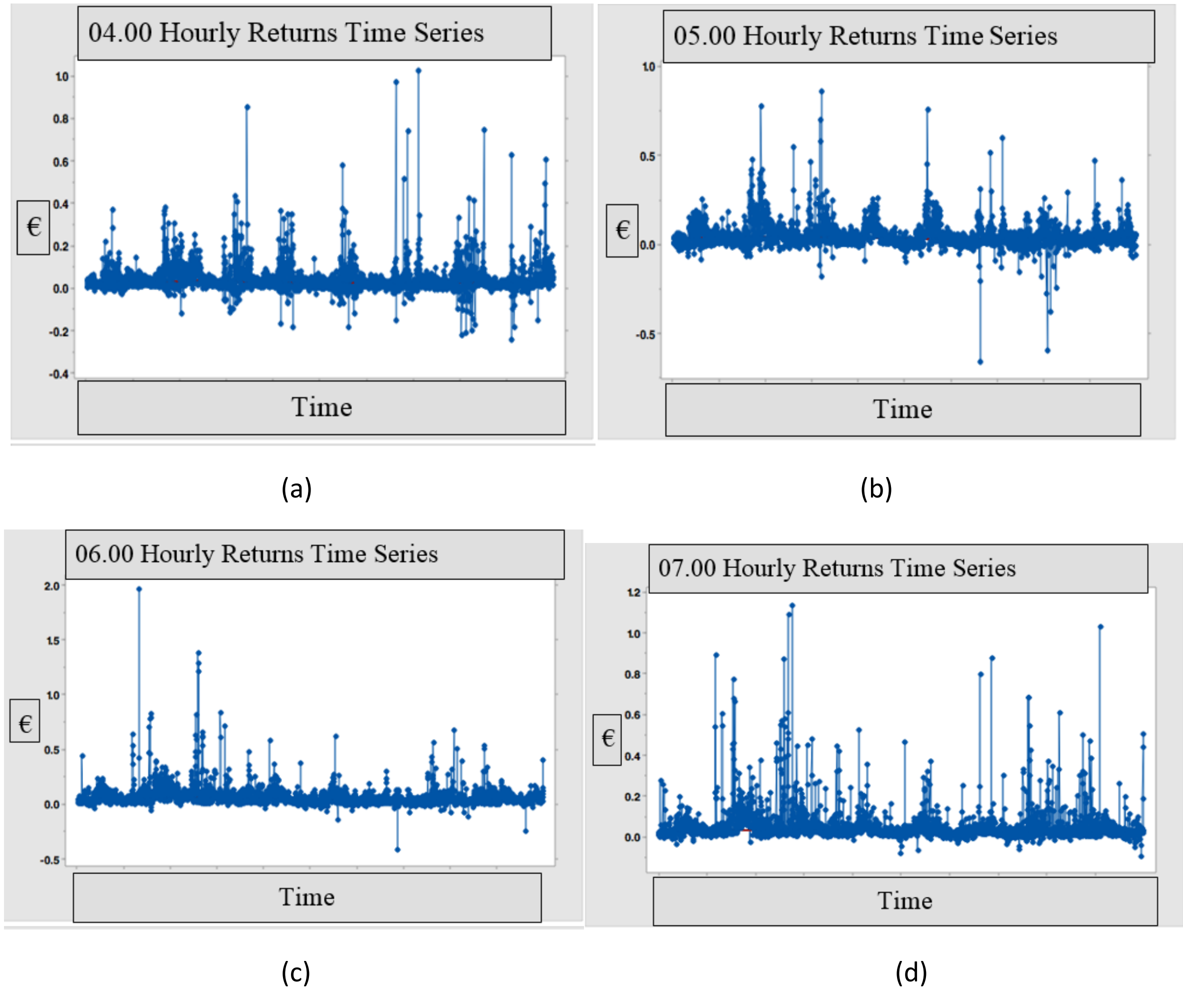


Figure 6: Time series graphs for (a) 04.00, (b) 05.00, (c) 06.00 and (d) 07.00.

From the hours 04.00 to 07.00 (Figure 6), there is a price increase from the hour before as these are the hours that most people start getting up for work or for school. Therefore, there is a higher demand for electricity and thus, a larger supply of electricity needs to be generated. This increases the electricity prices. In this 04.00 to 07.00 time range, 07.00 has the largest extreme events which could be attributed to households being active in time for rush hour.

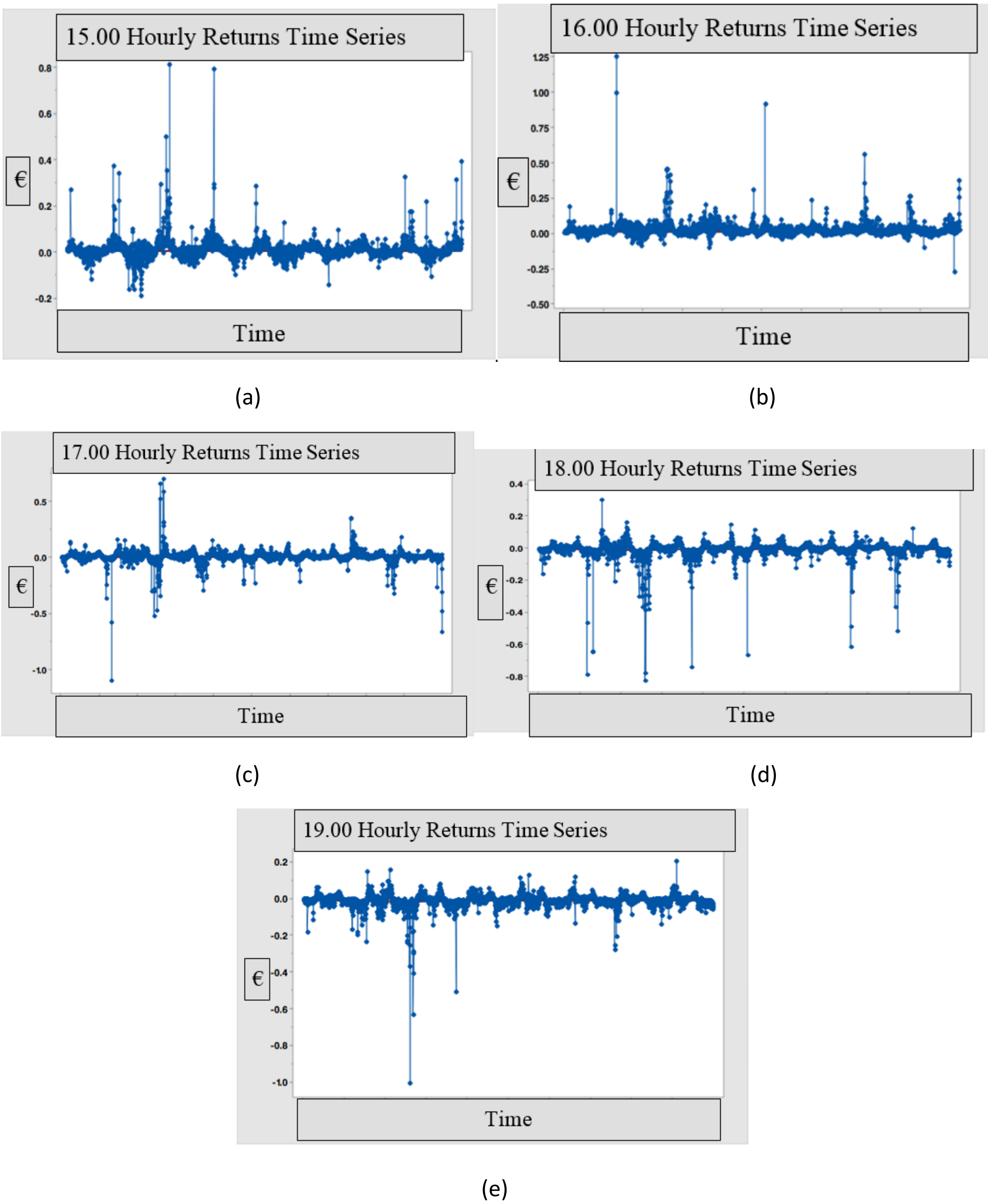


Figure 7: Time series graphs for (a) 15.00, (b) 16.00, (c) 17.00, (d) 18.00 and (e) 19.00.

The time series from 15.00 to 19.00 (Figure 7) show a relatively constant trends, similar to the 03.00 and 08.00 to 10.00 time series trends. This indicates that around this time, there is hardly any price changes from the hour before, which could be due to the fact that around these times, consumers are not at home and thus, do not use any electricity. There is slight periodicity in the time series and as mentioned earlier, the starting point of the data set is around winter and therefore, there are lesser light hours. Therefore, around this period, household users would need to use electricity to light their houses. Street lights would also need to be switched on during these times are it would be dark outside. Another possibility would be that since it is winter, public transports such as trains and well as work and public places would need to switch on the heaters. However, as these are public places that cater to multiple users, electricity consumption is spread out across many people and this consumption per capita is less than what is used for individual households on a similar basis.

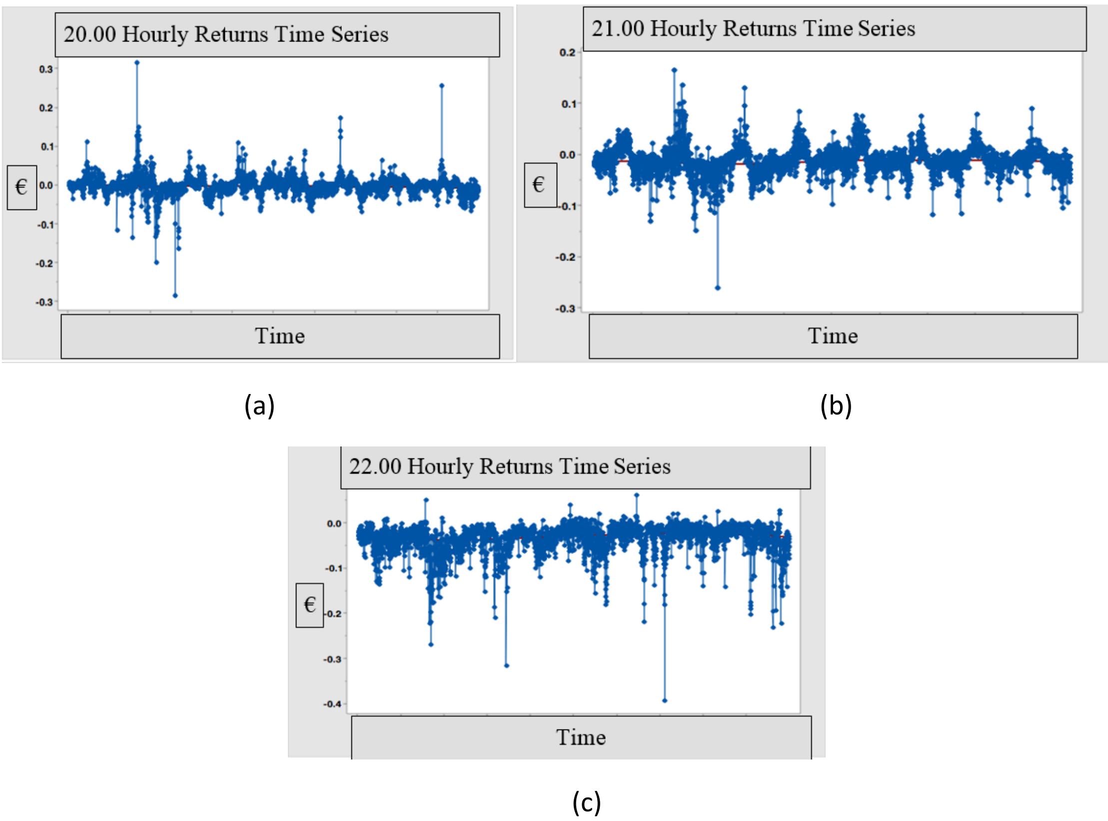


Figure 8: Time series graphs for (a) 20.00, (b) 21.00 and (c) 22.00.

Figure 8 shows the time series for 20.00 to 22.00. From these 3 time series, 20.00 and 21.00 have peak usage. This could be attributed to the fact that most people are home during this time, thus, a lot of appliances such as the television, stove, microwave and stoves, are switched on in households. At 22.00, people start going to bed and thus stop consuming electricity as they would switch off all their appliances as they would not be in use, explaining the downward trend.

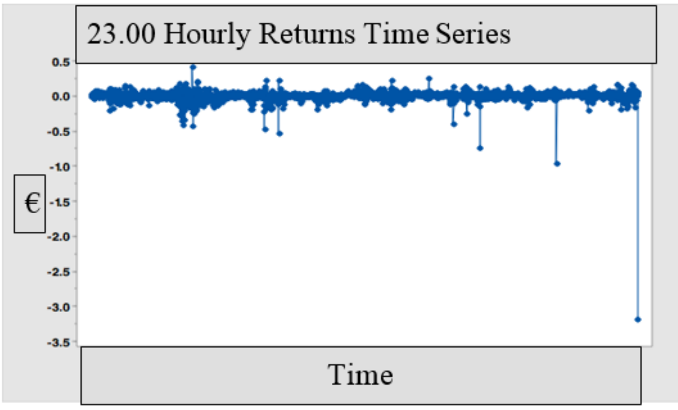
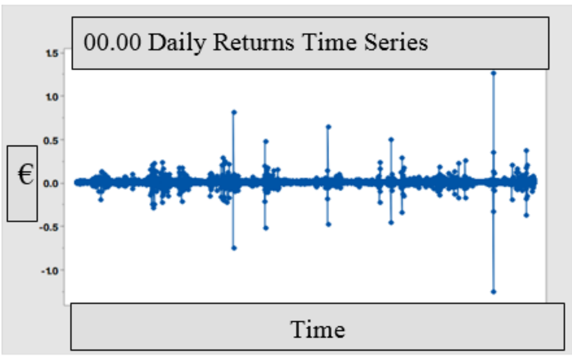


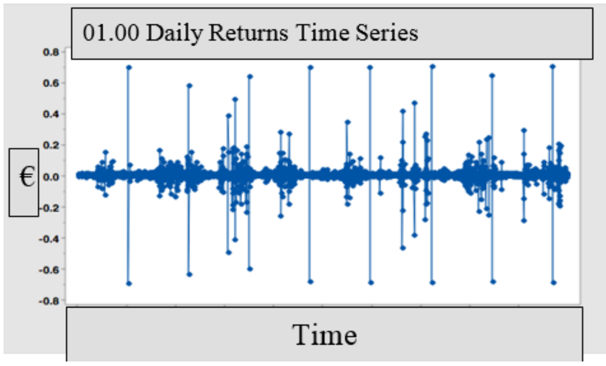
Figure 9: Time series graph for 22.00

The 23.00 time series (Figure 9) is relatively inactive as around this time, people are already in bed and therefore, there is no price change from the hour before as we have described in the 22.00 time series graph, people start going to bed at around 22.00 and thus, there is hardly any time change from 22.00 to 23.00.

4.2 Daily Time Series Results conditioned on the hour



(a)



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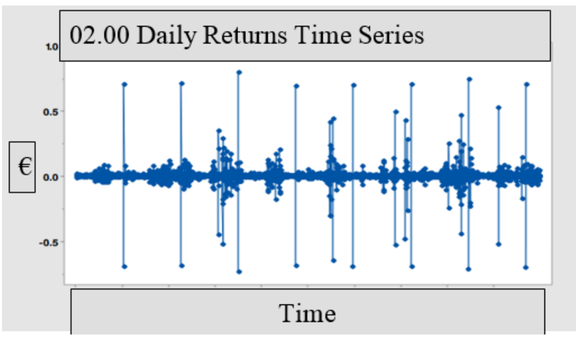

(c)

Figure 10: Daily returns time series graphs for (a) 00.00, (b) 01.00 and (c) 02.00.

The price fluctuations in Figure 10 imply that there is a price increase or decrease from the same hour the day before. One unique characteristic of these graphs are that when there is a positive price fluctuation, there is a negative price fluctuation of equal scales. This characteristic is intuitive as it is a common trait seen in all the 24 hourly returns time series graph.

5.0 Conclusion

To conclude, by finding the returns of the time series and conditioning on the hour, I am able to analyse the time to time variations of the prices more effectively. As this is real life data, it is harder to predict as they are dependent on real life situations and anomalies such as extreme weather conditions (*e.g.* draughts). This causes noise and outliers in the data set which affects the trends that we observe. As the Nordic Pool electricity market is run on hydroelectric dams, they would very much be affected if there was a draught. Moreover, human errors could be incorporated in the data set as perhaps somebody forgot to enter the data set or the person fell asleep on the keyboard and the wrong values were accidentally typed in. One way of countering the discrepancies in the data set is by using a large data set, which is what we did. With a large data set, a few wrong entries do not invalidate the data set completely.

Moreover, in this data set, we did not take into consideration daylight savings. This is an important factor to consider as daylight savings shifts the clock backwards/fowards by an hour and thus the data set will keep shifting back and forth by an hour for a given period of time. However, due to the lack of data, we were unable to incorporate this into the analysis. This is left for analysis in future work.

In future work, I would like to use the non-stationary and non-linear financial time series model to compare and contracts the data set and note if there are any difference as compared to using a mathematically transformed financial time series stationary model.

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