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Abstract

This thesis is investigating the level of market integration, as well as the volatility and inter-relationship in the Nordic spot market. The empirical analysis is using spot prices from 13 regions in the Nordic energy exchange. The purpose of the study is to find evidence of market integration between the system price and the regional price. Further, an assessment of the volatility in the regions will support the notion of market integration. A bivariate Autoregressive (AR) model is applied to the price series, and residuals is run through a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Inference tests are run for hypothesis regarding dynamics and long run integration.

The results show that Nord Pool is not perfectly integrated. The regions in Scandinavia show strong market integration with the system price. Low average price and a large, unpredictable price volatility is seen in all the regional prices in Norway, Sweden, Denmark, and Finland. The Baltic regions show signs of internal market power, indicating monopolistic production of electrical energy. The Baltic regions are not fully integrated with the system price. The results of the AR model support the findings of low market integration in the Baltic regions and high integration in Scandinavia.

The persistence in the volatility effects in Scandinavia show that volatility in previous observations have a permanent effect on the volatility level today. For the Baltic regions, the persistence show a mean-reverting structure where volatile price movement dampen down until it reaches a stable equilibrium. Capacity constraints during bottleneck periods cause the area price to deviate from the system price. Better transmission capacity will lead to a closer integration between the markets within Nord Pool Spot (NPS).

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Terje Jensen Sørås

Stavanger, 15. June 2016

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1 Introduction

The Nordic Energy market is an open, competitive market for sale and purchase of electrical energy. The energy market in Norway was deregulated in January 1991 following the implementation of the Energy Act of 1990. In 1996 the Norwegian power exchange merged with Sweden, forming Nord Pool as the world's first international power exchange. Since then the scope of the power exchange has grown, now including wholesale electricity trading in Scandinavian and the Baltic region. Electrical energy as a commodity is presumed to be monopolistic by default, as the owner of the electrical grid and the owners of power production have control over the supplied energy. The motivation for deregulating the market was to separate the production and sale of electrical energy from the transmission. The goal for Nord Pool Spot (NPS) is to act as a liquid and transparent market where free competition forces the price towards a social optimum and removes the possibility of market power being exercised by participants.

Spot electricity trading is conducted in the physical market. Nord Pool also has a financial market where trading in financial assets, like bilateral contracts, allow customers to hedge risk. Both the financial and the physical market trade across international borders. This indicates that production in one area of the market can reduce volatile price spikes in more risk exposed sections. The different bidding areas need a strong market integration in order to combat fluctuations in the area price. Bottlenecks in transmission capacity will create almost perfect inelastic prices. This lead to large differences between regional and system price. Regulatory mechanisms are in place to support the development of an efficient international market. To prove that the market is integrated a better understanding of the interrelationships is necessary.

Several studies have been conducted on electrical markets in order to determine volatile relationships and market integration. Energy prices are known to have uncertain price movement, and as a result multiple studies have been conducted on markets both internally and externally. The internal price volatility was conducted for the Australian power market by Higgs (2009); Becker et al. (2007); Worthington et al. (2005). The internal relationship in NPS will be analysed the same way as

Higgs (2009) has analysed the Australian National Electricity Market (NEM). Seasonality and spillover effects are strong in electrical spot prices due to the practical problem of storage. Several studies (Becker et al., 2007; Lucia and Schwartz, 2002) assume that electric energy is non-storable; once the power is produced it must be consumed. However, there are many ways to store the resources needed to produce electricity. The Norwegian hydro power section is an example of this. Johnsen (2001) present a relationship between price and exogenous variables like inflow, temperature and snowfall. Norway has a large storage of water due the the many reservoirs (Johnsen, 2001). This can be view as "stored electrical energy". Further, this reduces potential volatile effects of dry periods and force the producers to question the profitability of producing power. Still, the amount of precipitation will affect the price movement; increasing or decreasing both the price and the price variation. The finding of Higgs (2009) show that temperature gives a good representation of the price movement during seasonal changes. Like in NEM, the interconnector between certain regions in NPS have large capacity, whereas for some it does not exist. Strozzi et al. (2008) states that when there is no congestion in the transmission interconnector, the area price will be equal to the system price.

The volatile characteristics of the price during bottleneck periods can be seen when comparing the system price to the area price of the stressed region. Solibakke (2002) has analysed the price movement in the system price for the Nordic market and found significant patterns of volatile behaviour. Sotiriadis et al. (2014) have investigated the relationship between five major power exchanges in Europe, where NPS are one of the analysed markets. De Vany and Walls (1999) have analysed the US power market and how deregulation has affected the shocks in price during off-peak and peak periods. The strength of the interconnector and the effectiveness of the western transmission grid is then evaluated. These studies have the same goal, to understand the volatility in electrical energy prices during congestion in transmission capacity. The level of market integration can be seen as a direct link to the markets ability to handle volatile periods. Commodities traded at converging price in a market should, following theory, indicate market integration. Several studies have been conducted for market integration. Ravallion (1986) investigate market integration in the rice market in Bangladesh, Asche et al. (2004) test the degree of market integration in the French whitefish-market, and Slade (1991) investigate the international mineral market. Goodwin et al. (1990) define the Law of One Price (LOP) and test the US agriculture market.

The main objective of this thesis is to investigate the degree of market integration, and how volatility behaves in the system and area price movements in NPS. First, the thesis will determine whether there is market integration between the system price and area price for the different regions in Nord Pool. The analysis will also investigate if the expanded market has an effect on the stability of the system price. How the effect of the system price influences the different area prices will then be analysed in order to understand the relationship. Ideally, the LOP should apply, and this must be verified.

To parameterize the patterns of the price formation the region prices will be analysed using an AR model. The variables in the AR model will include the system price and lagged values of the area price under inspection. Analysing patterns of seasonality and mean-reversion, both between the regions own price and cross-area price, will answer the question if market integration exist. Dummy variables will be used to respond to trends set by seasonal components. This follows the methodology of several studies into the dynamics of electricity prices (Chevallier, 2012; Sotiriadis et al., 2014; Higgs, 2009; Worthington et al., 2005). The GARCH model proposed by Bollerslev (1986) will then be applied on the residuals of the AR model to estimate volatility parameters. The parameters will then be analysed in order to understand how the ARCH and GARCH effects vary in the different regions. The investigation of market integration draw on work by Asche et al. (2004); Ravallion (1986); Slade (1986); empirical tests will be performed on a dynamic model compromised of lagged values from both the region under investigation and the system price. The motivation for choosing this subject is to investigating the market integration between the different regions and countries in NPS. Further, an aim of the thesis is to see if the market integration affects the volatility level in NPS. As far as the author knows, a similar investigation into the internal relationships of NPS have not been conducted at the present day's structure.

The thesis will be organized as following: Section 2 will give an introduction to the organisation of NPS and its history. Section 3 will describe the theory behind price formation and market integration, before a brief description of the statistical elements of analysing data will be presented. In section 4, the methods applied to the data will be presented. A detailed description will be shown for each method. In section 5, summary statistics for the data used in the thesis will be shown. This will also include statistics describing the shape and stability of the price series. In section 6, the empirical results will be summarized and discussed. Section 7 will contain a conclusion.

2 Nord Pool

Nord Pool is Europe's largest energy exchange and was the first of its kind (Stavseth, 2013). NPS operate under the criterion that customer surplus is the key objective to maximize. Demand and supply sets the price of energy in a way that creates the most efficient market. Nord Pool is divided into two separate segments; Nord Pool Spot AS and Nord Pool ASA. Nord Pool Spot handle day-ahead (Elspot) and intraday (Elbas) trades. Nord Pool ASA handle bilateral contracts and other financial assets. NASDAQ bought Nord Pool ASA in 2007, and run this market segment today.

2.1 History

The Norwegian spot market was established in 1993 as result of the Norwegian Energy Act; issued in 1990 and implemented 01. Jan 1991 by the Norwegian Parliament. The Ministry stated that the marketplace should have two main functions: *(i) Administration of the marketplace for physical power by facilitating daily bidding and price determination, and (ii) clearing of all contracts entered on the marketplace, i.e. enter as the central counter party in all trades, guaranteeing settlement for trade and anonymity for participants* (Drønnem, 2010).

The System Operator (TSO) in Norway, Statnett SF, established Statnett Market in 1993. The framework for an integrated Nordic market was developed during 1995, with both the Norwegian Parliament and Norwegian Water Resources and Energy Administration (NVE) included in the process. Norway and Sweden combined to form a cross-border power exchange in 1996. The exchange was named Nord Pool. NPS became the world's first international power exchange. The scope of the marked expanded quickly; Finland joined in 1998, the western part of Denmark connected in 1999, and in 2000 Denmark East joined Nord Pool. Elbas trading was launched in 1999 to function as a balancing tool for adjusting imbalance in Sweden and Finland. Since then it has been expanded to function for all regions. In 2002 Nord Pool was divided into two separate sections; Nord Pool Spot AS and Nord Pool ASA. Nord Pool Spot opened a bidding area in Estonia in 2010, as well as prepared to launch a market in Lithuania, which opened in 2012. Latvia was included as a bidding area in 2013.

2.2 Bidding Areas

As of 31. Dec 2015, NPS consist of 15 different bidding areas, also referred to as regions, see Figure 1. The scope has changed during the sample period, beginning with only six bidding areas, and ending with 15 areas. Norway has five different bidding areas; Oslo, Kristiansand, Bergen, Trondheim and Tromso. Sweden was a single bidding area until 01. Nov 2011, when it was divided into four bidding areas. Denmark is divided into two regions and joined separately. Finland, Latvia and Lithuania have one bidding area each. The system price is calculated to mimic the optimal price based on supply and demand while ignoring any constraints in transmission. Capacity congestion in the transmission line cause the area price to differ from the system price. Area price is set for each individual bidding area, with the system price as basis. If demand is high and capacity pressured, the area price will increase in order to reduce demand and in turn reduce the congestion in transmission. I.e. the transmission capacity of the interconnectors between regions determine the threshold between the system price and extreme area prices.

The financial market in Nord Pool, now run by NASDAQ, handle trading of bilateral contracts and derivatives. The financial market run separate with the spot market. In 2005 Nord Pool opened for trading in Germany; the trade route is named KONTEK. In 2010, NASDAQ started to operate the power market in UK. Other countries managed by NASDAQ include France, Austria and several more. In early 2016 Nord Pool was appointed Nominated Electricity Market Operator (NEMO) in Bulgaria and in Germany. As NEMO, Nord Pool is from 2015 allowed to handle trade as a coupler in ten different European power markets. This is not a part of the spot market, which this thesis base its data on.

2.3 The physical market

The physical market handle trading of spot electricity; orders are placed for physical power traded the following day. The physical market has two sections; day-ahead

Figure 1: Nord Pool area prices 25. May 2016. Prices in NOK/MWh (Nord-Pool, 2016)

trade (Elspot) and intra-day (Elbas) trade. The NPS is jointly owned by the Nordic TSOs; Statnett (30 %), Svenska Kraftnät (30 %), Fingrid Oyj (20 %) and Energinet.dk (20 %). The system price in the spot market work as the principle guide for the financial market. The spot price and the financial derivative price is shown by Hoff (2010) to correlate at a significant level. NPS calculate the price of energy every hour, for delivery the next day. A synthetic equilibrium is created based on data and reports from producers, TSO's, and consumers. The bidding ends at 12:00 CET the day before the transaction will take place. Elspot is the main tool for trading energy in the day-ahead market, with Elbas available to balance market irregularities.

Contracts are placed for each hour, i.e. one must place one bid per hour of the day. The contract is physically delivered, which is why this called the physical market. From 00:00 CET and onward the power is transferred to the buyer at the hour according to the contract. Capacity constraints are solved by introducing different area prices. If there are bottlenecks in the power transmission, the price is increased in order to reduce demand. The intra-day market, Elbas, is a supplement to the day-ahead trading at Nord Pool. It helps to secure the necessary balance between supply and demand that cannot be adequately be covered by the day-ahead pricing. Unforeseen events between closing of bidding at 12:00 CET and delivery at 00:00 CET can happen. The main objective of Elbas is to prevent such events from affecting the efficiency of the market and to minimize losses due to irregular power supply. Using Elbas, the sellers and buyers can trade volumes close to real time with trading continuously through the day. Contracts are being negotiated an hour before delivery and this help reverting the market back in balance should there be any irregularities.

2.4 The financial market

The financial part offers market participants trading in bilateral contracts and derivatives in order to hedge away risk with regards to price volatility (Drønnem, 2010). There is no physical delivery in the financial market. The financial products are contracts, which vary in length between days and as much as five years into the future. The inclusion of speculation into the market will increase the detail of information, and may lead to a larger price stability, as noted by Cox (1976). However, Slade (1991) tests this hypothesis for the mineral market and concludes that exchange prices are more unstable than producer prices. Future work could be to conduct an analysis of the variability of spot prices before and after the financial market was established.

Nord Pool Clearing provides settlement for the different contracts traded in the financial market. By establishing a neutral interception between buyer and seller, the risk is reduced for the various market players. It is the overall key to the efficiency displayed in the Nordic power market. The Ministry of Finances oversee that the rules of free competition are not violated (Drønnem, 2010). Kredittilsynet, a subordinate of the Norwegian Ministry of Finances, manages Nord Pool's license to operate the derivative exchange.

There are several different products in the Financial market. These financial products do not result in a physical delivery, instead the trader is compensated financially for price movements (Kroken, 2009). Options, Forwards, Futures, Contracts for Difference and Carbon Emission are some of the derivatives for sale in the financial market. In the financial market in NASDAQ OMX, either a forward or a future contract is the underlying product (Regjeringen, 2008). This segment is not a part of the thesis, but is mentioned due to its importance in creating an effective market. See Botterud et al. (2010); Weron and Zator (2014); Solibakke (2006); Lucia and Schwartz (2002); Vehviläinen and Keppo (2003) for a more thorough analysis on interaction between the financial and the physical market.

2.5 Power Generation

In Norway, approximately 96 percent of the power generation stems from hydro power. With 1510 different hydro power plants spread across the country; total production from hydro power per 01.01.2015 yield a yearly production of 136.18 TWh (SSB, 2015). Other power productions in Norway are wind power (1.9 %) and thermal power (2.5 %). These figures show that Norway is dependent on hydro power; the seasonal cycle and weather affect the output of energy which then lead to volatile energy prices. Figure 2 show the produced electrical energy in NPS.

Sweden's main source of energy is hydro power and nuclear power, the former is represented by 42.4 % while the latter have a share of 40.9 % of the indigenous production in 2014. Else, Sweden have 9 % combustible fuels and 7.7 % of wind, solar etc. Annual production is 150.6 TWh. Sweden, like Norway, export more energy than they import (IEA, 2016). In Denmark, the energy production is divided between combustible and wind/solar energy. 44.6 % of the production stems from wind, which makes production very difficult to predict. This leads to a dependency for imported energy, and unstable price behavior. As a result of this Denmark import more energy than they export. When the wind is strong, Denmark have excess energy which in turn lead to profitable export.

The Baltic states mainly produce electricity using thermal power. This has a higher marginal cost than hydro power. It can be seen using the merit order chart that

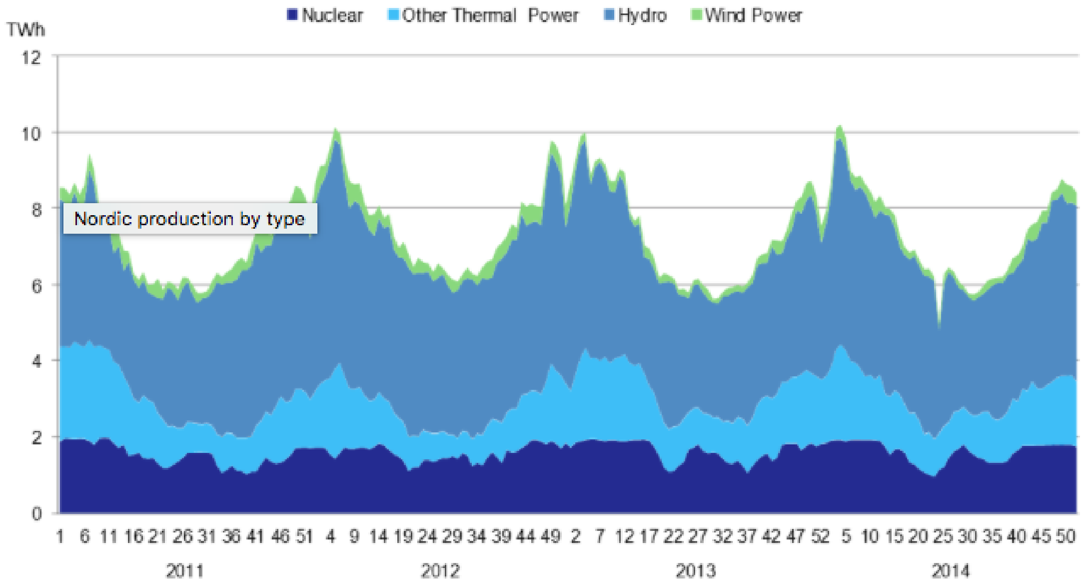

Figure 2: Nord Pool Nordic production (Nord-Pool, 2016)

hydro- and nuclear-power are lowest in cost per produced quantity, with thermal, gas and oil power at a higher marginal cost per produced quantity (Nord-Pool, 2016). Change in demand can be adjusted using hydro power, since it has a low marginal cost and can be regulated quickly by the producers. Nuclear power lays the foundation in NPS, as it is difficult to adjust and must be kept stable. The variability comes from hydro power, which move in seasonal patterns.

2.6 Turnover and trade in Nord Pool Spot

The total traded energy in 2014 amounted to 501 TWh. Of this, 361 TWh was traded in the Nordic/Baltic area, 135.5 TWh was traded in the UK market and 4.9 TWh was traded in the Intra-day (Elbas) Nordic/Baltic market (NPS, 2015). Nord Pool does make a profit on the transaction of electrical energy. Nord Pool does not add a fee per transaction conducted between buyer and seller. The only income Nord Pool has is earned via annual-fees, volume dependent fees and FX (for traders who operate with a different currency than EUR)-fees. With a revenue of NOK 310.1mill for Nord Pool Group and NOK 301.5mill for Nord Pool Spot the net income is respectably NOK 45.3mill and NOK 49.3mill per section of Nord Pool. The figures from 2014 are used, as the yearly report for 2015 is not yet ready. In 2014 Norway imported 6.123 TWh and exported 21.6 TWh (Statnett, 2016a). With an indigenous production of 141.7 TWh the electricity supplied from Norwegian power plants to the Norwegian market was a total of 126.1 TWh (SSB, 2015). With the outlook of a future with a higher degree of export, the volatility of the energy prices will require risk management to account for unstable price fluctuations.

There is an ongoing discussion about Norway being Europe's "Green Battery". North Europe, with Germany leading, is rapidly expanding the capacity of renewable energy (sun and wind). Due to the unpredictable nature of both wind and solar power, there will be a need for a back-up source of energy (Lindberg, 2008). Norway, with its vast hydro resources, can supply electrical energy when there is a need to maintain stability in the German grid. In return, when excess power is produced in Europe this can be sold to Norway. The Norwegian hydro plants can use this excess power as a mean to pump water into the reservoirs, thus storing water for future use. Dry years can create a lack of energy in Norway; the interconnection will then provide energy from the continent, stabilizing the prices in the Nordic region. Statnett has received concession from the Norwegian Parliament, and work has begun on the transmission line between Norway and Germany, named Nordlink (Overton et al., 2015). The plan is to connect the two countries by 2019, with commercial operations in 2020. There is also several plans for interconnectors between Norway and UK, Sweden and Germany among other (Statnett, 2016b).

Stability in the electrical grid means keeping a stable frequency, the set level is 50 HZ in Europe. Frequency drift is the main indicator of imbalance between generation and demand for electrical energy. If power generation exceeds consumption, the frequency rises. Likewise, if demand is bigger than supply, the frequency falls. Short et al. (2007) states that frequency control of a power system endeavours to match power supply as closely as possible to the time varying demand. Norway, with vast hydropower supply, can deliver a sufficient quantity of spinning reserve generation on the electrical grid when the frequency is dropping. Thus the hydro power plants can stabilize the frequency in a way that is not possible with volatile energy resources, like wind and solar.

Given the huge development of wind and solar energy in Europe, Norway can act as an available, renewable power supply to stabilize the grid, e.g. a green battery. Unlike thermal power plants, which require long start-up and shutdown time, hydro generation can be brought up to full effect in less than five minutes. This indicates that hydro is well suited to turn off and on to meet change in demand (Bergen and Vittal, 2000, p. 11). The industry might in the future induce a cost to the spinning reserve, making the commodity an extra cost for the end-consumer. Especially when a more integrated system leads to lower prices, e.g. smaller revenue for producers.

3 Theory

This section will explain the basic principles of price formation and market integration. The theory will be connected to the factual description of the Nordic energy market. Econometric methods are applied to financial data in order to use statistics to explain relationships and shape of the distributions. A theoretical foundation will be presented for the methods applied in the analysis.

3.1 Price Formation

NPS handle large quantities of trade, setting the price for both bilateral trading and financial derivatives. The spot price is determined at the market clearing point, i.e. where supply and demand meet to form the optimal price and quantity. Smith and Garnier (1838) facilitated the notion of an "invisible hand" that force supply and demand to meet at the point most efficient for both producer and consumer. This is the rule for which the price is set in NPS. An algorithm calculates the equilibrium point based on continuously updated data from the market, and determines the best fit for the day-ahead price. The price is calculated for each hour of the day, being valid for the next transaction day. Since the bidding area include several producers it is difficult to exercise market power. Without the transmission constraints and congestion between areas, the system price would be the region trading price in each bidding area.

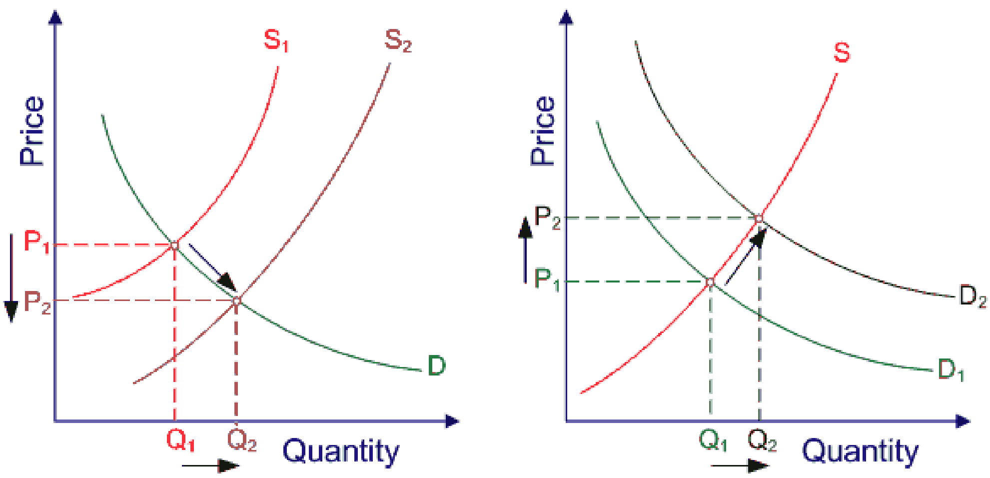

Figure 3: Market equilibrium when supply or demand shift position (Spaulding, 2016)

Demand for a given commodity can be defined as a customer's willingness and ability to purchase the commodity at the current price. This can be further defined using what is known as a demand equation. The price of the commodity is given by:

$$P = D(q), \tag{1}$$

where P is the price of a unit determined by the demand equation and the need for a given quantity Q of the commodity. The demand equation is a relationship between price and quantity per unit when other factors are being held fixed. (Tomek and Kaiser, 2014, p.10). The demand equation has an inverse relationship, i.e. when the price increase the demand for the commodity will fall. This is known as the Law of Demand (McConnell et al., 1969, p.94). There are several other factors that shift the shape of the demand curve. Income, taste, number of buyers, and related goods all will have an impact on the curve. With related goods we have substitutes, e.g. margarine versus butter. The customer may be indifferent to the brands and let the price determine the choice. Increased price for a commodity such as lettuce can decrease the demand for dressing. Wood, oil and gas, as primary commodities, are theoretical substitutes for electrical energy. Taking the inverse of Equation 1 based on quantity, demand is shown to be:

$$q^D = a + cP_s + dI + bP + yt \tag{2}$$

where the quantity demanded is decided by the price of substitutes P_s, the income I, the price of the given commodity P, and a factor for habit yt. The elasticity coefficients c, d and b explain the level of power that is given to the different components. In Norway, the majority of housing and industry are dependent on electrical energy. The power industry in general tend to deliver unsteady supply due to the costs of changing production (Nakajima, 2013). The reason to deregulate the Nordic market was to reduce the arbitrage problem of supply versus demand. Separating the grid, production and consumption reduced the issues and as a result the price stabilize the market. The TSO inform producers when they need to change production.

The Law of Supply states; when the price increases, the quantity of supplied goods increase (McConnell et al., 1969, p.89). The marginal costs and marginal revenues determine the best amount of goods to produce. There are several input variables to the supply equation that affect the amount produced. Technology, taxes and subsidies, price of other goods, and expectations to the demand all have an impact on how the producer plans the supply. The formula for price as a function of supply is given by:

$$P = S(Q) \tag{3}$$

Still, the amount of costs invested in production can change. For electric power it is difficult to price the value of the water in the reservoirs. Further, changes in demand and uncertain prices makes the supply of electricity tricky to predict. The composition of the supply equation can be described as follows:

$$q^S = \alpha + \mu P_x + \beta P + \gamma t \tag{4}$$

where the input variables are described by P_x, the price of the electrical energy by P, and the γ represent the technical change in supply. Supply in NPS is aggregated from all the producers. Johnsen (2001) offers an extensive guide to the development of price and demand equations for the Norwegian power market. Hydro power is known to be rational, i.e. high inflow is known to lead to lower prices. Exogenous variables such as temperature, activity level, alternative fuel prices and time of year are used by Johnsen (2001) in the development of the demand equation. Combining Equation 2 and 4 will give the exact quantum needed to meet the equilibrium state of stability for the day ahead price:

$$\begin{gathered} q^D = q^S, \\ a + cP_s + dI + bP + yt = \alpha + \mu P_x + \beta P + \gamma t \end{gathered} \tag{5}$$

solving with regards to P:

$$P = \frac{\alpha + \mu P_x + \gamma t}{(a + cP_s + dI + yt)} \frac{1}{(b - \beta)} \tag{6}$$

Solving Equation 6 will give the optimal price for a given market. The equilibrium price will account for reported demand from consumers, availability of production, the price of water, marginal costs of production, as well as other shocks in the market. The Nordic energy market has several input factors to consider for both supply and demand, but those factors will not be discussed further here. The price is the only variable to consider.

The supply of electrical energy to NPS can be ranked after a merit order. This shows the available energy sources ranked from lowest marginal cost to the highest (Fiorenzani, 2006). By using this merit order curve we can see that the supply in NPS has the shape of a "hockey stick", i.e. the prices are stable and almost perfectly elastic until demand force the capacity into a bottleneck situation, i.e. to the right in Figure 4 where production cost increase rapidly. Not only weather, but the days of the week also been proved to affect the price movement in a significant way (Johnsen, 2001; Higgs, 2009; Solibakke, 2002).

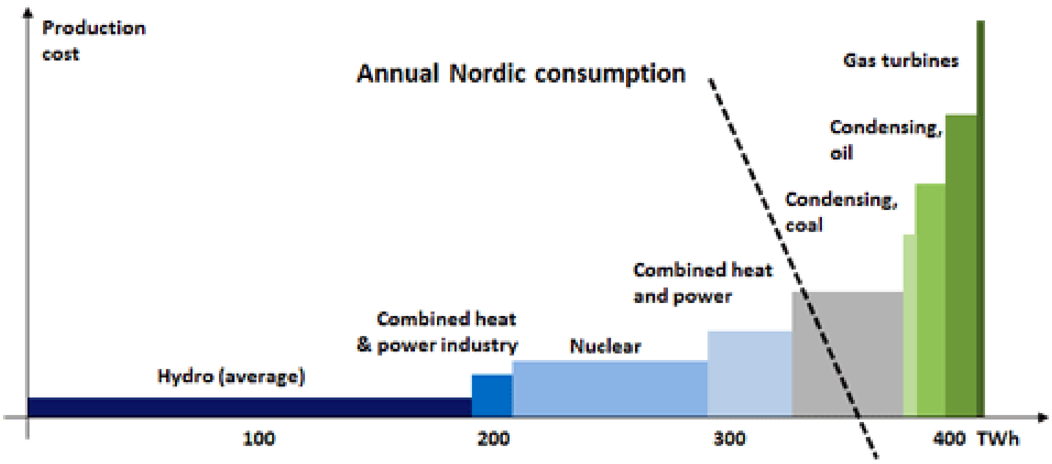

Figure 4: Merit order and demand in Nord Pool (Nord-Pool, 2016)

There as been done a substantial amount of research in the formation and behavior of energy prices. Electricity is a non-storable commodity, something that increase volatility (Strozzi et al., 2008). Natural mean-reversion and positive skewness is also a characteristic of the price formation. Furthermore, energy prices show signs of strong seasonality and also volatility clustering during spikes in prices (Sotiriadis et al., 2014). Higgs (2009) shows that own-mean spillover is present in the different regions in NEM. In all instances, the spillover is positive, indicating that today's level will have an impact on tomorrow. The area price is regulated according to transmission capacity in the different regions; the demanded load will force the price away from the system price. Higgs (2009); Worthington et al. (2005) have found that integration between regions in NEM has reduced volatility although not the critical peaks during bottleneck periods. The volatile movement is further supported by Becker et al. (2007), who finds that price peaks tend to cluster around other price peaks. Becker, like Higgs, concludes that the weather conditions and load demand are important when explaining the shift in pressure. In a market of several regions, the inclusion of an interconnection benefits the volatility during normal periods but do not reduce the extreme price peaks during stressed periods. Arbitrage conditions appear, as shown by De Vany and Walls (1999), to reduce and smooth the difference between prices even when energy is transferred over great distances.

Weron (2000) compare energy prices to other, extreme volatile commodities in order to show the level of variation. While stocks can have a daily standard deviation exceeding 4%, electrical energy can have a volatility of up to 50%. The volatility is calculated as standard deviation of the logarithm price change per period. The price formation depends on supply and demand, but during bottleneck periods the possibility of large energy prices increase. Large price peaks are followed by similar peaks, indicating volatility clustering. In addition, as NPS expands its working area the prices will be affected by the native price level in new areas.

3.2 Market Integration

Trading one commodity for the same price in another region, accounting for transportation costs and quality difference, gives strength to the assumption of market integration. The Nordic energy market is an example of how market integration have maximized the social optimum. Bottlenecks will prevent full price equalization between regions and borders, and create a price difference between the importing and exporting countries, preventing perfect market integration.

The equilibrium price in NPS, i.e. the system price, is accepted as the common price when ignoring transmission constraints and other factors (taxes, currency, etc.). Electricity is a homogeneous commodity, i.e. it does not matter which source is used to produce the electrical energy. This is shown by Asche et al. (2006) for the UK energy market prior to the interconnection to Europe. In an efficient market where two equal assets are traded, the LOP will apply if the assets sell at the same price (Akram et al., 2009). However, constraints in transmission capacity, taxes, and other factors creates differences between regions. This can be seen in the various area prices. Still, this does not reduce the efficiency of the integration between regions. Tangerås (2013) finds that national policies must support the market integration in order to increase the total surplus. Importing countries needs a clear incentive when investing in cross-border transmission capacity. In order to obtain maximum market integration, domestic objectives must not overshadow the needs for investment in transmission. Subsidies into transmission can promote a better utilization of resources, thus creating a more welfare-supporting market integration. Proposition 2 by Tangerås (2013) review objectives that are important when supporting market integration of renewable energy under a decentralized policy. There are many mechanisms that will distort the optimal trade-off between import and export, as well as price, for renewable energy.

The European Union (EU) have imposed a national target for renewable energy consumption, the RES-E, in 2009 (UNION, 2009). By promoting the production and trade of renewable electrical energy, the consumer will have a surplus with regards to both prices and environment. Market integration between two separate markets will not only affect the investment in power plants but also in transmission capacity. Market integration can be measured as the volume of trade and the level of price stability. However, it is important to remember that a small price differences between regions is not sufficient evidence of market integration (Tangerås, 2013). The relationship between energy production, energy intensive industries, and the European Union emission allowance are shown by Aatola et al. (2013) to be able to predict the movement. NASDAQ OMX trade in Carbon Emission contracts; this further strengthens the market integration between the Nordic and European market.

Donaldson (2015) has analysed market integration between different countries, as well as between regions internally in countries. The study shows that exogenous variation in openness (import and export as a factor divided by the GPA of the given region or country) was biased, and that placement in regards to equator also affected the level of openness. Whereas the trade across borders can be complicated by policies and taxes, these can often be ignored between regions. Donaldson (2015) states that it is natural to assume that transportation will be lower within a country than outside its borders. Electrical energy demands a solid transmission network, and the cost of building new lines can be substantial. In the Norwegian sector, the different regions produce mostly hydro power energy and we can see from Section 2.5 that it is the main source of energy. There are no common substitutes for hydro power in Norway, making market integration within the country important in order to prevent power loss in critical periods when the water levels in the reservoirs are low.

Slade (1991) states that when the market is organized and competitive it will make trading more stable and reduce price volatility. However, by including speculators the price was found to be more unstable. The risk of instability is still present but the cost is minimized when considering the benefits of a market that handle large volumes. By adding the brokerage in the exchange, the volatility of the price is increased. Market integration is dependent on a well-functioning system that can balance these unstable conditions. As shown by Higgs (2009), the interconnector between regions in Australia have reduced the overall volatility, but not the critical peaks. As more regions are embedded into NPS, the less market power is given to the big producers. This is further implicated with the addition of exchanges, introducing new actors such as speculators and brokers. All have different motives, and will try to shift the price in a way that suits their risk level. The level of influence has an impact on the stability of the price, i.e. the level of volatility both during bottleneck periods but when the conditions are normal. This will make the trading competitive even if one would think that large actors could control the price formation. Higgs (2009) found that a larger electricity market will reduce the probability of price spikes. It will also handle external shocks well, given that the interconnection between regions is in place and working.

Nord Pool Spot have a 20-year history, with a continuously rising number of participants. As less and less of the northern energy market is perceived to be autarky and interconnections is increasing, investment and support for policies and development across national borders is crucial in an effective energy exchange. The EU have begun the process of supporting the development of renewable energy for its members. The directive has presented the foundation for increased investment focus in renewable energy. Despite the dependency on fossil fuel today, the plan of the Price Coupling of Regions (PCR) is to have a single energy exchange for Europe (Nord-Pool, 2016).

3.3 Econometric Analysis

In both the financial world and in other trades, statistical methods is used to analyse sample data. Econometric uses statistical methods to develop and analyse models. This can give valuable information about the relationship and how to best forecast future values. Further more, it is used to test and evaluate theories, and to describe the strength of them.

Empirical analysis on sample data is used to test the inference and establish connections between the different variables. The composition of the regression model is modeled to test relationships. The input and output variables tell something about what the user aims to learn more about; e.g. weather versus gas prices or smoking and male users. By choosing how to approach the models outputs and inputs we will form an opinion of which results we want to see. By looking at the kind of buyer, income, and other factors we can form an understanding of what factors that influence demand the most. Time series data is also an important element in financial analysis. Price movement over time can give valuable information about relationships and volatility. The notion ceteris paribus is important in econometrics; we hold all other relevant factors fixed as we analyse data (Wooldridge, 2015, p.12).

3.3.1 General regression

Regression analysis is explained simply by saying that we want to describe y in terms of x. The regression will yield an equation that fit as best as possible. Ordinary Least Squares (OLS) obtained using Gauss-Markov assumptions ensures that we choose the equation that best fit our observed data. The difference between the fitted estimate and the observed data is called a residual. OLS chooses the coefficients for the Sample Regression Function (SRF) that minimize the sum of squared residuals, i.e. that choose the equation with the best fit. The general equation for a multiple regression is a description of how we assume the actual values of the input variables describe the output. This is sometimes referred to as the population model or the true model.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + u \tag{7}$$

β is the coefficient for each variable; the level of influence the explanatory variable has on the explained variable. u is random noise; the error term due to misspesification. Generally assumed to be white noise, i.e. a mean equal zero and a constant variance. However, the regression analysis only gives an estimate of what the true coefficients are. We base our estimates on a sample of data, thus we do not know exactly what the coefficient in the model should be. The regression analysis gives a fitted value for what we expect to resemble the true model:

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + ... + \hat{\beta}_k x_{ik} \tag{8}$$

The fitted estimate will normally not yield the exact value of the observation. The difference between the actual value and the estimated value is described as the residuals of the regression:

$$\hat{u}_i = y_i - \hat{y}_i \tag{9}$$

The residuals of an OLS fitted estimate has an average value of 0. This assumption is known as the zero conditional mean. For homoskedasticity, the variance of the residuals is constant. If it is changing through the sample, there is evidence of heteroskedasticity (Wooldridge, 2015, p.93). The covariance between any of the independent variables and the residuals is zero. The covariance between the fitted values and the residuals therefore also is zero (Wooldridge, 2015, p. 65).

R^2 is a measurement of the goodness-of-fit for the SRF. It is sometimes known as the coefficient of determination, i.e. it gives a value between 0 and 1 for how much of the sample that is explained by the estimates. It is also the square of the sample correlation between the observed value and the estimated value. R^2 never decrease when other variables are added to the regression. It therefore makes a poor tool for determining if the model is misspecified. R^2 cast a light on the observed object; a low value can also indicate that the observation is difficult to predict (Wooldridge, 2015).

The estimates for the different coefficients are obtained via the OLS estimation. We have $k+1$ estimates from the OLS, where the +1 is the intercept for the regression line, and k are the number of input variables. The power of the multiple regression is that it allows the investigation of phenomena in a non-experimental environment, i.e. do tests similar to what is usually done in a controlled environment like a laboratory (Wooldridge, 2015, p.65). This is achieved by keeping other factors fixed and analysing the effects of a single variable. The estimated coefficients, β_j, will be subject to a t test. The estimated coefficient divided by its standard error will produce the t value. This can be tested using the Student t table for its significance.

In order to determine if the regression result is valid we need to test the significance of the estimates. As R^2 only quantify the goodness-of-fit for the collective estimate, we need to look closer at the different variables in the model. The significance of each coefficient will give an indication on the effect it has on the estimated output. The OLS method estimates the model with the minimum variance among the unbiased estimators. In order to determine the significance of the estimate β_j for a given regression we use the following equation:

$$\frac{(\hat{\beta}_j - \beta_j)}{se(\hat{\beta}_j)} \sim t_{n-k-1} = t_{df} \tag{10}$$

Here we test the estimate against our hypothesized value for the actual value. Normally our null hypothesis will be that the estimated coefficient is assumed to be zero. The null hypothesis can be specified any way that suits the goal of the analysis.

The normal null hypothesis, where assumed value β_j is zero, is calculated like this:

$$t_{\hat{\beta}_j} \equiv \frac{\hat{\beta}_j}{se(\hat{\beta}_j)} \tag{11}$$

Where $H_0 : \beta_j = 0$ using Equation 10 leads to the t value in Equation 11. This value is tested against the Student-t table, and reveals how probable the value is. The probability given by the t table is a reflection on how often we find the estimated value in a distribution with heavy tails. With a 5 % significance we find the estimate to be true 95 out of 100 times. The better the estimate, the lower p value should we expect. The p value tells us how strongly we can reject the null hypothesis. This is an important value when addressing large regression results.

The error term is of key importance in regression analysis. The error term (u) is a measurement for the accuracy of the estimate. When the variance of the error term is constant we have homoskedasticity. This gives us a Best Linear Unbiased Estimator (BLUE) specification. When the variance of the error term changes across different parts of the sample we have heteroskedasticity. Heteroskedasticity does not add any trouble when using the OLS estimators, but it creates faulty values in the standard error of the estimated coefficients. Breusch and Pagan (1979) and White (1980) both have developed tests for discovering heteroskedasticity. Heteroskedasticity will most likely appear in large sets of samples. Further more, we can divide the explanatory variables into either exogenous and endogenous explanatory variables. Whether or not the error is correlated with the explanatory variables have an important effect on the interpretation of the result. Endogenous variables are correlated with the error term, where as the expectation for the value of the error is zero given exogenous explanatory variables.

Sample data is not consistent with perfect statistical data, and will not inhibit the normal shape and distribution. Skewness, kurtosis and other characteristics changes the shape of the distribution to that of a normal distribution. Several tests are used in order to discover trends, seasonal patterns, non-stationary samples, unit root and other noise. Including the correct variables can also be a challenge. Over-specifying the model by including irrelevant variables will not affect the general coefficients but it can create problems with the variance in the error term.

Normality is not an assumption, but given large enough sample size the Gauss-Markov assumption will hold and can justify the use of the central limit theorem (Wooldridge, 2015, p. 143). The estimates need to be consistent, i.e. that more data will lead us closer to the parameter of interest. Another problem can arise if two explanatory variables are almost perfectly correlated, known as multicollinearity. This can create fuzzy standard errors. Leaving one of the variables out of the equation is optimal, as they behave in similar fashion and affect the output in a similar way. A combination of endogenous and exogenous variables can be a good solution. Many of the area price samples will show signs of multicollinearity, as they move in the same pattern.

3.3.2 Autoregression

Time series tend to present a difficulty in finding a pattern between current and lagged values. Random walk is often present in time series, i.e. that the relationship between lagged values seemingly have no pattern but rather move at random. The AR process tries to describe the relationship using lagged values. It is a stochastic difference equation designed to specify the output based on its previous values. The general formula for an AR(p) model is:

$$y_t = \phi_1 y_{t-1} + ... + \phi_p y_{t-p} + \varepsilon_t \qquad t = 1, ..., T \tag{12}$$

It is important to establish that the stochastic process is stationary. See Harvey (1993, p.15) for the correct procedure. The model consist of a moving average of white noise variables and lagged values from the output variable. A goal of the process is to predict the future value based on a weighted average of the previous values. Below a AR(1) model is presented.

$$y_t = \phi y_{t-1} + \varepsilon_t \qquad t = 1, ..., T \tag{13}$$

The AR model have similarities to the multiple regression model. The only difference is that AR use lagged values of the output variable while the multiple regression model uses the explanatory variables to predict the output. For the electrical prices this will give an idea of the movement of the price. As the strong seasonal factor apply, using monthly arithmetic aggregated average will show large differences between the lagged values. Using daily aggregated prices will require a larger span of lagged values in order to discover patterns.

The more lagged values that are added, the more insight into more complicated patterns are presented in the results. When analysing time-series one can analyse univariate series, i.e. only a single time series, or multivariate series. With energy prices, the relationship to the lagged values are very important. Seasonal patterns are shown to have a great influence on the stability of energy prices (Higgs, 2009; Becker et al., 2007; Sotiriadis et al., 2014). Understanding seasonal patterns and the influence of the lagged values on today's volatility is important in order to assess the risk when dealing with energy spot prices.

3.3.3 ARCH & GARCH

Ordinary time series operate under the assumption of constant variance. Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which allowed the conditional variance to change during the course of the time series. A common way to include past conditional variance into the current conditional variance is to use the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)(p,q), as described by Bollerslev (1986). The GARCH model will allow a much more flexible approach to the lag structure. The ARCH model specify the conditional variance as a function of past variances in the sample. The main difference between ARCH and GARCH is that the latter also process the lagged conditional variance. The ε_t denotes the real-value stochastic process and ψ_t describes the information set through the time. The GARCH(p,q) model is describes as:

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \tag{14}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{15}$$

where

$p \geq 0, \qquad q > 0$

$$\alpha_0 > 0, \qquad \alpha_i \geq 0, \qquad i = 1, ..., q,$$
$$\beta_i \geq 0, \qquad i = 1, ..., p.$$

With $p = 0$ we have a normal ARCH(q). If $p = q = 0$ the ε_t simply resembles white noise. The GARCH model enables learning from previous lags to enter into the current model. For a more detailed description, see Bollerslev (1986). The coefficients given by the GARCH model reveals how shock and volatility affects the observations.

3.4 Lag Length

A problem in time series data is the appearance of autocorrelation in the error terms or more general dynamics. This correlation violates one or more of the assumptions of the Gauss Markov theorem, that the residuals have no correlation or that the model is correctly specified. The presence of autocorrelation will not affect the parameter estimates, but the standard error will not be correct, invalidating regular hypothesis testing. With more general dynamic misspecification, the estimated parameters can be inconsistent. Breusch-Godfrey test (Breusch, 1978; Godfrey, 1978) and Durbin-Watson (Durbin and Watson, 1950) statistics are used to discover autocorrelation in the first order. Depending on the level of lags and inclusion of the dependent variable, one chooses between the two methods.

Hendry (1995) note that there are two main approaches when investigating dynamics. The first and traditional method is the specific-to-general. Here one start with a static model that display the long-run relationship. The goal is to provide the most parsimonious model specification without dynamic misspecification. The model is estimated, and tested for autocorrelation. If the null hypothesis is rejected, one add a lag to the model and try again. There are a number of tests available, where the Breusch-Godfrey is among the most general. A key problem with the specific-to-general approach is the lack of information with regards to the cause of symptoms detected by the diagnostic statistics. Adding variables to the model might not fix the problem if the model requires joint modeling in order to get consistent parameters. The functional form is essential in finding the root cause for autocorrelation. The misspecification that leads to errors must be accounted for, re-specifying the model in order to remove error and get a BLUE estimate.

The next method is the general-to-specific method. Here the first model is specified with a very generous lag structure, certainly long enough to capture all dynamics. For daily data samples a reasonable start can be with 365 lags. One then use F-test to remove insignificant lags or lags that contain no information. However, this leads to quite complicated models, and one will often find that the data set is not large enough, leading to what Hendry (1995) labels the “curse of dimensionality”.

A common alternative, but which is not based on statistical inference is to use an information criterion like Akaike or Schwartz. These criterions acknowledge the dimensionality challenge as they weight the improved explanatory power of the model by increasing an extra lag against the loss in degrees of freedom. Hence, the information criterions provide a pragmatic trade-off between the general-to-specific and the specific-to-general approaches. It is worthwhile to note that as long as one are accounting for the dynamics using lags, the approaches are all asymptotically equivalent.

The Schwarz Criterion (SC) is an index that choose the optimal model specification. The first term measure the increased explanatory power of the additional lag, while the second term imposes a penalty associated with the additional lag. Akaike information Criterion (AIC) is similar, but with a different penalty function it tends to recommend a large number of lags. The general formula for calculating the SC index is:

$$SC = -2 * Lm + m * ln(n) \tag{16}$$

The maximized log-likelihood, the number of samples (n) and the number of parameters (m) are used to calculate the index. The SC is simply a criterion used selecting among formal econometric models (Schwarz et al., 1978). In order to create a correct model that eliminates autocorrelation, the correct level of lags must be chosen. Although asymptotically equivalent, the different methods can provide different recommendations in small samples. Given the large number of models to be estimated here and the high frequency of the data, the SC will be used.

4 Method

This is a quantitative analysis, and will use raw data supplied by Nord Pool. To understand the degree of market integration, the different markets have been tested using statistical inference tests on short and long term parameters. The dynamic component will be subject to testing, as price movement in financial environments must be view as non-normal and time-dependent. Tests for structural change are conducted since price fluctuations give an indication on how the market integration is affecting the price. Granger Causality is used to analyse the feedback relationship between the region price and the system price. The AR model developed is used to specify own-price spillover as well as cross-spillover between the system and area price. The GARCH(1,1) model will analyse the volatility and shock spillover from the residuals of the AR(8) model.

4.1 Collection of data

The quantitative nature of this thesis require only raw data to run tests for integration and volatility. It also require cross-referencing towards similar studies, since comparison to other theories can validate the methods chosen (Eisenhardt, 1989). Triangulation of result, data and theory must be present in order to verify the process. The nature and integration of the Nordic energy prices can be analysed using both quantitative and qualitative methods. The author chose to focus on a pure quantitative approach, as the case study has several hypothesis present to test. This can cause a biased view of the tests, but since the sample was different from other comparable studies this is accepted. Eisenhardt (1989) states that it can be wise to choose a study that are likely to replicate or expand the current theory. The sampling in the thesis follow the description; statistical sampling done in order to uncover evidence of distribution and relations between the variables within the Nordic market. While the quantitative evidence speaks for itself, care has to be taken when trying to interpret them in a qualitative fashion (Eisenhardt, 1989). Anecdotes are needed when building theories, and soft data needs to be combined with the hard data in order to explain the results (Mintzberg, 1979). The Nordic energy market presents the opportunity to test conflicting hypothesis. There are much literature available, and this can be used to form a more creative approach to the research (Eisenhardt, 1989), and to validate results.

Schneider (2005) describe four key statistical coefficients to include in data analysis; the strength of relations between two series, tendency of a relation, percentage of the variance explained and the significance level of the model. In order to produce correct models the data will have to be cleaned for fuzziness, and missing data must be accounted for. Nord Pool has a complete log of prices, and there were no missing values. The cross-case approach meant that instead of testing the whole region together the individual region was tested against the system price. This was done because the system price is perceived to be the one price, and market integration, theoretically, mean that these series should converge.

4.2 Structural Change

Since the Nordic market have expanded several times during the observational period there is a need to examine the possibility of a structural change in the system price. The fitted empirical fluctuation of the price will determine the level of variation both in the given price series and in the residuals. Brown et al. (1975) developed the method known as the Cumulative Sum of Residuals (CUSUM). Chow (1960) developed a test of the parameters in a model, searching for a single break in the stability, known as the Chow test. This thesis will test the system price for structural change using the OLS-CUSUM model. First, the system price for the entire period (96-15) will be subject to the test for structural change. This will include both the system price and the differentiated system price. Second, a historic period will be selected, and the same test will be applied to the full span of the sample. CUSUM is calculated:

$$W_n(t) = \frac{1}{\tilde{\sigma}\sqrt{\eta}} \sum_{i=k+1}^{k+t\eta} \tilde{u}_i \qquad (0 \le t \le 1), \tag{17}$$

Where η is the number of recursive residuals. The process is limited by the Standard Brownian Motion, and the null hypothesis of no structural change is calculated using a empirical fluctuation process. The Moving Sum of Residuals (MOSUM) is another way to detect structural change. Again, the process is calculated in the same way as the CUSUM, albeit it includes a bandwidth parameter for the moving window of data. See Kuan and Hornik (1995) for details. Independent of which test used, the null hypothesis is that there is no structural change in the data series. If the fluctuation gets too large the null is rejected, and we can conclude that we have a structural change. The methods applied in this thesis follow the description by Zeileis et al. (2001).

To test the system price for structural change two models will be proposed. The first regression will have the system price as dependent variable, and the explanatory variables will be the residuals of an AR process with three lags and the difference between the daily system price. The OLS-CUSUM model is chosen to test for structural change in the system price. First an AR(3) model is calculated:

$$p_t = \beta_0 + \beta_1 p_{t-1} + \beta_2 p_{t-2} + \beta_3 p_{t-3} + \varepsilon_t \tag{18}$$

The residuals of the AR(3) model in Equation 18 is used in conjunction with the squared differentiated value of the system price. The regression used for testing the empirical fluctuation is:

$$p_t = \varepsilon_t + \Delta p_t^2 \tag{19}$$

The same model will be specified for the differentiated system price, where the residuals of the regression and the squared difference price will be used as explanatory variables. It is natural, given the shape of the system price, to assume that the price experience structural change. By testing the difference, the test can determine whether the volatility is changing as time moves, or if it is stable through the sample period.

The next model tested monitor the occurrence of a structural change based on a historic sample. Leisch et al. (2000); Chu et al. (1996) have developed tests for recursive and estimates tests using statistical tools such as R. The models presented by Zeileis et al. (2001) will be applied to the OLS-CUSUM model. To test for structural change using a historic period the approach is to use a sequential procedure. First the model under investigation have to be developed based on the historical period for which we investigate. When this model is defined we can change the data-frame from just the historical period to the whole sample. Structural change is detected by monitoring the change between the parameters in the historical period against the entire scope of sample.

4.3 Autoregressive Model

The AR use the conditional mean model for bivariate price series. Added lagged values remove serial correlation and account for seasonal components. Adding the correct lag-order to the model will filter the data and creating serial uncorrelated residuals (Sotiriadis et al., 2014). A lag order of eight is selected using the SC criterion. Exogenous variables include dummy variables for days and months. Temperature is a key variable in determining electrical energy prices, as shown by Weron (2000); Johnsen (2001). However, as the lagged price observations and seasonal dummies had a more profound impact, the temperature was dropped from the equations in order to avoid overparameterization. This ensures that the most efficient estimators are used and gives the best, parsimonious model.

The model consists of the full time-series for the system price and each region. In addition to the prices and its lagged values, the model include dummy variables for both weekdays and months. As energy prices have strong seasonality this will show significance both in short term and for longer stretches. Harvey (1993, p.152) points out how adding explanatory variables to an AR process gives the possibility to partially account for the movement of the explained variable. The model is named Autoregressive Distributed Lags. The disturbance in the model is considered white noise, and therefore can be estimated using the OLS regression.

$$p_t = \alpha + \Delta \times DV_d + \Delta \times DV_m + \sum_{k=1}^{m} \phi^{(k)} p_{t-k} + \varepsilon_t \tag{20}$$

Equation 20 show the general equation for the AR model applied. The Δ is a $N \times 1$ vector for the coefficients of the weekday and month dummy variables, where an estimated coefficient respond to the different day and month. The DV_d is the dummy variable vector for the days, and the DV_m is the dummy variable for months.

The $\phi^{(k)}$ is the coefficient for the price at a given k lag of the AR model, where P_{t-k} is the respective price. The innovation of the model is described in ε_t. The model will take the following shape for each region, based on the model described by Slade (1986). The model account for the dynamic adjustment present in time series. The following regression is run:

$$p_t = \alpha + \sum_{a=1}^{7} \delta_a DV_{dt} + \sum_{b=1}^{12} \delta_b DV_{mt} + \sum_{i=0}^{8} \beta_i p_{t-i}^S + \sum_{j=1}^{8} \gamma_j p_{t-j} + \varepsilon_{it} \tag{21}$$

Where the DV_{mt} and DV_{dt} denotes the dummy variables for months and days at time t. The model will run the selected amount of lags for each of the area price series under investigation, and the system price. The intercept α is included as a baseline, accounting as a proportionality coefficient. For the system price, p_{t-i}^S, observations range from $t = 0$ to lag eight. The region under consideration will have lagged values from $t = 1$ to lag eight as explanatory variables. By regressing the model using lagged values, it will be possible to see the effects of integration over time, as well as the influence of seasonal components. The inference will show significant relations and the result can be compared with other regions to form an understanding of the difference in the price movement.

4.4 Long term stability and dynamic

Drawing on Ravallion (1986); Slade (1991); Asche et al. (2004), the next tests will test for validity in the LOP. The system price is perceived to be the "one price" in NPS. The LOP is used to describe a market that removes the notion of one-way arbitrage, i.e. two identical assets in a efficient market should trade at the same price (Akram et al., 2009). Stationary data is required to test for LOP using the methods described here, as non-stationary data fail to give valid inference in linear regression.

4.4.1 Instantaneously Adjustment

The first model test whether there is instantaneously adjustment in the area price, based on the movement of the system price. A linear regression is fitted for each region; the region price is the observation and the system price is the explanatory variable. The relation between region and system price is:

$$p_t^R = \alpha_0 p_t^{\beta_j} \tag{22}$$

Taking the logarithm and separating the factors, the model is as follows:

$$\ln p_t^R = \alpha + \beta_j \ln p_t \tag{23}$$

The general form for the estimated coefficients then become:

$$p_t^R = \alpha + \beta p_t^S + \varepsilon_t \tag{24}$$

The constant, α, is a proportionality coefficient. Should the prices be identical this would be close to zero. The more the two series deviate from each other, the larger value α will inhibit. The region price, p_t^R, is described by the system price p_t^S and its coefficient β. The results from this regression will be used to form the following null hypothesis:

$$H_0 : \beta = 1 \tag{25}$$

The null specified in Equation 25 is a test for the constant relationship between the two prices, and for the assumption of LOP. If the t test fails to reject the null hypothesis and the test for dynamics (Equation 28) is rejected, the movement of the area price is integrated with the system price for one time period, i.e. the "one price" holds short term (Ravallion, 1986). With the null hypothesis $H_0 : \beta = 0$, the assumption is that there is no possible substitution between the two regions (Asche et al., 2004). This means that the system price does not influence the price in the given region.

4.4.2 Dynamics in the price series

The next test will test whether there are dynamics in the price series. To test the null hypothesis of no dynamics, a F test must be applied to the residuals of both a restricted and an unrestricted model. First, an unrestricted model will be applied to the price series under investigation. The model described in Asche et al. (2004) is used to form the regression:

$$p_t^R = \alpha + \sum_{j=1}^{8} \gamma_j p_{t-j}^R + \sum_{i=0}^{8} \beta_i p_{t-i}^S + \varepsilon_t \tag{26}$$

The region price will be explained by estimates from the system price at time t, and eight lagged periods from both the investigated area and the system price. The constant, α is a term describing the arbitrage between the explained and explanatory variable. The coefficients β_i demonstrate the relationship between the region price and the lagged value p_{t-i}^S for the system price. γ_j is the elasticity of the lagged region price at time $t-j$. Next, a restricted regression is run:

$$p_t^R = \alpha + \beta p_t^S + \varepsilon_t \tag{27}$$

The null hypothesis assume that the lagged values are insignificant, and equal to zero. The null hypothesis is formulated:

$$H_0 : \beta_1 = ... = \beta_i = \gamma_1 = ... = \gamma_j = 0 \tag{28}$$

Thus, the restricted model will only include the system price at time t. The Sum of Squared Residuals (SSR) and degree of freedom will be used in formulating the F statistics; see Equation 29, as described by Wooldridge (2015, p.122).

$$F \equiv \frac{(SSR_r - SSR_{ur})/q}{SSR_{ur}/(n-k-1)} \tag{29}$$

Where q denotes the restriction imposed on the model. The denominator is the SSR unrestricted divided by the unrestricted degree of freedom. The F-value will be tested against the F distribution; $F \sim F_{q,n-k-1}$. If the F value is below our chosen significance level, we cannot reject the null hypothesis of no dynamics. If H_0 is rejected, we have jointly statistically significant variables.

4.4.3 Long run parameter

The last test evaluate the short and long run LOP inference. The regressive element is added to combat serial correlation. While the assumption of the residuals acting as white noise still holds, there can still be unexplained variations in the residuals. The same AR model as in the test for dynamics is applied to the region price. See Equation 26. In order to find a suitable null hypothesis the long term price must be described:

$$p^R = \frac{\alpha}{1-\sum_{j=1}^{m}\gamma_j} + \frac{p^S\sum_{i=0}^{n}\beta_i}{1-\sum_{j=1}^{m}\gamma_j} + \frac{\varepsilon_t}{1-\sum_{j=1}^{m}\gamma_j} \tag{30}$$

We formulate a t-test for the estimated coefficients, with the null hypothesis being that the long term parameter is one, i.e. $H_0: \sum_{j=1}^{8}\gamma_j + \sum_{i=0}^{8}\beta_i = 1$. Any misspesification may be due to omitting of a key variable or lack of adequate regression lag length. If the dependent explanatory variable inadequately account for the observed variable, the model have functional form misspecification (Wooldridge, 2015, p.242). The goodness-of-fit can still be significant, but the variance of the standard error are wrong. Since the lag selection is done using SC, the lag length is chosen for a valid number of lags.

To find the t value for the test, the standard error of the entire range of coefficients must be calculated. Once the error is found, the t value can be used to test the significance of the null hypothesis. The value and degree of freedom for each regression is used in the calculations. Should the long run hypothesis be rejected, one has to re-evaluate the results from the short run models (Ravallion, 1986).

4.5 Granger Causality

The test for Granger Causality is a statistical method that test the relationship between two or more variables to determine how the variables affect each other (Granger, 1969). The causal inference tests the relationship between the variables (Calhoun, 2002). The asymmetric relationship between X and Y is known as the causality, and the Granger causality conclude whether X Granger-cause Y and opposite. The endogenous properties of the price series are tested to see if the causality moves both ways. Should the movement be significant one way, the price that does not adjust is believed to be the price leader (Asche et al., 2004).

The past and present values of $y_{1,t}$ should be part of explaining the forecasting value of $y_{2,t}$ (Burda, 2001). For the test of causality between a bivariate time series, the causality test in R use a Wald test to compare models. It compares the restricted versus the unrestricted model of Y and X. Stationary data is required when testing for LOP using the causal relationship. Lags are included in order to capture the dynamic elements in the price movement. The lagged values of the test should prove significant if there is a causal relationship between the two variables.

$$E(y_t|I_{t-1}) \neq E(y_t|J_{t-1}) \tag{31}$$

where
I_{t-1}: information on past information about X and Y
J_{t-1}: information on past information of X

Equation 31 show the requirement for a Granger causality relationship between two variables. This can be extended to apply for AR models as well as bivariate time series. Granger (1969) claims that the feedback mechanism in a relationship can be viewed as the sum of two separate causal mechanisms. By decomposing and analysing cross relations and partial cross relations one can uncover direct methods of predicting future values of a given variable based on the past behaviour of another. Given two different equations for a time-series, a simple causal model can be shown as:

$$\begin{aligned} X_t &= \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t, \\ Y_t &= \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \eta_t, \end{aligned} \tag{32}$$

Where ε_t and η_t are white noise that is uncorrelated. Equations 32 implies that there is a relationship between X and Y. If these events take place as specified above (b_j and $c_j \neq 0$) then we have a feedback relationship, see Granger (1969) for details. Equation 33 show how the causal relationship of Y Granger cause X. Using all available information, U, will lower the variance as opposed to ignoring the information from Y.

$$\sigma^2(X|\overline{U}) < \sigma^2(X|\overline{U-Y}) \tag{33}$$

Equation 33 have a feedback relationship if it is the same for Y as for X. However, this is based on the assumption of stationary data. The dynamic nature of financial time series changes the causal relation over time. For time series that are non-stationary we can discuss the notion of causality relation existing in this moment of time. Cointegration tests by Johansen (1988) can be used to empirically test for market integration when the data are non-stationary, even if traditional econometric approaches cannot be applied (Asche et al., 2004).

To check for a causal relationship, the system price will be tested against the different regions. The same test will be reversed, testing the different regions against the system price. The SC criterion selected the number of lags to included equal $p = 8$. The test in RStudio use the Wald test as a basis for examining the stochastic elements as well as the dynamic properties of the time series. Since the region prices are based on the system price, there is a natural expectation for a relationship to be present between the series.

4.6 Generalized Autoregressive Conditional Heteroskedasticity

The GARCH(1,1) process will be applied to the residuals of the AR model in Equation 21. The AR will describe the conditional mean of the different regions, and the GARCH model describe the structure of the conditional volatility. This is the simplest of the processes, but it suffices and give good results, as stated by Bollerslev (1986). The innovations are then used to form a linear regression:

$$\varepsilon_t = y_t - x_t^{'} b \tag{34}$$

where y_t is the dependent variable and $x_t^{'}$ is a vector of explanatory variables. b is a vector of unknown parameters. The innovation is then processed through the variance of the GARCH model. The estimated coefficients for the ARCH effect is the parameter β_1, and for the GARCH effect α_1.

$$\begin{aligned} h_t &= z_t^{'}\omega, \\ z_t^{'} &= (1, \varepsilon_{t-1}^2, h_{t-1}), \\ \omega^{'} &= (\alpha_0, \alpha_1, \beta_1) \end{aligned} \tag{35}$$

Since the GARCH(1,1) model is employed, the variance will be as shown in Equation (35). The log likelihood function is described as:

$$l_t(\theta) = -\frac{1}{2}\log h_t - \frac{1}{2}\varepsilon_t^2 h_t^{-1} \tag{36}$$

The likelihood function is then differentiated for the various parameters to calculate the maximum likelihood estimates. The ω is tested against the null hypothesis $H_0 : \omega = 0$. The statistical inference is tested using the Lagrange multiplier test statistics, see Bollerslev (1986). The Box-Ljung test is applied to the squared residuals. The null hypothesis is that the data is independently distributed, i.e. there are no correlation between the data in the time-series (Box and Pierce, 1970). Any correlation is due to the randomness of the sampling. Should this hypothesis be rejected we have evidence of serial correlation.

The goal of the GARCH regression is to obtain the coefficients for variation due to shock and innovation in the residuals from the autoregression. These estimated coefficients will provide information about how the price series in the regions handle volatility. The coefficients will reveal the own-innovation of the price movements and how lagged values of volatility affect the present level. A persistence coefficient will be calculated; it is defined as the sum of the ARCH and GARCH effects. The persistence will describe how the volatility process acts in the different regions.

4.7 Limitations

With financial statistical methods there are many aspects to consider when developing models. Exogenous and endogenous variables have a strong impact on the residuals of a model. Serial correlation can distort the estimates and create biased values. Misspecification will remove the validity of the estimates. Non-stationary data can distort the inference given by the OLS estimates.

The temperature has been shown by several studies to be dominant in the development of electrical energy price (Weron, 2000; Johnsen, 2001). A limitation of the tests is that temperature is not included in the autoregressive model. The price series all have a different number of observations. The lack of similar time length can reduce the strength of the analysis. The volatile movement seen in mid-2000 are not present in the analysed data for Lithuania, Latvia and Estonia. Also, outlier observations in bottleneck periods create extreme price movement that have an impact on the development of the model. The exchange rate between the Baltic regions and the Northern regions can also introduce error. By introducing the exchange rate between EUR and NOK the results may be biased due to the different currency in the regions.

Pragmatic limitations can account for the scope of the thesis. The sheer possibilities for cross-testing and other methods, based on comparable literature, makes it possible to construct several theoretical case studies. As such, theoretical saturation is not the reason for limiting the thesis; the lack of time prevent further studies. A parsimonious approach to the empirical analysis benefits both the reader and the outcome.

4.8 Overview of methods

An overview of the methods applied are summarized in Table 1. The results are presented in Section 6.

Table 1: Summary of methods applied

Method	Description	Parameter-restriction	Results
Autoregression	Autoregressiv model for the regions	Eight lags	Table 6, Appendix D
Structural Change	Test for structural change in the system price		Table 4 and 5
Long term stability and dynamics			
a)	Tests if the region price is proportional to the system price	$H_0 : \beta_j = 1$	Table 8 and 9
b)	F-test for dynamic relationship.	$\beta_0 = ... = \beta_k = 0$	Table 10
c)	t test for the short and long term parameter	1: $H_0 : \beta_0 + ... + \gamma_8 = 0$ 2: $H_0 : \beta_0 + ... + \gamma_8 = 1$	Table 11
Granger Causality	Tests for a causal relationship	$E(y_t \mid I_{t-1}) \neq E(y_t \mid J_{t-1})$	Table 12
GARCH	Tests the volatility in the regions	GARCH(1,1)	Table 13

5 Data

The data used consist of daily spot prices for each respective bidding area in NPS[1]. The first sample begins 01. January 1996, and the last ends 31. Dec 2015. The spot prices for Estonia, Latvia and Lithuania were only reported as Euro per MWh, and were converted to NOK using currency data from Norges-Bank (2016). The natural logarithm is applied to the daily spot price. There are 7305 observations for the bidding areas that have been connected since the start. The lowest observational data describes the price movement in Latvia, with an observation count of 942. The spot price and the log spot price is reported, as well as corresponding statistics. See Table 2 and 3 for the summary statistics. All the prices are denoted as NOK/MWh.

5.1 Summary statistics

The different bidding areas are named as following: In Norway there are five bidding areas; NOR_Bergen, NOR_Oslo, NOR_Kristiansand, NOR_Trondheim, and NOR_Tromso. Sweden had one region until 01. January 2011; then the Swedish region was divided into four different bidding areas. The data for Sweden before and after the split show a high correlation in descriptive properties[2]. The regions will be aggregated, averaged and treated as one region for the remainder of the thesis[3]. Denmark have two regions, DK_W and DK_E. Since the bidding areas are included at different times, and don't share similar descriptive data they must be treated as two separate bidding areas. Both regions in Denmark have experienced a negative spot price during certain dates. The negative, outlier observation is shown as the minimum average daily price for DKW and DKE. Finland, Estonia, Latvia and Lithuania all have one bidding area each.

NOR_Kristiansand has the overall lowest average price (239 NOK/MWh), and Latvia has the highest average price (402.5NOK/MWh). The system price has an average of 246.20 NOK/MWh for the entire sample period. The lowest price, ignoring the

[1] Data supplied via Nord Pool FTP server

[2] Summary statistics and correlation matrix for each region in Sweden are available in appendix

[3] The General Composite Commodities Theorem (GCCT) by Lewbel (1996), is used by Asche et al. (1999) to allow product aggregation when the products move proportionally over time. If the markets are well integrated, the validity of the aggregation should hold.

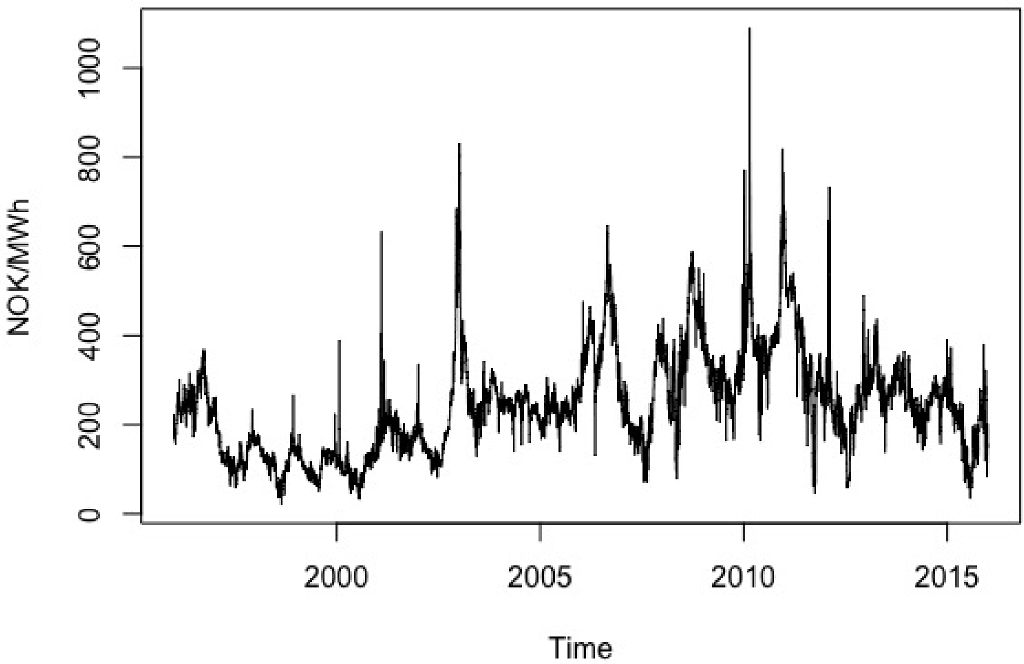

Figure 5: System price Jan 1996 - Dec 2015

Source: Nord Pool FTP-server

negative value seen in Denmark, can be found in the southern Norwegian region (Bergen, Oslo and Kristiansand) with a price of 16.61 NOK/MWh. The system price has a minimum of 21.27 NOK/MWh, and Latvia have the highest minimum level (165.8 NOK/MWh). The difference between Norway and Latvia is of course a time-span of more than 16 years. The northern parts of NPS have the highest maximum price (4089 NOK/MWh) whereas Bergen and Oslo have the lowest maximum price (831.40 NOK/MWh). Denmark East have the highest standard deviation (141.59) and Lithuania have the lowest standard deviation (97.68).

The Coefficient of Variation (CV) is calculated for each set of data. CV is the standard deviation divided by the mean of each sample. This is a measurement for how volatile the price is during the sample period. Latvia have the lowest CV (0.25) and Trondheim have the largest CV (0.5377). The boxplot in Figure 6 show the mean and the variation most notably in each consecutive year for the system price.

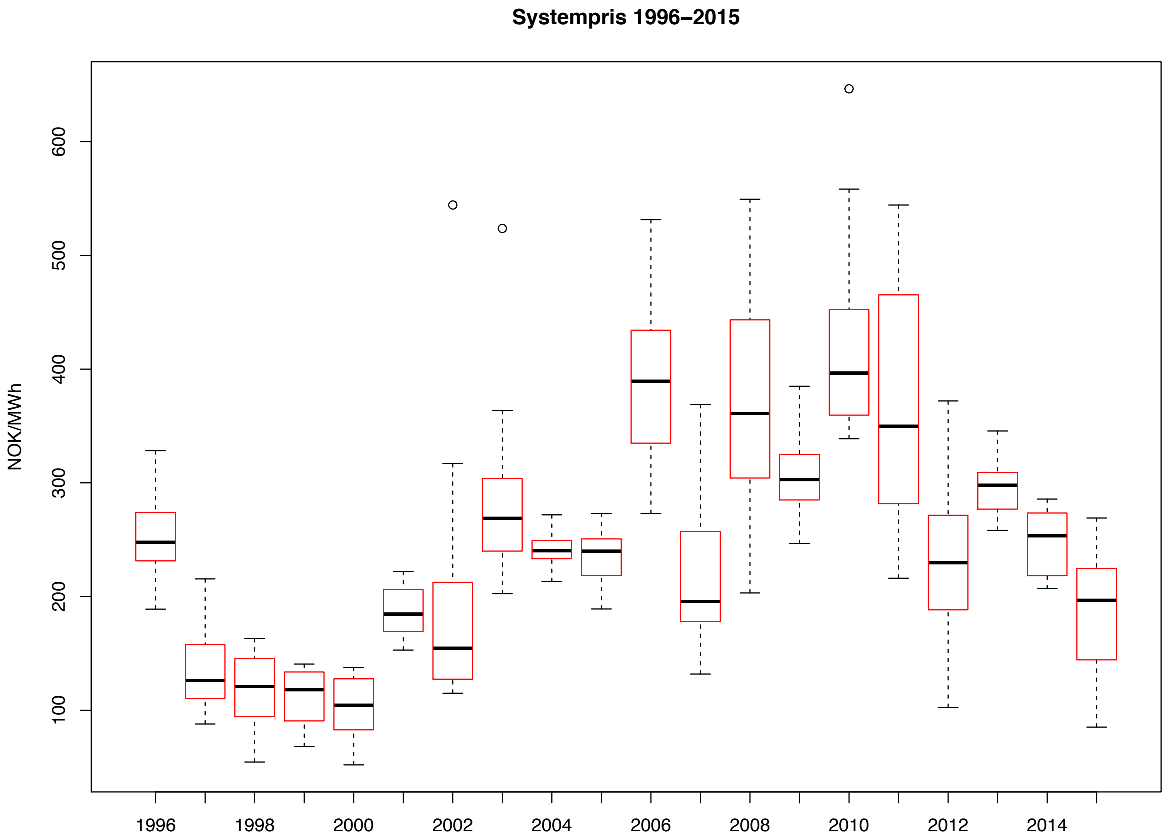

Figure 6: Boxplot for the system price 1996 - 2015

Source: Nord Pool FTP-server

The difference in length can challenge the robustness of the summary statistics. Comparing Bergen against Latvia will not give concluding evidence of difference, since the overall price level has shifted in the course of the sample section. However, both the statistical properties in the tests and the selection criterion for the AR model fail to give evidence of misspesification.

5.2 Statistical properties

The skewness and kurtosis have been analysed for each data set to see how the distribution is shaped. Kurtosis is a measurement on the distribution of the values across the mean. The value of kurtosis supplied in Table 2 and 3 are the excess kurtosis. The normal distribution has a kurtosis of 3, and the excess kurtosis is

Table 2: Summary statistics of daily spot electricity prices in Nord Pool; 1. Jan 1996 – 31. Dec 2015

Statistics	Spot electricity prices						
	NPS_SYS	NOR_Ber	NOR_Osl	NOR_Kri	NOR_Trond	NOR_Trom	SE
Mean	246.2	239.3	240.7	239.0	253.5	252.0	254.6
Median	237.4	233.5	233.7	233.5	240.8	240	240.8
Maximum	1090	831.4	1226	831.4	4089	4089	4044
Minimum	21.27	16.61	16.61	16.61	21.17	21.17	21.17
Std. dev.	116.5361	116.8263	120.1752	114.8036	136.2992	133.9874	135.5121
Skewness	0.9701	0.8845	1.1117	0.8168	4.8741	5.0600	4.8215
Kurtosis	1.7576	1.3112	2.8570	0.9818	101.1409	108.3156	99.1822
CV	0.4733	0.4882	0.4993	0.4803	0.5377	0.5317	0.5323
J-B	2086.1	1475.7	3989.1	1105.6	3142500	3602200	3022500
J-B $p-value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF	-4.205	-4.1577	-4.292	-4.0687	-5.2585	-5.1011	-5.4154
ADF $p-value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	7305	7305	7305	7305	7305	7305	7305

Statistics	Spot electricity prices					
	Denmark_West	Denmark_East	Finland	Estonia	Latvia	Lithuania
Mean	276.3	303.5	270.5	319.6	402.5	384
Median	264	276.2	259	310.8	394.7	371.6
Maximum	3321	4089	4089	3665	1071	1071
Minimum	-284.2	-283.8	21.17	58.49	165.8	123.9
Std. dev.	121.2447	141.5906	139.3778	103.0270	100.6163	97.6800
Skewness	3.5085	5.8009	4.8572	16.8017	1.6472	1.6957
Kurtosis	69.0293	112.8208	100.4105	529.8587	7.0653	7.3618
CV	0.4388	0.4665	0.5153	0.3224	0.2500	0.2544
J-B	1209200	2985300	2788800	24676000	2385.3	3536.7
J-B $p-value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF	-5.6009	-6.6716	-6.4497	-8.1373	-5.0677	-5.8264
ADF $p-value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	6028	5570	6577	2101	942	1292

Prices in NOK/MWh

Source: Nord Pool FTP server

simply the difference from 3. NOR_ Trondheim is an example with excess kurtosis for the spot prices equal to 101.14, and a kurtosis then would be 104.14. This is known as a leptokurtotic distribution. This means that there are fat tails in the data distribution, leading to large, outlier values. Skewness explains how the curve of the distribution is shaped. A positive skewness means that more of the distribution leans towards an increase from the expectation of the distribution.

The Jarque-Bera test (JB) determines whether the data sample follow a normal or non-normal distribution (Jarque and Bera, 1980). The null hypothesis is that the series are normal distributed; should it be rejected the distribution is non-normal. The responding p values will determine the strength of the null hypothesis. For

Table 3: Summary statistics of logarithm of the daily spot electricity prices in Nord Pool; 1. Jan 1996 – 31. Dec 2015

Statistics	Log spot electricity prices					
	NPS_SYS	NOR_Ber	NOR_Osl	NOR_Kri	NOR_Trond	NOR_Trom	SE
Mean	5.389	5.347	5.351	5.35	5.407	5.405	5.416
Median	5.47	5.453	5.454	5.453	5.484	5.48	5.484
Maximum	6.994	6.723	7.112	6.723	8.316	8.316	8.305
Minimum	3.057	2.81	2.81	2.81	3.053	3.053	3.053
Std. dev.	0.5049	0.5453	0.5432	0.5322	0.5280	0.5171	0.5109
Skewness	-0.5059	-0.7702	-0.6722	-0.6926	-0.5861	-0.5264	-0.3968
Kurtosis	0.2379	1.0375	0.8462	0.7698	1.0555	0.8711	0.4594
CV	0.0937	0.1020	0.1015	0.0995	0.0977	0.0957	0,0943
J-B	328.78	1050	768.01	764.48	757.35	568.34	255.99
J-B $p-value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF	-4.1006	-4.6132	-4.5577	-4.5009	-4.41	-4.052	-4.5185
ADF $p-value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	7305	7305	7305	7305	7305	7305	7305

Statistics	Log spot electricity prices					
	Denmark_West	Denmark_East	Finland	Estonia	Latvia	Lithuania
Mean	5.5260	5.6310	5.4830	5.7380	5.9690	5.9220
Median	5.5760	5.6210	5.5570	5.7390	5.9780	5.9180
Maximum	8.1080	8.3160	8.3160	8.2060	6.9770	6.9770
Minimum	-5.6500	-5.6480	3.0530	4.0690	5.1100	4.8200
Std. dev.	0.4985	0.4447	0.4997	0.2377	0.2354	0.2385
Skewness	-4.5870	-4.4374	-0.4313	-0.2569	0.1488	0.1736
Kurtosis	83.5146	104.9370	0.3911	10.5668	1.5407	1.6330
CV	0.0902	0.0790	0.0911	0.0414	0.0394	0.0403
J-B	1772900	2573900	245.83	9797.7	96.6490	150.05
J-B $p-value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF	-6.2232	-6.1515	-5.3914	-6.9742	-4.7606	-5.5850
ADF $p-value$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	6028	5570	6577	2101	942	1292

Prices in NOK/MWh

Source: Nord Pool FTP server

the daily spot prices and logarithmic values, we can reject the null hypothesis of a normal distribution with a 1% significance.

The next initializing test is the Augmented Dickey-Fuller test (ADF), which test the sample data against the null hypothesis of a unit root (Dickey and Fuller, 1979). The test will answer whether the data are stationary or not. This is important in order to create a complete model for prediction and identification of volatile elements. To test the data for market integration using causal methods the data will need to be stationary. If there is a presence of unit root the process will drift far differently than a process without unit root (Wooldridge, 2015, p.505). The ADF include lagged elements in order to reduce serial correlation in the data. For all our daily spot price and logarithm spot price we can reject the null hypothesis of a unit root. All the data, both ordinary price and logarithm of the price, are stationary.

5.3 Seasonality

The seasonal component is defined using dummy variables. Dummy variables will be assigned to the different months as well as the days of the week. Weekly seasonality can be significant, and must be analysed. The price moves differently throughout the day, and it is possible to see large changes in the price during the course of a day. By using the average for each day the model will be simpler to use, and the number of observations needed to process will be reduced.

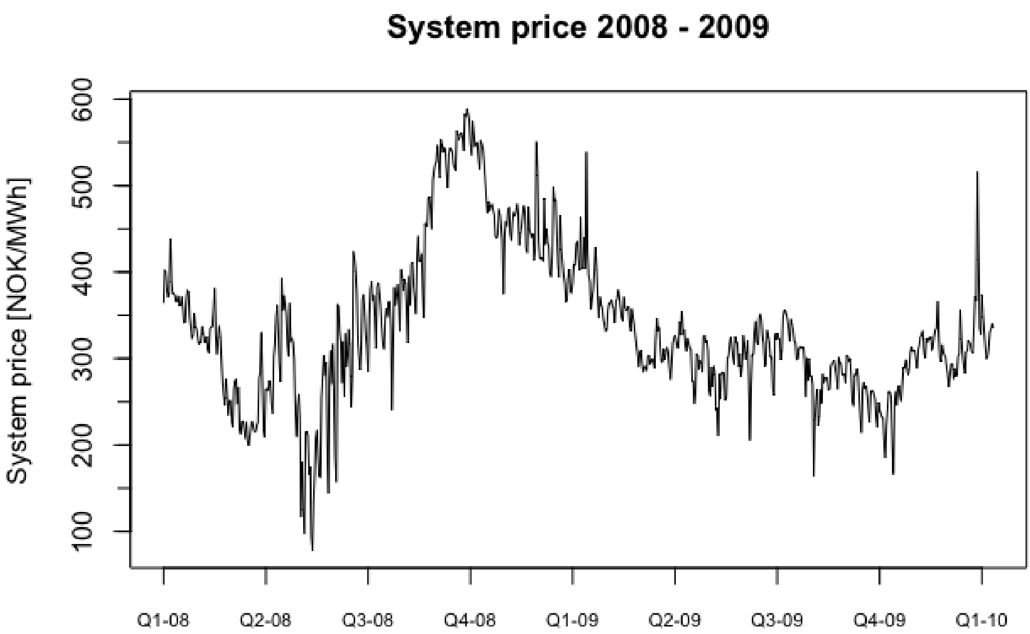

Figure 7: Seasonality in the system price Jan 2008 - Jan 2010

Johnsen (2001) use both temperature and weather as input variables in the price algorithm. The hydro power reservoirs in Norway and Sweden are dependent on inflow. As a result, the weather influence the price level. Further, regulations with regards to the level of water in the reservoirs are given by the concession for the field.

There are minimum and maximum levels in the dams that need to constantly be regulated by the producer. When snow melts in the spring and summer the water levels in the reservoirs rise. This means that electricity has to be produced in order to gain an income from the excess water. As a result, in the summer a lower demand and high supply lead to decreasing prices. This is a seasonal pattern that repeats itself each year. The difference between a dry and a wet period can most notably be seen in the fall and winter when dam levels are low and demand is high. Figure 7 show how a two-year cycle of the system price has a cyclical movement. Further, there tends to be a correlation between the temperature and the consumption. Higgs (2009) finds that demand increases during warm periods. In Australia, the need for electric energy to cool down during warm periods is similar to the Nordic use of energy to heat during cold periods[4].

5.4 Summary

The initial analysis of the different data has given the following results. The sample size for the daily data is sufficient, even for the newest additions into NPS. Sweden is aggregated into one region, due to the similarities between the bidding areas. Denmark experience negative price levels on four occasions. The data is confirmed to be stationary by the ADF test. All the data are non-normal distributed and follow the same seasonal pattern.

[4]In this thesis the use of temperature was considered, but as the market integration between the bidding areas could be tested without the use of weather, the author has chosen not to include the temperature data in any of the tests performed later. For further studies of the integration, temperature can be a suitable variable to include.

6 Empirical Results

This section present the empirical result of the tests for market integration and investigation of volatile behaviour in the regional price series. An AR(8) model has been run, and the residuals from this has been used in a GARCH(1,1) model to find volatility parameters. The result of the tests and models will be presented in the same structure as the methodology. The plots and tables not presented in this section will be added to the appendix.

6.1 Structural Change

The tests for structural change was done using the methodology described by Zeileis et al. (2001) using the OLS-CUSUM model developed by Brown et al. (1975). Both the system price and the differentiated system price was tested. The results of the tests are presented in Table 4 and 5.

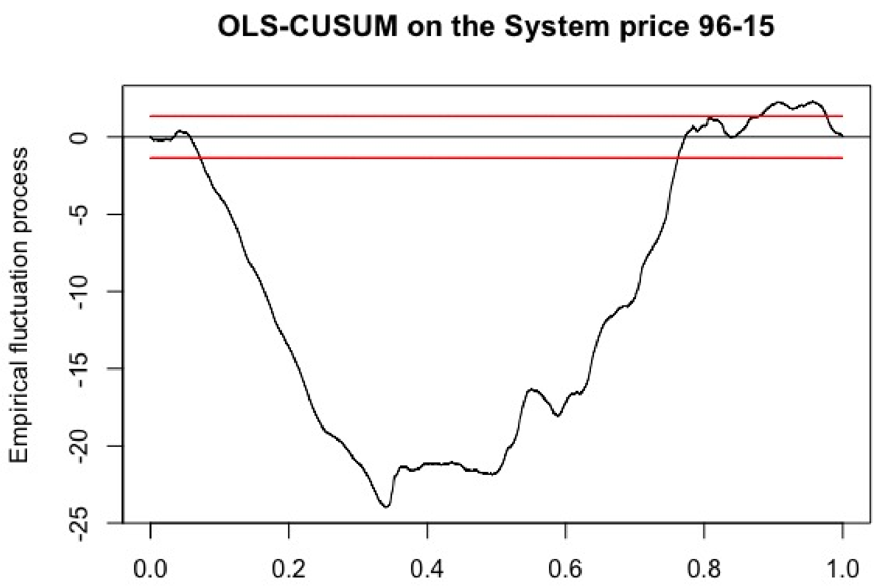

Figure 8: Structural change for the system price

The result of the empirical fluctuation test reveal that the system price has multiple structural changes throughout the entire period of the sample. This can be attributed to the constant expansion of markets and unstable production conditions. Johnsen (2001) found that several of the years experienced changing precipitation, and that this in turn lead to volatile price movement. The system price show signs of multiple structural changes. The volatility of energy prices in the Nordic market are shown to be higher than other commodities and equities (Solibakke, 2002). The differentiated system price has no structural change. The variability of the price is stable though the entire sample period.

Table 4: Results for tests of structural change

	$S0$	p-value
Test 1: $p_t = \text{res.sys} + \Delta p_t^2$	23.955	0.0000
Test 2: $\Delta p_t = \text{res.sys} + \Delta p_t^2$	0.610	0.8498

Table 5: Results for tests of structural change part 2

Historical Change: $p_t = \text{res.sys} + \Delta p_t^2$	$S0$	B.P	H.S	L.P
Hist. period 1 – 365:	0.05	390	365	7300
Hist. period 390 – 550:	0.05	162	161	6756
Hist. period 712 – 800:	0.610	90	88	7305

B.P = Break Point, H.S = Historical Sample, L.P = Last point
Sample values range from 1 to 7305. B.P is calculated from last historical observation

Figure 8 show that the majority of the period under investigation is subject to a structural change. Only a few periods seem to be stable, such as around 2004 - 2005. The system price show signs of stability for the first period, before it fluctuates out of control for the next years. The last period also move out of bounds, before it converge towards the null again. The conclusion is that the system price is extremely volatile, and have multiple structural changes during the sample period.

The differentiated price shows no signs of structural change. This means that the change between the daily prices are stable and that it stays so for the entire sample period. Figure 9 show how the fluctuation moves around the center. It does not violate the constraints set by the confidence interval, and thus the null hypothesis of no structural shift cannot be rejected. The historical period does not adequately describe the whole sample. Even with different periods, the system price break fast. See Table 5.

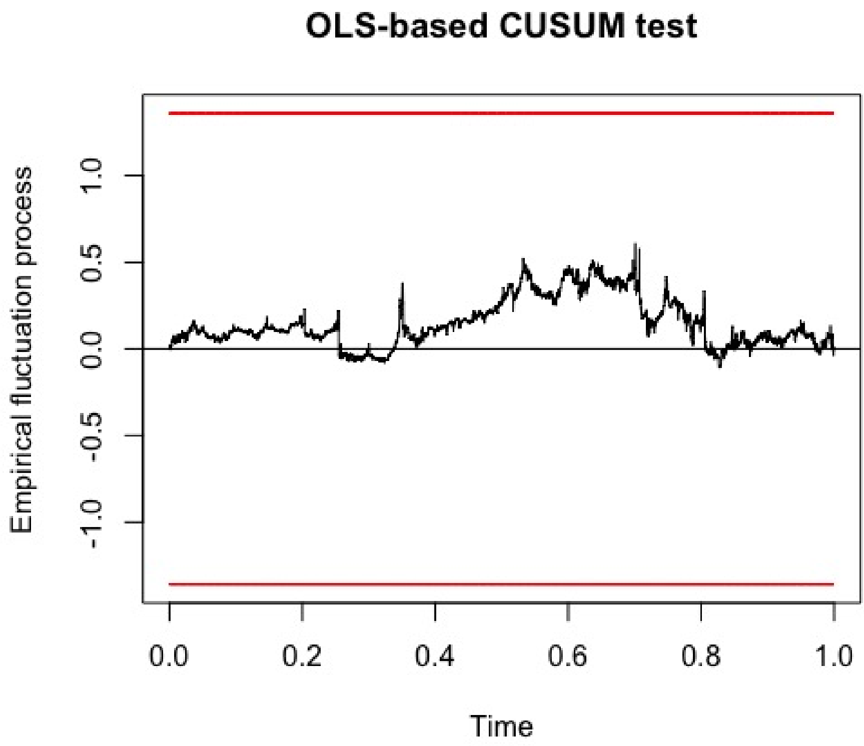

Figure 9: Structural change for differentiated system price

6.2 Autoregressive Model

The bivariate autoregressive procedure is applied to a conditional mean model. The dummy variables for weekdays and months are added to the regression equation. The area price is the explained variable, with lagged values of both the specified area price and the system price as explanatory variables. The lag selection is chosen using the SC criterion. Table 6 show the coefficients, standard error and p values for the own mean spillover and cross spillover between the region under investigation and the system price. The first table is presented in the text; the rest are placed in the appendix. The goodness-of-fit is reported in Table 7 for all the conditional mean models.

The result of the AR regression model show the effects and significance of lagged values, both from own and from the system price. The intercept, α_0, is a proportionality coefficient, which determine the difference between the two price series other than the strength of relation. Impact of transportation, production and qual-

Table 6: Summary of estimated AR coefficients Bergen, Oslo and Kristiansand

	NOR_Bergen			NOR_Oslo			NOR_Kristiansand		
	Coefficients	Std.error	p-value	Coefficients	Std.error	p-value	Coefficients	Std.error	p-value
α_0	-0.0009	0.0093	0.92089	-2.975e-03	8.436e-03	0.724356	0.0011	0.0087	0.899315
γ_1	0,7313	0.0118	0.0000	0.7467	0.01177	0.0000	0.7343	0.0118	0.0000
γ_2	0.0244	0.0146	0.09394	0.004218	0.01467	0.773665	0.0300	0.0146	0.039967
γ_3	0.1236	0.0146	0.0000	0.1159	0.01471	0.0000	0.0986	0.0146	0.0000
γ_4	-0.0345	0.0147	0.01929	-0.02835	0.01478	0.055216	-0.0203	0.0147	0.167766
γ_5	0.0153	0.0147	0.30021	-0.02234	0.01479	0.130904	-0.0250	0.0147	0.088470
γ_6	0.0244	0.0147	0.09625	0.05344	0.01473	0.000288	0.0547	0.0146	0.000191
γ_7	0.0664	0.0147	5.94e-06	0.07566	0.01475	0.0000	0.0601	0.0147	4.12e-05
γ_8	-0.0110	0.0118	0.34995	-0.0004079	0.01179	0.972398	0.0123	0.0118	0.297980
β_0	0.7722	0.0089	0.0000	0.7969	0.0080	0.0000	0.7778	0.0083	0.0000
β_1	-0.4863	0.0142	0.0000	-0.5242	0.0136	0.0000	-0.5241	0.0138	0.0000
β_2	-0.0168	0.0152	0.27150	-0.0066	0.0148	0.655231	-0.0103	0.0150	0.493916
β_3	-0.1122	0.0153	0.0000	-0.0958	0.0149	0.0000	-0.1033	0.0151	0.0000
β_4	0.0369	0.0154	0.01647	0.0150	0.0150	0.315940	0.0293	0.0152	0.053886
β_5	-0.0217	0.0154	0.15888	0.0120	0.0150	0.424097	0.0144	0.0152	0.341556
β_6	-0.0435	0.0152	0.00427	-0.0576	0.0148	0.000105	-0.0566	0.0150	0.000169
β_7	-0.0788	0.0153	0.0000	-0.0951	0.0149	0.0000	-0.0789	0.0151	0.0000
β_8	0.0111	0.0127	0.38249	0.0120	0.0124	0.333371	0.0072	0.0124	0.560355
δ_{mon}	-0.0020	0.0035	0.56593	-0.0023	0.0032	0.463902	-0.0032	0.0033	0.326685
δ_{tue}	-0.0054	0.0035	0.12090	-0.0056	0.0031	0.073304	-0.0023	0.0033	0.486226
δ_{wed}	-0.0057	0.0034	0.09722	-0.0047	0.0031	0.131047	-0.0057	0.0032	0.077670
δ_{thu}	-0.0076	0.0034	0.02655	-0.0076	0.0031	0.014789	-0.0035	0.0032	0.277114
δ_{fri}	-0.0076	0.0034	0.02793	-0.0056	0.0031	0.071272	-0.0039	0.0032	0.233949
δ_{sat}	0,0014	0,0033	0.66251	0,0022	0,0030	0.468120	0,0036	0,0031	0.250259
δ_{jan}	-0.0025	0.0036	0.48476	-0.0017	0.0033	0.597789	-0.0019	0.0034	0.583338
δ_{feb}	-0.0016	0.0037	0.66529	-0.0008	0.0033	0.803855	-0.0016	0.0035	0.652036
δ_{mar}	-0.0013	0.0036	0.71909	-0.0022	0.0033	0.511623	-0.0012	0.0034	0.723415
δ_{apr}	-0.0023	0.0037	0.53363	-0.0024	0.0033	0.466517	-0.0023	0.0034	0.501510
δ_{may}	-0.0075	0.0036	0.03876	-0.0076	0.0033	0.020918	-0.0074	0.0034	0.031689
δ_{jun}	-0.0037	0.0037	0.32173	-0.0022	0.0033	0.501430	-0.0017	0.0035	0.627853
δ_{jul}	-0.0050	0.0037	0.17475	-0.0056	0.0033	0.090928	-0.0050	0.0035	0.150444
δ_{aug}	-0.0077	0.0037	0.03796	-0.0064	0.0034	0.055765	-0.0035	0.0035	0.318582
δ_{sep}	-0.0063	0.0037	0.08611	-0.0041	0.0033	0.221110	-0.0045	0.0035	0.194807
δ_{oct}	0.0016	0.0036	0.66388	0.0009	0.0033	0.782987	0.0020	0.0034	0.553247
δ_{nov}	0.0006	0.0036	0.87478	0.0000	0.0033	0.992520	0.0005	0.0034	0.885530

α_0 is the intercept, γ_i is the coefficient for the regions lagged value, and β_i is the coefficient for the lagged values of the system price. δ is the coefficient for the dummy variable.

ity can increase the difference between two regions, and will change the estimated coefficients. In the Norwegian regions, the intercept is insignificant, and have a very low estimated value. This could be due to the low production cost of hydro power, and good possibilities for transmission between regions. For the Baltic regions however, the intercept is significant and have a large value. This indicate that Baltic area are less integrated with the system price, and that there are other variables that could specify the model better. As expected, the significance of the own and cross mean spillover is most significant in the lags closest to the present time. The system price at time t is dominant and positive, as it should be according to the theoretical specification of the spot price in NPS. All the regions experience a significant and positive own spillover from its own lagged observation, at time $t-1$. The first lagged value for the system price, $t-1$, is significant and negative.

This can be seen in most of the results. The system price is significant for most regions, showing signs of integration. The only deviation can be seen in Latvia and Lithuania. The price in these regions are mainly determined by the current system price and the first lagged value of its own price. Lagged values from the system price behind time t is not significant, and this indicated that integration is somewhat weaker. Lag five and six have a degree of significance but only in the 10 and 5 % range.

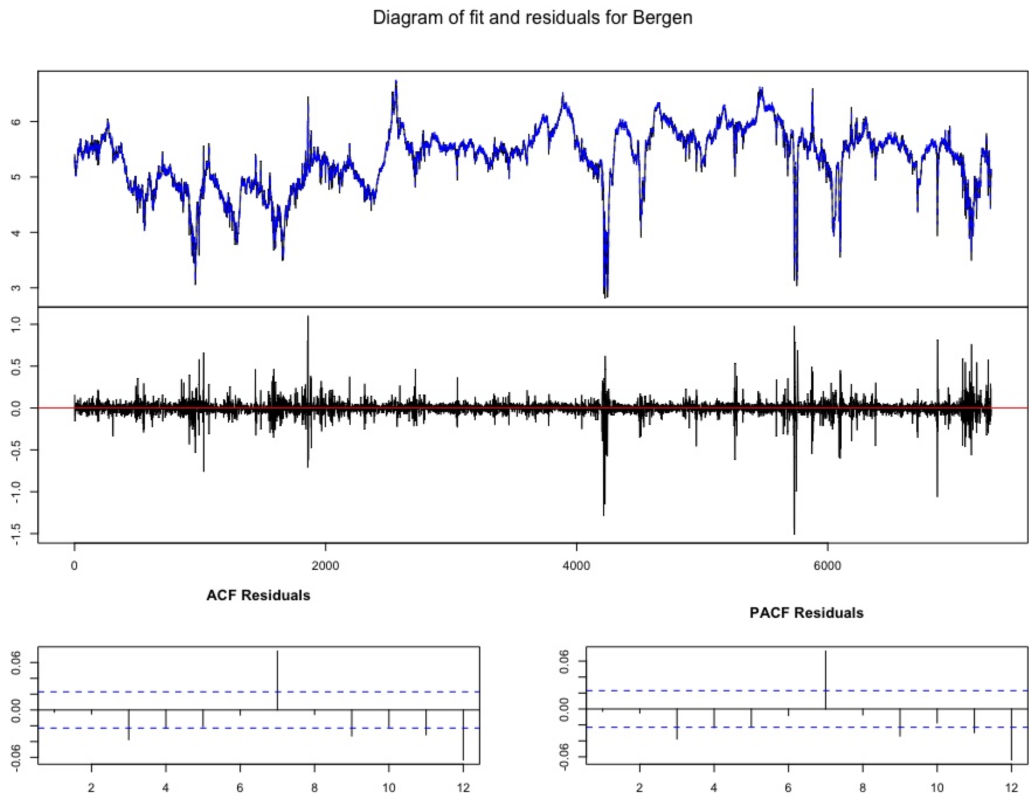

Figure 10: Fitted value and residuals for Bergen

The seasonal movement is captured using two sets of dummy variables. The first dummy set tries to capture the weekly seasonality. In previous work by Sotiriadis et al. (2014); Higgs (2009); Worthington et al. (2005) it is shown that the weekly seasonal component is significant and has a large impact on the conditional mean model. The result from the regression show that the weekly component is less significant for the Norwegian regions than for the rest of the market sections. This can be due to the close resemblance between the area price and system price in Norway.

The southern parts (Bergen, Kristiansand and Oslo) have both mean, max and min values similar to the system price. For the whole sample selection, it can be seen that Monday are the most significant of the days in the week. This is previously shown by Solibakke (2002) for the Nordic region. In the Baltic region, the weekly dummy are significant, more so than lagged price observations. Due to the poor explanatory ability of the lagged values, the weekly movement give more information than the lagged regional price observations. The second seasonal dummy variable test the significance of the monthly movement. Again, the Norwegian regions experience less impact of the monthly component. May is significant, with August and September significant for Bergen and Oslo. During the spring the snow in the mountains melt, creating an excess of water in the reservoirs. To reduce the loss due to overflow the producers will generate more energy than what is necessary in order to maintain the equilibrium in the market. This in turn, as described by the Law of Supply, reduce the price.

Table 7: AR(8) estimation results

	R^2	F-Statistic	p-value
NOR_Bergen	0.9865	15600	0.0000
NOR_Oslo	0.9888	18910	0.0000
NOR_Kristiansand	0.9875	16840	0.0000
NOR_Trondheim	0.9857	14750	0.0000
NOR_Tromso	0.9866	15740	0.0000
Sweden	0.9853	14350	0.0000
Denmark West	0.6455	320.6	0.0000
Denmark East	0.7101	398.2	0.0000
Finland	0.9646	5244	0.0000
Estonia	0.6407	108	0.0000
Latvia	0.6682	53.1	0.0000
Lithuania	0.6459	67	0.0000

Diagnostic checking is an indispensable first step when establishing a model (Box et al., 1976, p.289). Visual inspection of the residuals from an AR process give an indication if randomness is present. Figure 10 show the ACF and PACF for the residuals. The goodness-of-fit for the model is close to 1, and all the F-statistics reject the null hypothesis that the coefficients are zero. Denmark and the Baltic states have a lower goodness-of-fit, with a R^2 value between 0.60 and 0.70 for the regions. The model appear to be correctly specified.

6.3 Long term stability and dynamics

The level of market integration and the appearance of LOP is tested using inference on a dynamic model. The object of the tests is to detect the occurrence of instantaneous market integration or a long run equilibrium. While correlation can describe much about prices, the dynamic component shift due to seasonality and technical change. The results from the tests for market integration and the LOP are presented in each subsection.

6.3.1 Instantaneously Adjustment

The summary statistics for the test of instantaneous adjustment is presented in Table 8 and 9. The estimated coefficient are tested against the null hypothesis of $\beta_0 = 1$. If the t test fails to reject the null hypothesis the assumption is that the region price is moved entirely by the price movement of the system.

Table 8: Summary statistics for the static test

		Estimate	Std. Error	t value	p value
Bergen	$\widehat{\alpha}_0$	-0.2346	0.0194	-12.0900	0.0000
	$\widehat{\beta}_0$	1.0357	0.0036	288.7500	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			9.9626	0.0000
Oslo	$\widehat{\alpha}_0$	-0.2444	0.0179	-13.6900	0.0000
	$\widehat{\beta}_0$	1.0384	0.0033	314.8400	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			11.6325	0.0000
Kristiansand	$\widehat{\alpha}_0$	-0.1148	0.0182	-6.2960	0.0000
	$\widehat{\beta}_0$	1.0141	0.0034	300.9540	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			4.1840	0.0000
Trondheim	$\widehat{\alpha}_0$	-0.0984	0.0142	-6.9400	0.0000
	$\widehat{\beta}_0$	1.0216	0.0026	390.0900	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			8.2463	0.0000
Tromso	$\widehat{\alpha}_0$	0.0014	0.0132	0.1090	0.9130
	$\widehat{\beta}_0$	1.0027	0.0024	409.9770	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			1.1137	0.2654
Sweden	$\widehat{\alpha}_0$	0.0879	0.0136	6.4590	0.0000
	$\widehat{\beta}_0$	0.9888	0.0025	393.2510	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			38.8229	0.0000

The Scandinavian regions have a significant relationship to the system price. The regions in Norway are closely connected with the system price, but the results reject the hypothesis of a proportional relation. The results show that the Baltic regions are less dependent on the system price. Further, for the Baltic regions, the constant

Table 9: Summary statistics for the static test cont'd

		Estimate	Std. Error	t value	p value
	$\widehat{\alpha}_0$	1.3776	0.0524	26.2900	0.0000
Denmark W	$\widehat{\beta}_0$	0.7574	0.0095	79.4500	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			25.4456	0.0000
	$\widehat{\alpha}_0$	0.9758	0.0538	18.1300	0.0000
Denmark E	$\widehat{\beta}_0$	0.8388	0.0097	86.7200	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			16.6648	0.0000
	$\widehat{\alpha}_0$	0.5654	0.0243	23.2700	0.0000
Finland	$\widehat{\beta}_0$	0.9089	0.0045	203.3200	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			20.3739	0.0000
	$\widehat{\alpha}_0$	4.0029	0.0583	68.7000	0.0000
Estonia	$\widehat{\beta}_0$	0.3112	0.0104	29.8600	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			66.0731	0.0000
	$\widehat{\alpha}_0$	5.2340	0.1204	43.4600	0.0000
Latvia	$\widehat{\beta}_0$	0.1362	0.0223	6.1200	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			38.8179	0.0000
	$\widehat{\alpha}_0$	5.5125	0.0975	56.5510	0.0000
Lithuania	$\widehat{\beta}_0$	0.0755	0.0179	4.2060	0.0000
	$H_0 : \widehat{\beta}_0 = 1$			51.5279	0.0000

α indicate that additional costs are connected to the price movement. Tromso is the only region that fail to reject the null hypothesis of $\beta_0 = 1$, and the LOP applies when examining the price movement in Tromso. The coefficient β indicate if the prices share a relation, and if the LOP is valid (Asche et al., 2006).

6.3.2 Dynamics in the price series

The results for the F test on dynamic properties is shown in Table 10. The SSR for the unrestricted and restricted model are used to form a F-statistics. The null hypothesis is that there is no dynamic relationship in the price series. Testing the inference of the coefficients will indicate if the market integration is present in the short run. The null hypothesis of no dynamics is rejected at the 1% level for all the regions. It can be concluded that the lagged values have significance and must be applied when testing the series. All the regions are better specified using lagged values. As shown in the AR results, the Nordic regions (Norway, Sweden, and Finland) are more dependent on lagged values than the newer additions.

Table 10: Test statistics for the AR model testing for dynamic relationship

	SSR unrestricted	SSR restricted	df_{ur}	df_r	q	F-statistics	p-value
NOR_Bergen	29.445	174.923	7279	7303	24	1498.481	0.000
NOR_Oslo	24.159	147.884	7279	7303	24	1553.207	0.000
NOR_Kristiansand	25.993	154.372	7279	7303	24	1497.962	0.000
NOR_Trondheim	29.157	93.249	7279	7303	24	666.695	0.000
NOR_Tromso	26.299	81.330	7279	7303	24	634.622	0.000
Sweden	28.265	85.956	7279	7303	24	619.036	0.000
Denmark West	548.387	731.432	6002	6026	24	83.474	0.000
Denmark East	323.982	468.549	5544	5568	24	103.077	0.000
Finland	59.867	225.342	6551	6575	24	754.459	0.000
Estonia	44.477	83.316	2075	2099	24	75.499	0.000
Latvia	19.369	50.151	913	937	24	60.457	0.000
Lithuania	27.743	72.421	1266	1290	24	84.952	0.000

6.3.3 Long run parameter

This section provides results from tests of the appearance of a short or long run equilibrium. The first null hypothesis check if the summed parameter equal to zero, which test for the short run market integration. The second null specified tests if the long term parameter for the sum of the coefficients is one. The results from both hypothesis tests are presented in Table 11. The first hypothesis is rejected at a significant level for all regions. The short run market integration can not be accepted, due to the variance of the prices. Both the AR model and the test for a dynamic relationship has already shown that the lagged components are significant. The second hypothesis for a long run integration cannot be rejected for Tromso and Kristiansand. According to Ravallion (1986), this is an indication of market integration in the long run. For Oslo, the null can be rejected at the 10 % level. For Sweden at the 5% level and Bergen at the 1% level. The rest of the regions rejects the null hypothesis at the 0.1% significance. The result concludes that for the oldest regions the long term parameter converges towards one. The regions are integrated with the system price, as hypothesized. For the newer additions to NPS, the average value from previous periods dictate the price level at time t, and the long term parameter does not converge towards one. While the hypothesis of market integration in the long run is rejected for most regions, it cannot be concluded that NPS is poorly integrated and noncompetitive. Transmission constraints prevent full utilization of capacity, and prevents the validity of the LOP in both short and long run.

Table 11: Statistics for tests on the long term parameter

		Long term parameter	Std. Error	t-value	p-value
$H_0 : \beta_0 + ... + \gamma_8 = 0$	NOR_Bergen	1.0017	0.0007	1518.1937	0.0000
	NOR_Oslo	1.0020	0.0007	1534.2208	0.0000
	NOR_Kristiansand	1.0008	0.0007	1532.3966	0.0000
	NOR_Trondheim	1.0021	0.0007	1522.1514	0.0000
	NOR_Tromso	1.0004	0.0006	1583.6336	0.0000
	Sweden	0.9973	0.0007	1346.8305	0.0000
	Denmark West	0.9271	0.0018	501.5923	0.0000
	Denmark East	0.9547	0.0016	589.0370	0.0000
	Finland	0.9906	0.0009	1108.1567	0.0000
	Estonia	0.8463	0.0016	522.4648	0.0000
	Latvia	0.860305	0.0023	367.8681	0.0000
	Lithuania	0.8682	0.0021	414.7625	0.0000
$H_0 : \beta_0 + ... + \gamma_8 = 1$	NOR_Bergen	1.0017	0.0007	2.5977	0.0094
	NOR_Oslo	1.0020	0.0007	3.1173	0.0018
	NOR_Kristiansand	1.0008	0.0007	1.3473	0.1779
	NOR_Trondheim	1.0021	0.0007	3.2116	0.0013
	NOR_Tromso	1.0004	0.0006	0.6733	0.5007
	Sweden	0.9973	0.0007	-3.6178	0.0002
	Denmark West	0.9271	0.0018	-39.4022	0.0000
	Denmark East	0.9547	0.0016	-27.9391	0.0000
	Finland	0.9906	0.0009	-10.4251	0.0000
	Estonia	0.8463	0.0016	-94.8461	0.0000
	Latvia	0.860305	0.0023	-59.7338	0.0000
	Lithuania	0.8682	0.0021	-62.9424	0.0000

The tests show the difference between the old and new additions in NPS. The Baltic and Danish regions have less integrated price movement. The consistency of this observation can be linked to the more stable areas in Norway and Sweden. Both the intercept and the lagged observations are significant, and the result of the AR model confirms that some of the regions are integrated with the system price. From the results it is clear that the old regions are more integrated with the system price than newer additions. The high level of correlation between some of the region clearly show that there are some form of integration in the market.

6.4 Granger Causality

The result of the test for causality between the various regions and the system price shows that the relationship is significant both ways, and that the null hypothesis of no relationship is rejected at the 1% level for all the regions. The test statistics and p value is reported in Table 12.

Table 12: Test results for Granger Causality test

	$R = R + SYS$		$SYS = R + SYS$	
	F-statistics	p-value	F-statistics	p-value
NOR_Bergen	43.6350	0.0000	34.0900	0.0000
NOR_Oslo	38.3500	0.0000	28.9200	0.0000
NOR_Kristiansand	41.6060	0.0000	24.8750	0.0000
NOR_Trondheim	48.1580	0.0000	5.9284	0.0000
NOR_Tromso	41.7230	0.0000	5.7126	0.0000
Sweden	44.8560	0.0000	4.4188	0.0000
Denmark West	51.4390	0.0000	7.5324	0.0000
Denmark East	48.0140	0.0000	6.0748	0.0000
Finland	25.5990	0.0000	22.9710	0.0000
Estonia	17.0090	0.0000	10.0820	0.0000
Latvia	5.4429	0.0000	5.6276	0.0000
Lithuania	7.9958	0.0000	6.2228	0.0000

The idea and goal of NPS is to deliver social optimum prices for all participants in the Nordic and Baltic sector. The system price acts as the guideline for all trade, and congestion in transmission lines force the area price to deviate from the given level. Thus, the null hypothesis of no relation between system and area price is unreasonable, and it comes as no surprise that it is rejected at a significant level. The area prices mimic the system price, and moves in the same way. This means that we should be able to describe the price in the system by looking at the area price. Since the system price acts as the one price, and we have an arbitrage relationship between region and system, it indicates that indeed NPS have market integration between the bidding areas and the system price. The causal and significant relationship between area and system price indicate that the market has reached a mature, stable state.

6.5 Generalized Autoregressive Conditional Heteroskedasticity

The coefficients in the GARCH result shows the degree of innovation and volatility spillover in each of the regions. The ARCH coefficient is a description on the level of own innovation in the price series that spill over into the next period, and is denoted by β_1. The ARCH effects are present in all the price series and are significant. The GARCH effects are denoted with the coefficient α_1, and describe the lagged volatility effects on the current volatility. The results are presented in Table 13.

Table 13: Summary statistics for the GARCH(1,1) model

	Bergen			Oslo			Kristiansand		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value	Estimate	Std. Error	p value
α_0	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000
α_1	0.5854	0.0108	0.0000	0.5969	0.0118	0.0000	0.5964	0.0119	0.0000
β_1	0.5666	0.0057	0.0000	0.5491	0.0064	0.0000	0.5563	0.0063	0.0000
Loglik	9773.2180			10495.2600			10225.2700		
Box-Ljung	0.0036664		0.9517	0.00022		0.9881	0.0000284		0.9957
persist	1.1520			1.1460			1.1527		

	Trondheim			Tromso			Sweden		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value	Estimate	Std. Error	p value
α_0	0.0003	0.0000	0.0000	0.0002	0.0000	0.0000	0.0002	0.0000	0.0000
α_1	0.4502	0.0050	0.0000	0.4704	0.0056	0.0000	0.5174	0.0061	0.0000
β_1	0.6173	0.0032	0.0000	0.6164	0.0031	0.0000	0.5886	0.0044	0.0000
Loglik	9806.2170			10192.1600			9948.6320		
Box-Ljung	0.0090403		0.9243	0.0020033		0.9643	0.000307		0.986
persist	1.0675			1.0868			1.1060		

	Denmark West			Denmark East			Finland		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value	Estimate	Std. Error	p value
α_0	0.0017	0.0001	0.0000	0.0010	0.0000	0.0000	0.0004	0.0000	0.0000
α_1	0.9510	0.0031	0.0000	1.1920	0.0076	0.0000	0.3604	0.0051	0.0000
β_1	0.5807	0.0014	0.0000	0.4589	0.0048	0.0000	0.6874	0.0040	0.0000
Loglik	-1224.8840			67.1513			6213.0280		
Box-Ljung	0.056044		0.8129	0.038639		0.8442	0.00023964		0.9876
persist	1.5317			1.6509			1.0478		

	Estonia			Latvia			Lithuania		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value	Estimate	Std. Error	p value
α_0	0.0055	0.0003	0.0000	0.0017	0.0003	0.0000	0.0020	0.0003	0.0000
α_1	0.1803	0.0164	0.0000	0.1587	0.0211	0.0000	0.1688	0.0162	0.0000
β_1	0.5683	0.0270	0.0000	0.7684	0.0269	0.0000	0.7472	0.0211	0.0000
Loglik	1105.5490			536.0373			691.0141		
Box-Ljung	0.0023462		0.9614	0.34273		0.5583	1.1309		0.2876
persist	0.7485			0.9271			0.9160		

The effects of innovation is significant, both statistically and in effect, for all the regions. Latvia and Lithuania have the largest ARCH effect; change in demand, supply and other shocks have a profound effect on the volatility. The ARCH effects are large for the rest of the regions as well, confirming the assertion of high volatility in energy prices. The lagged volatility, the GARCH effects, is also significant in all the price series. Denmark has the largest GARCH effects, with (0.951) for Denmark West and (1.192) for Denmark East. The deviation from the mean of previous values has a large impact on the current variation in the Danish prices. Similarly, the Baltic regions have a small GARCH effect but a higher innovation impact. The sum of the ARCH and GARCH effects are known as the persistence coefficient. A persistence value less than one implies that the volatility shocks are transitory. The variation in price is mean-reverting and any effects of volatility will dampen out until the mean condition is reached. If the persistence coefficient is larger than one it implies that the shocks have a permanent impact on the volatility. It does not dampen out like it does if the coefficient is less than one. Only the Baltic regions have a persistence coefficient of less than one. The result show that volatility clustering have a permanent impact on the majority of the regions in NPS.

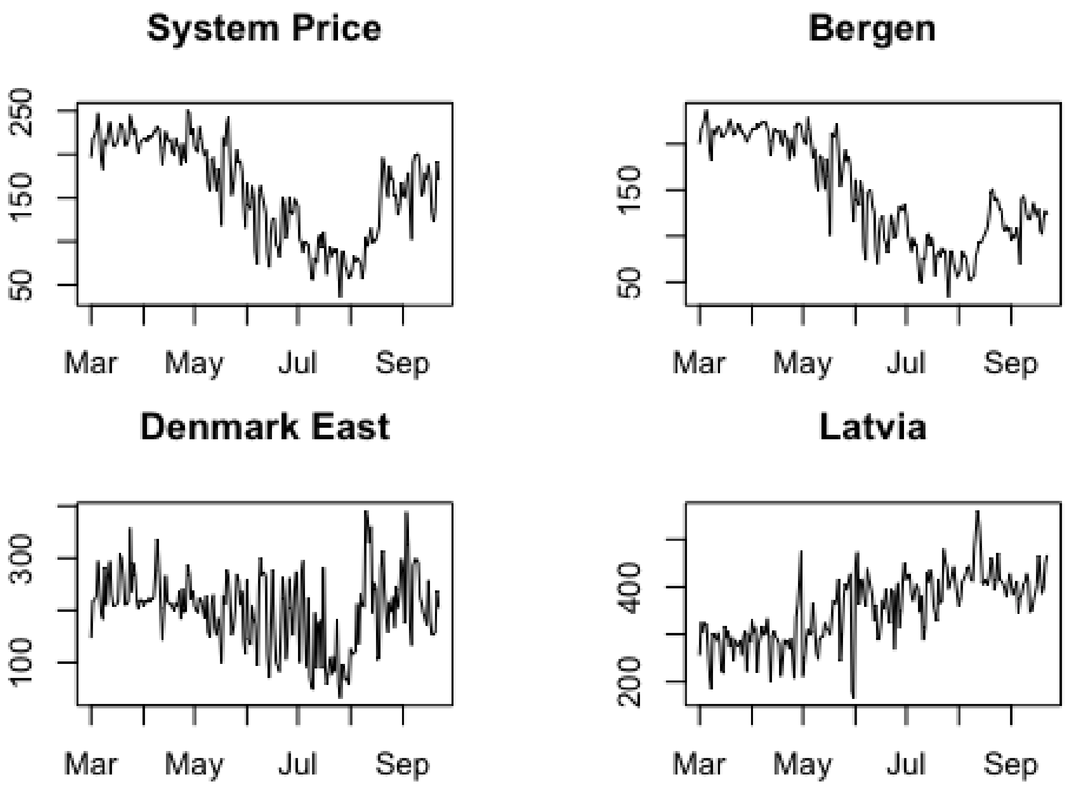

Figure 11: Price movement March 2015 - September 2015

Source: Nord Pool FTP-server

The norther regions have a equal innovation and volatility effect. The persistence is larger than one, indicating that the volatility have a permanent effect on the future price movements. Both regions in Denmark have a large volatile effect, and a smaller innovation effect. The GARCH model show that these two regions are most affected by volatile prices. The Baltic regions have a low GARCH effect, and uneven price movement is mostly due to shocks and innovation. This follows the results of Slade (1991), who found a competitive market with speculators to have a large volatility in the prices. persistence coefficient is lower than one, indicating a mean-reverting state for the volatility. The result of the GARCH model concludes with several studies of electrical energy prices; stating that electrical energy prices are the most volatile commodity in the energy market, far more uncertain than gas and oil (Weron, 2000; Higgs, 2009; Worthington et al., 2005; Vehviläinen and Keppo, 2003). Risk management when facing electrical prices is difficult, and a direct application of financial theory is not possible due to the non-storable condition (Vehviläinen and Keppo, 2003). Figure 11 show the price movement of the system price, Bergen, Denmark East and Latvia. Based on the results in Table 13 and Figure 11 it can be shown that large volatile shifts occur in the Danish price movement. The transitory conditional volatility does not die down like it does in the Baltic regions.

7 Conclusion

The purpose of this study has been to review the level of market integration and effects of price volatility in the Nordic energy spot market Nord Pool Spot. The data set consist of daily average spot prices from 01. January 1996 to 31. December 2015. Through this period NPS has undergone large changes. From being a power exchange between Norway and Sweden, it has grown to encompass wholesale electricity trading for the Scandinavian region and several countries in the Baltic region. As such, one can question the efficiency of the market and whether the regions encompassed are fully integrated with the system price.

To test for market integration and volatility, a dynamic approach was chosen to remove serial correlation from the time series. A univariate AR(8) model has been estimated on the data sets, both with and without dummy variables for seasonality. Lag length was selected using the SC criterion. The residuals from the AR model were used in a GARCH(1,1) model to estimate volatility effects. The sum of the ARCH and GARCH effects gives the persistence of the volatile movement. Inference was tested using static and dynamic models of bivariate price series, to analyse the arbitrage conditions needed to have market integration and validity for LOP.

The results of the tests for market integration indicate a close to perfect integration in the Nordic regions. Due to capacity constraints during bottleneck periods regional prices deviate from the system price under such circumstances. Norway, Sweden, Finland and Denmark have energy prices with a low mean and extreme volatility. This is consistent with Slade (1991), who found that exchange prices are more volatile than producer prices. The long run market integration is valid for Kristiansand and Tromso. For the Baltic regions, high prices and low volatility indicate that the regions are not yet fully integrated with the system price. The AR model for the Baltic region show a unidirectional relationship between the lagged Baltic prices and the system price, indicating weak integration. Few large producers use market power to increase stability, but at a higher price per quantity of electrical energy. As these markets get more integrated with the rest of NPS, implications from the rest of the regions would expect the prices in the Baltic regions to reduce and the volatility to increase.

The second part of the thesis consist of testing for volatility in NPS. The volatility is largely driven by the available power in each region, and the congestion constraint between stressed and unstressed regions during bottleneck periods. The seasonality has also proven to impact the volatile behavior of the energy prices. Volatility clustering can be expected during shifts in weather, and during holidays. Norway and Sweden have equal ARCH and GARCH effects, i.e. shock and previous volatility have a similar influence on the future volatility. The Danish market exhibit extreme volatility due to unpredictable energy production, constraints in transmission, and other unknown factors. This is seen in large GARCH effects, and smaller ARCH effects. Innovation and shocks are more influential in the Baltic regions and Finland. The persistence measures if volatile movement is permanently induced into the price or if it is temporary. The Scandinavian regions all have a persistence level indicating that volatile movement have a permanent effect on the future volatility. The Baltic regions have a mean reverting persistence effect. Large shocks dampen down until the volatility is back at a stable level. The difference in volatility behaviour indicate difference in market integration.

Nord Pool Spot today is not fully integrated. Better transmission capacity between regions and a more diverse set of producers will diminish market power and shift the regions closer to the ideal state that is the system price. This concurs with the findings of Higgs (2009) and Worthington et al. (2005), who states that a physical connection is required should the markets be fully integrated.

Abbreviations

ADF Augmented Dickey-Fuller test. 47

AR Autoregressive. iii, x, 3, 24, 29, 31–33, 36–38, 45, 51, 53, 56, 58–60, 65

ARCH Autoregressive Conditional Heteroskedasticity. 25, 26, 39, 61, 62

BLUE Best Linear Unbiased Estimator. 23

CUSUM Cumulative Sum of Residuals. 30, 31, 51

CV Coefficient of Variation. 44

EU European Union. 18, 20

GARCH Generalized Autoregressive Conditional Heteroskedasticity. iii, 25, 26, 29, 38, 39, 51, 61–63, 65

JB Jarque-Bera test. 46

LOP Law of One Price. 3, 18, 33, 34, 36, 37, 57–59, 65

MOSUM Moving Sum of Residuals. 30

NEM the Australian National Electricity Market. 2, 16, 17

NEMO Nominated Electricity Market Operator. 6

NPS Nord Pool Spot. iii, 1–3, 5–7, 9, 10, 13, 15–17, 19, 33, 43, 44, 49, 54, 59–61, 63, 65

OLS Ordinary Least Squares. 20–22, 30–32, 40, 51

PCR Price Coupling of Regions. 20

SC Schwarz Criterion. 27, 32, 36, 53

SRF Sample Regression Function. 21, 22

SSR Sum of Squared Residuals. 35, 58

TSO The System Operator. 5, 7, 14

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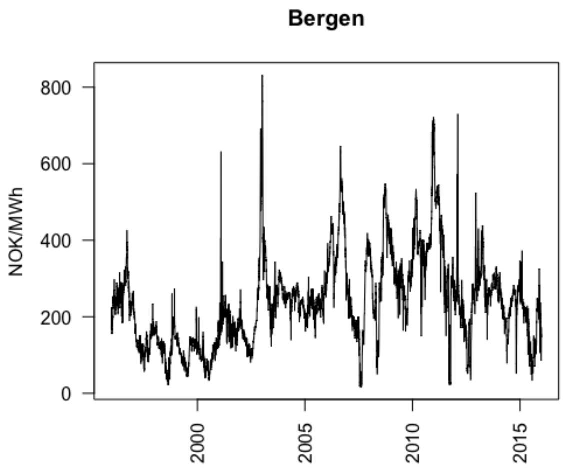
A Correlation Matrix

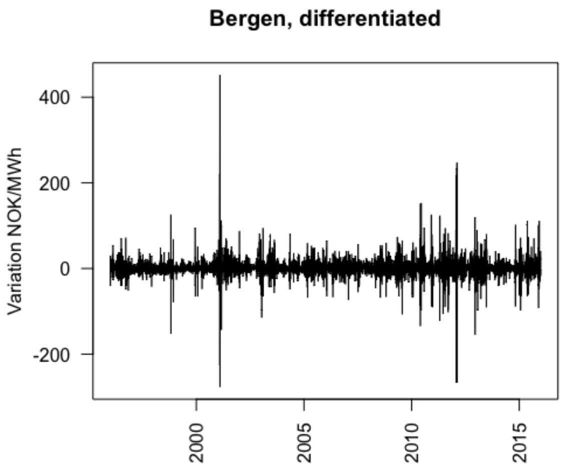
	Systempris	Bergen	Oslo	Kristiansand	Trondheim	Tromso	Sverige
Systempris	1.000	0.976	0.980	0.976	0.929	0.927	0.925
Bergen	0.976	1.000	0.988	0.997	0.862	0.862	0.849
Oslo	0.980	0.988	1.000	0.987	0.892	0.892	0.879
Kristiansand	0.976	0.997	0.987	1.000	0.860	0.860	0.848
Trondheim	0.929	0.862	0.892	0.860	1.000	0.996	0.989
Tromso	0.927	0.862	0.892	0.860	0.996	1.000	0.987
Sverige	0.925	0.849	0.879	0.848	0.989	0.987	1.000
Danmark V	0.723	0.654	0.643	0.661	0.660	0.653	0.680
Danmark O	0.789	0.670	0.712	0.671	0.883	0.880	0.903
Finland	0.882	0.794	0.828	0.794	0.954	0.950	0.967
Estland	0.378	0.334	0.340	0.338	0.375	0.367	0.399
Latvia	0.242	0.138	0.140	0.139	0.283	0.256	0.327
Litauen	0.136	0.039	0.040	0.040	0.182	0.162	0.234

	Danmark V	Danmark O	Finland	Estland	Latvia	Litauen
Systempris	0.723	0.789	0.882	0.378	0.242	0.136
Bergen	0.654	0.670	0.794	0.334	0.138	0.039
Oslo	0.643	0.712	0.828	0.340	0.140	0.040
Kristiansand	0.661	0.671	0.794	0.338	0.139	0.040
Trondheim	0.660	0.883	0.954	0.375	0.283	0.182
Tromso	0.653	0.880	0.950	0.367	0.256	0.162
Sverige	0.680	0.903	0.967	0.399	0.327	0.234
Danmark V	1.000	0.697	0.707	0.330	0.236	0.190
Danmark O	0.697	1.000	0.894	0.382	0.404	0.302
Finland	0.707	0.894	1.000	0.502	0.533	0.448
Estland	0.330	0.382	0.502	1.000	0.576	0.545
Latvia	0.236	0.404	0.533	0.576	1.000	0.664
Litauen	0.190	0.302	0.448	0.545	0.664	1.000

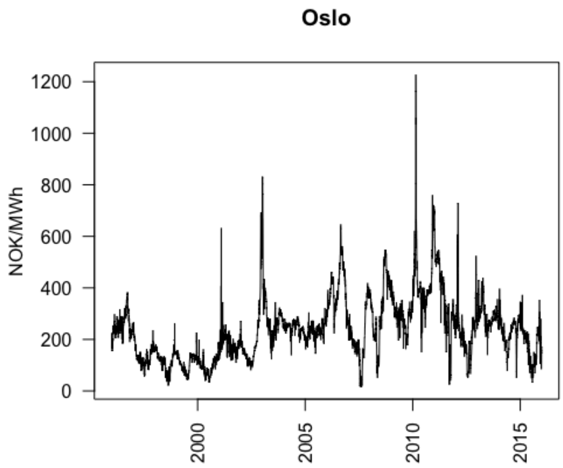
B Plot

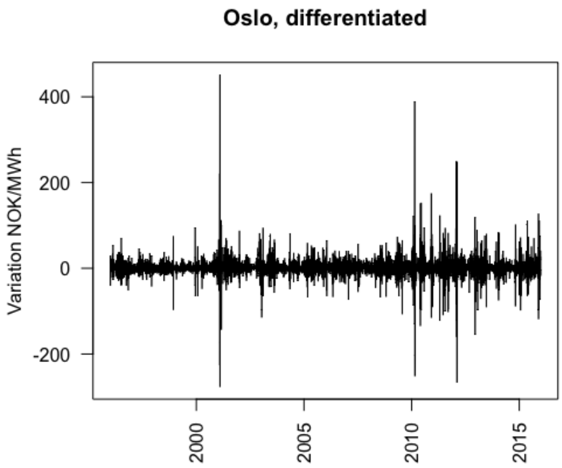
B.1 Bergen



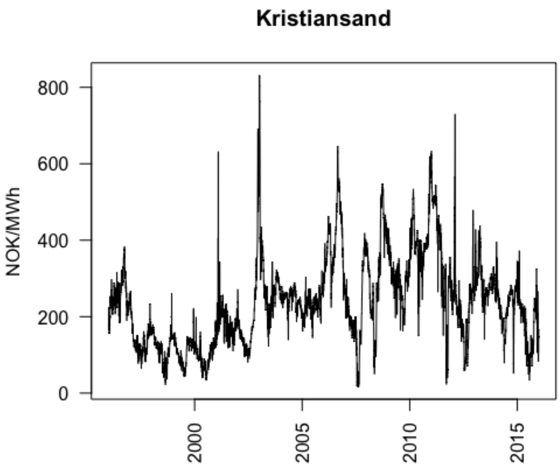


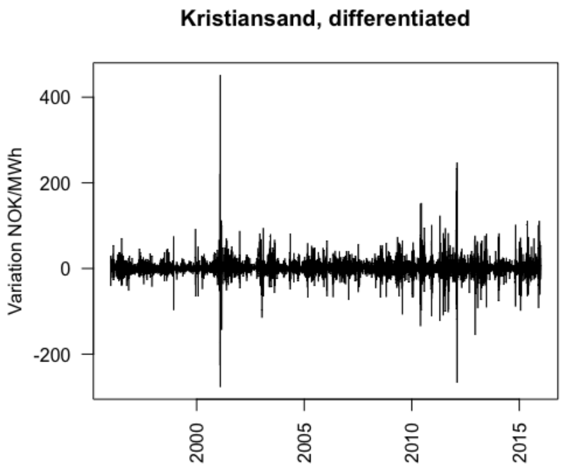
B.2 Oslo



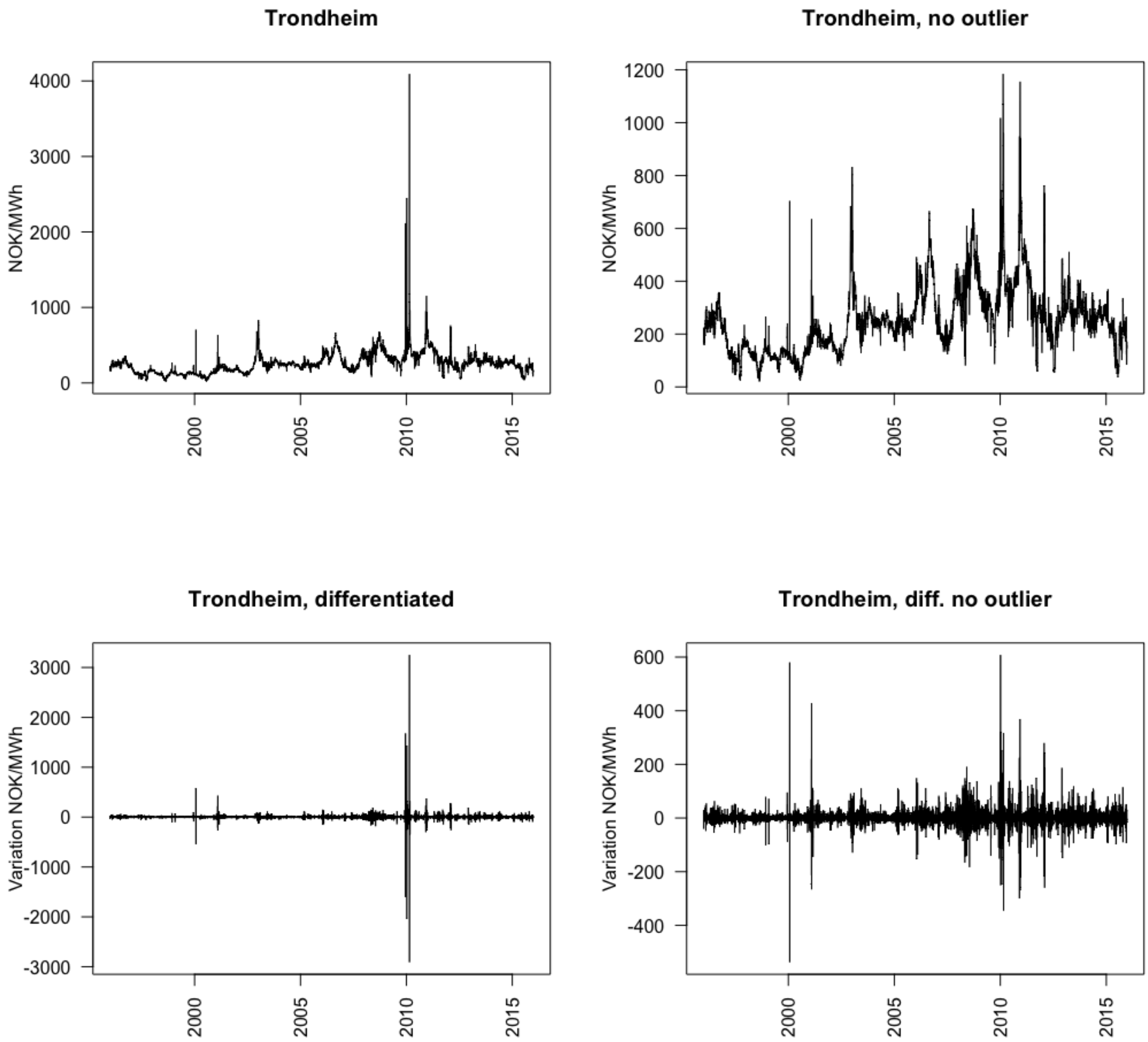


B.3 Kristiansand

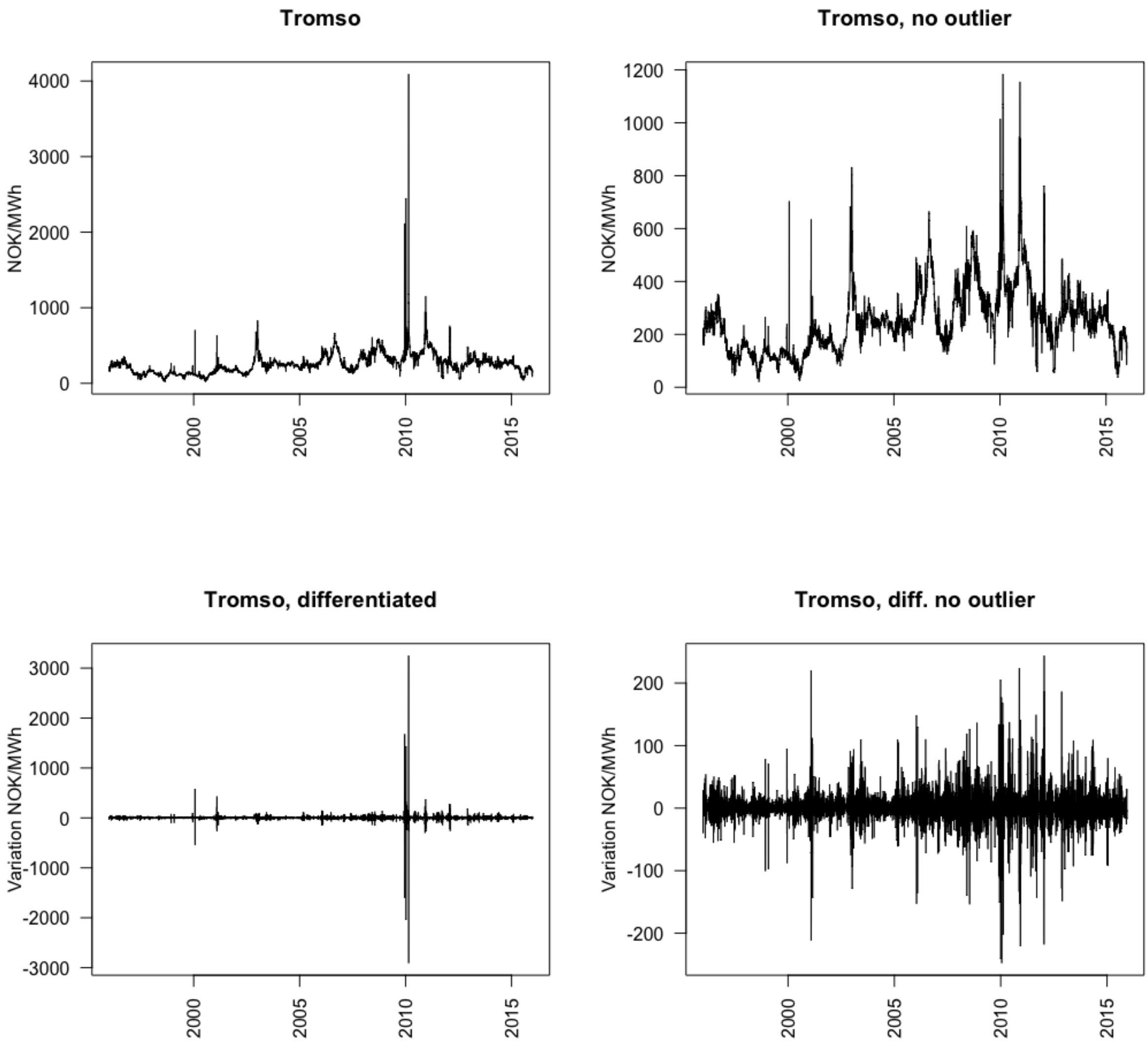




B.4 Trondheim

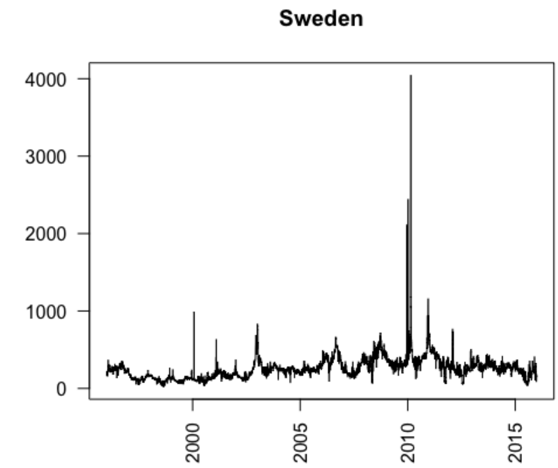


B.5 Tromso



Tromso
NOK/MWh
4000
3000
2000
1000
0
2000
2005
2010
2015
Tromso, no outlier
NOK/MWh
1200
1000
800
600
400
200
0
2000
2005
2010
2015
Tromso, differentiated
Variation NOK/MWh
3000
2000
1000
0
-1000
-2000
-3000
2000
2005
2010
2015
Tromso, diff. no outlier
Variation NOK/MWh
200
100
0
-100
-200
2000
2005
2010
2015

B.6 Sweden


Sweden
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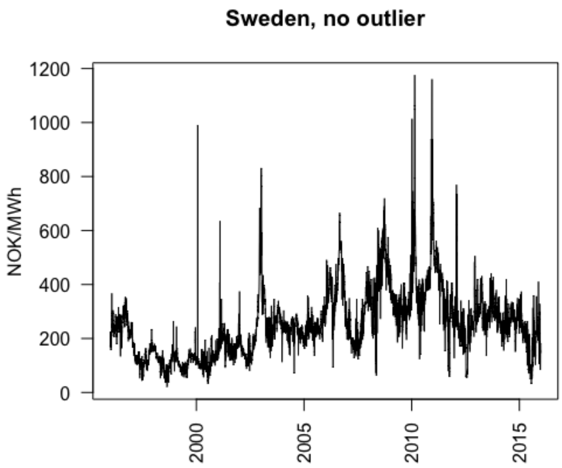
Sweden, no outlier
NOK/MWh
1200
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600
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2000
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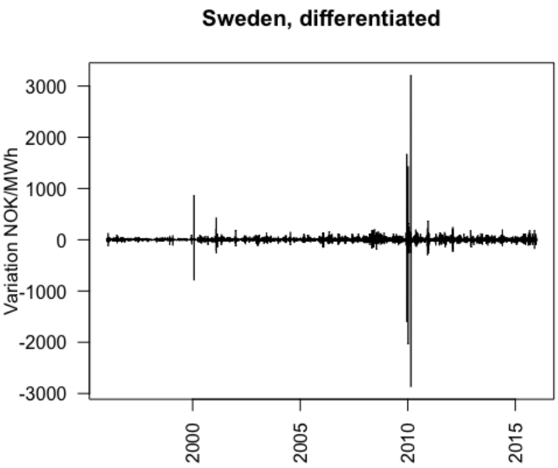
2015


Sweden, differentiated
Variation NOK/MWh
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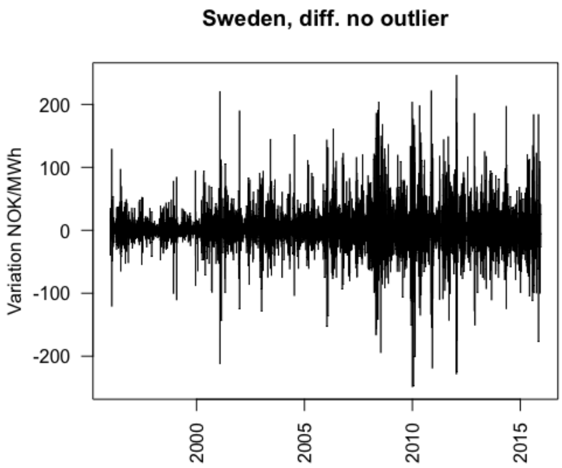
-1000
-2000
-3000
2000
2005
2010
2015


Sweden, diff. no outlier
Variation NOK/MWh
200
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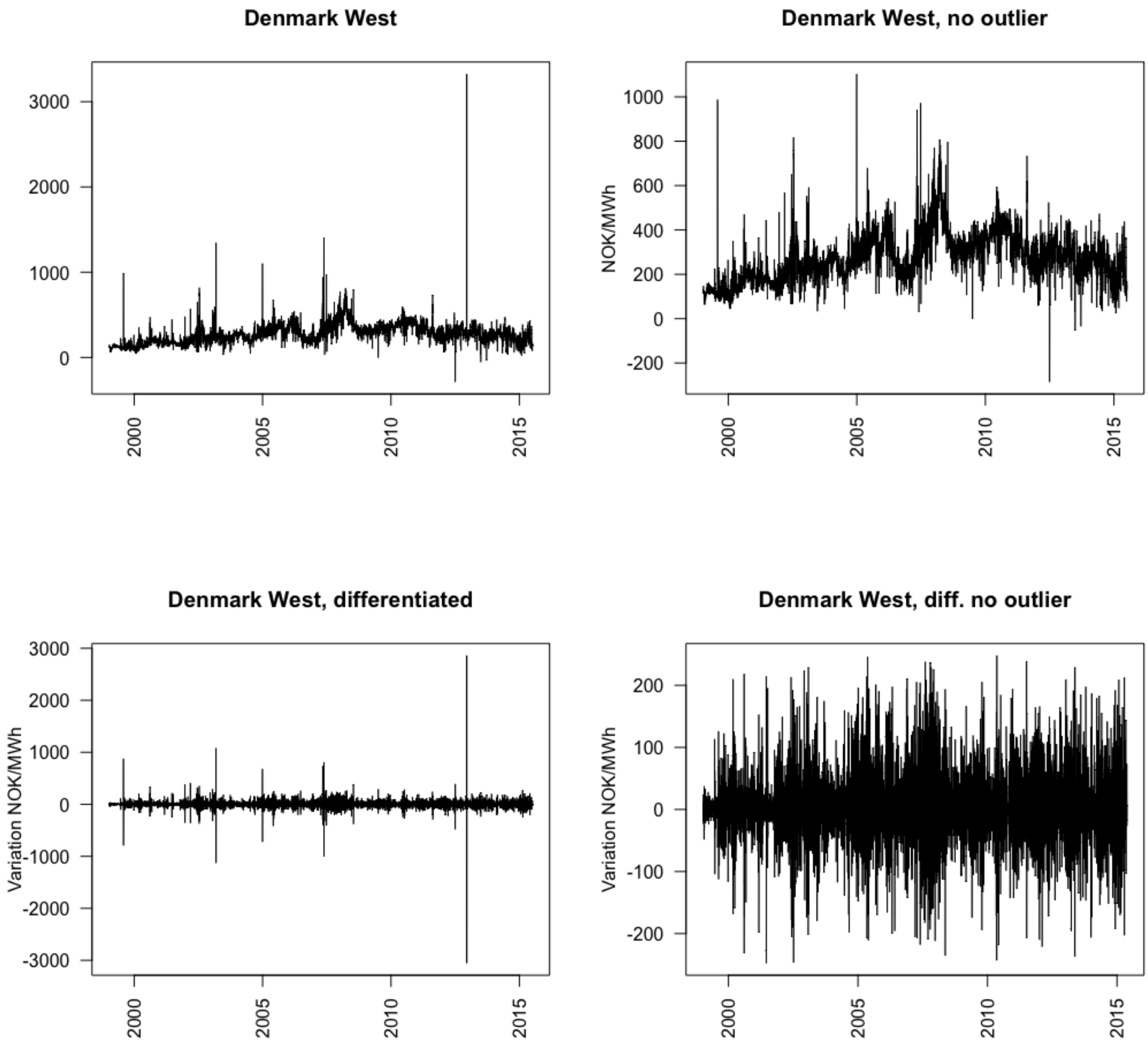
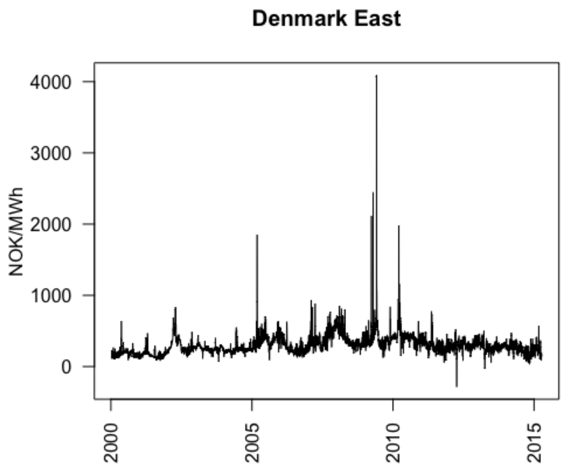
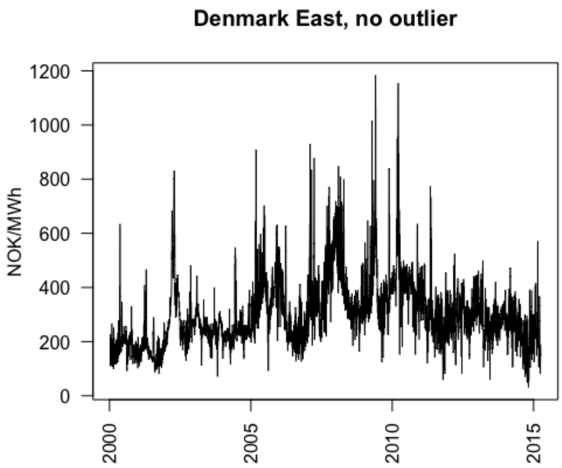
-200
2000
2005
2010
2015

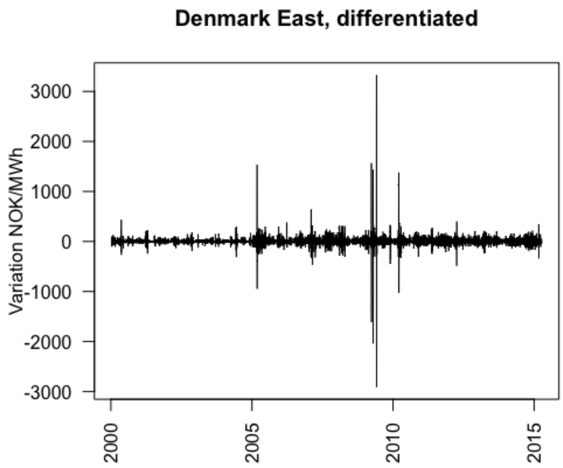
B.7 Denmark West

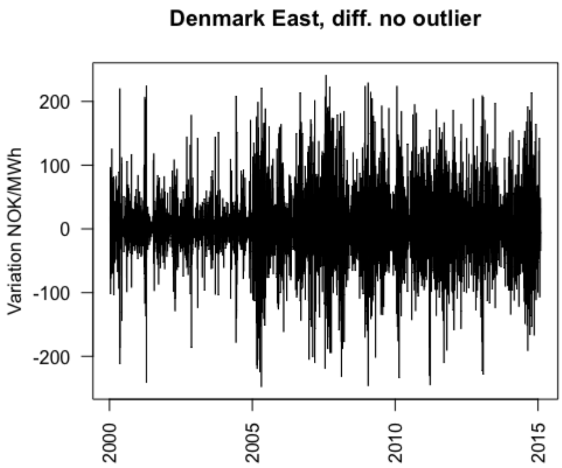


B.8 Denmark East

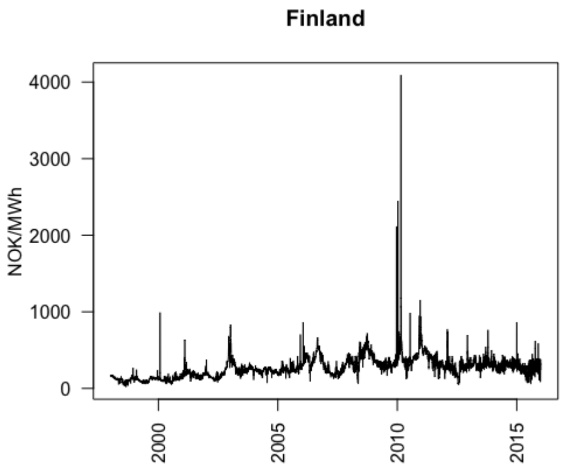


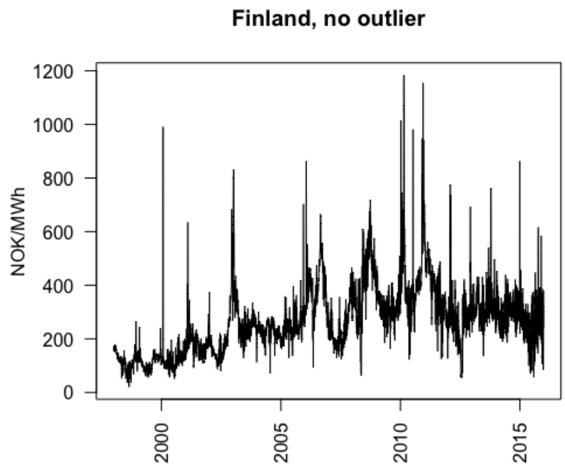


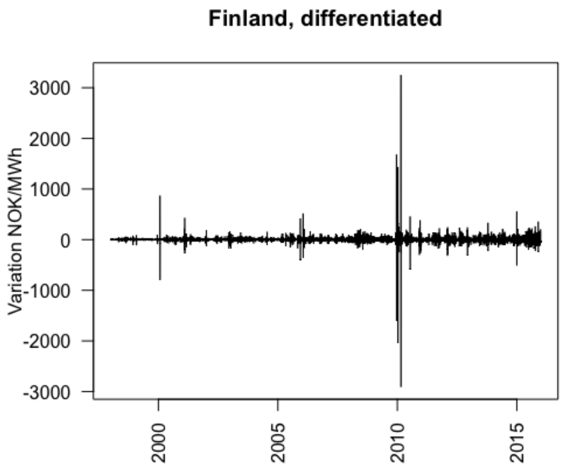


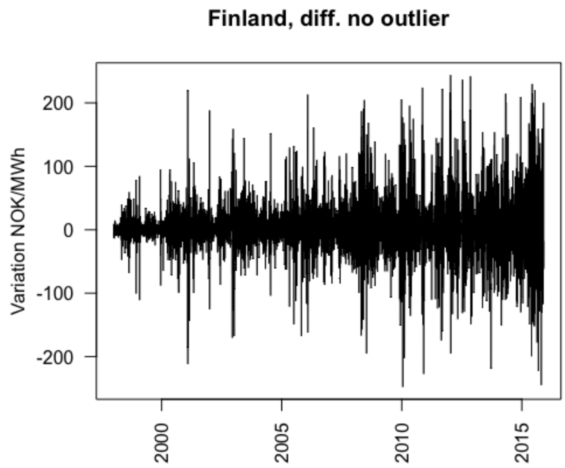


B.9 Finland

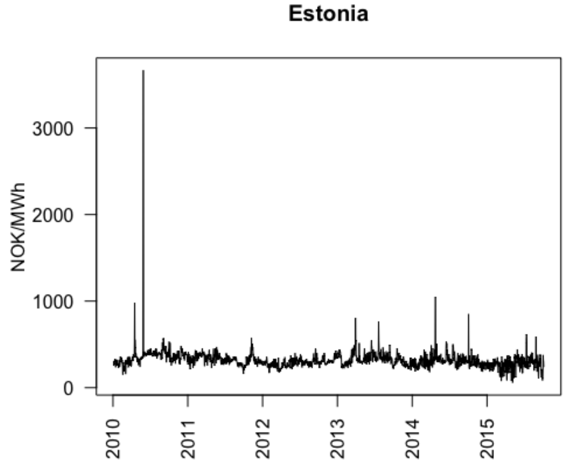

Finland
NOK/MWh
0
1000
2000
3000
4000
2000
2005
2010
2015

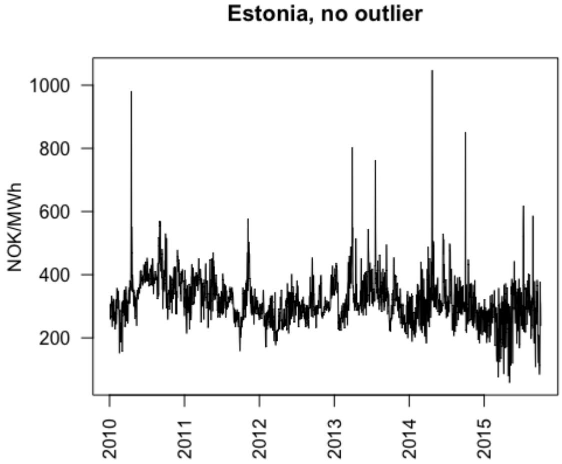

Finland, no outlier
NOK/MWh
0
200
400
600
800
1000
1200
2000
2005
2010
2015

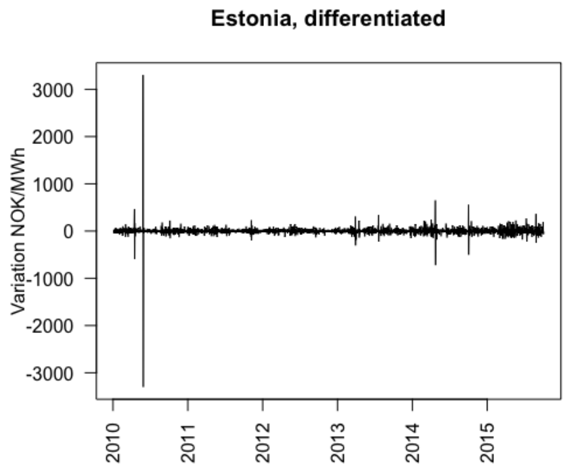

Finland, differentiated
Variation NOK/MWh
-3000
-2000
-1000
0
1000
2000
3000
2000
2005
2010
2015

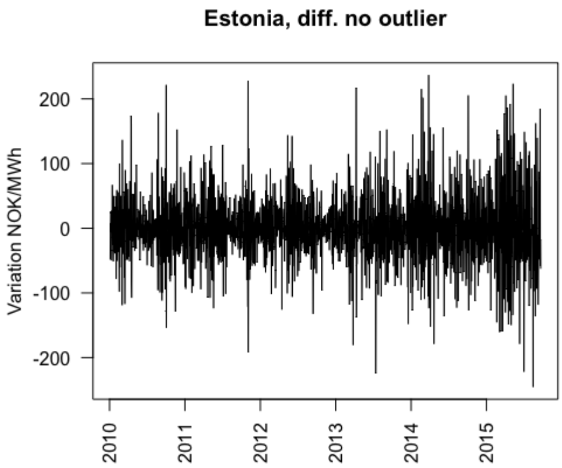

Finland, diff. no outlier
Variation NOK/MWh
-200
-100
0
100
200
2000
2005
2010
2015

B.10 Estonia

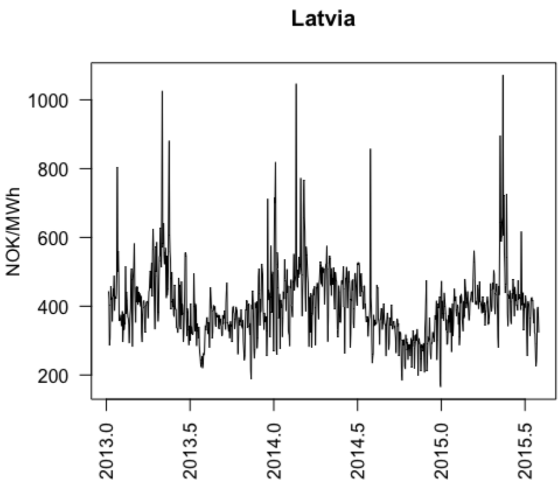

Estonia
NOK/MWh
0
1000
2000
3000
2010
2011
2012
2013
2014
2015

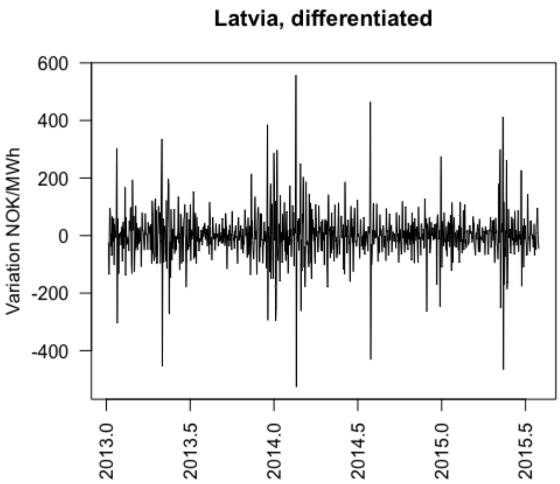

Estonia, no outlier
NOK/MWh
200
400
600
800
1000
2010
2011
2012
2013
2014
2015

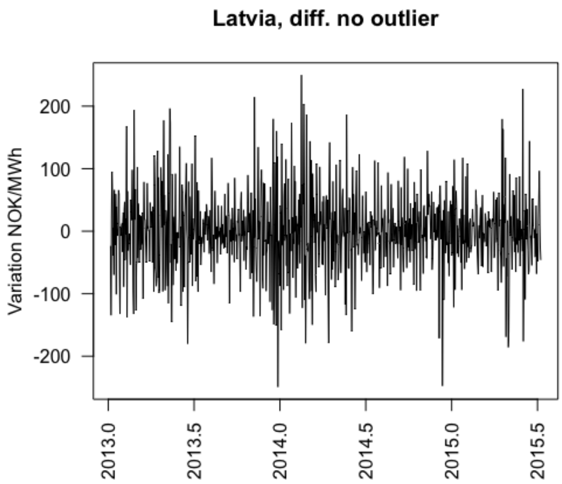

Estonia, differentiated
Variation NOK/MWh
-3000
-2000
-1000
0
1000
2000
3000
2010
2011
2012
2013
2014
2015


Estonia, diff. no outlier
Variation NOK/MWh
-200
-100
0
100
200
2010
2011
2012
2013
2014
2015

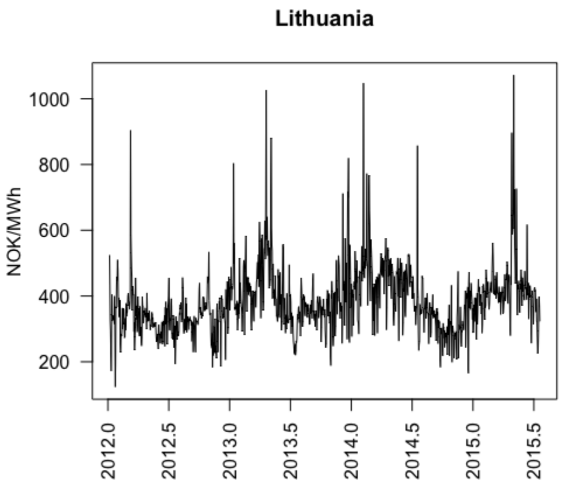
B.11 Latvia

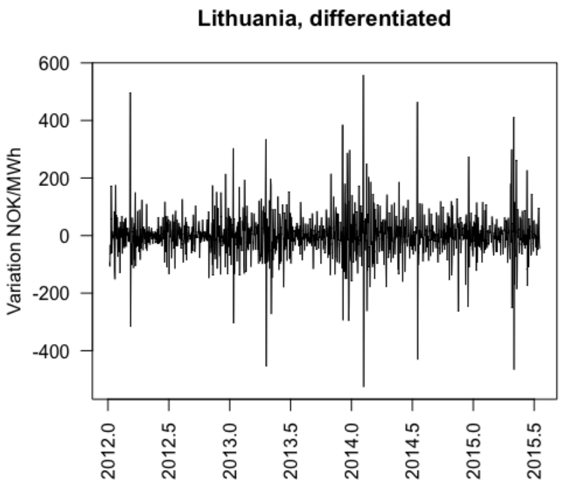

Latvia
NOK/MWh
1000
800
600
400
200
2013.0
2013.5
2014.0
2014.5
2015.0
2015.5

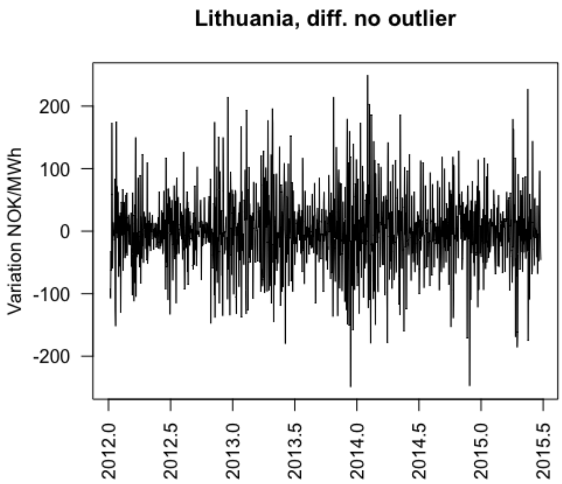

Latvia, differentiated
Variation NOK/MWh
600
400
200
0
-200
-400
2013.0
2013.5
2014.0
2014.5
2015.0
2015.5


Latvia, diff. no outlier
Variation NOK/MWh
200
100
0
-100
-200
2013.0
2013.5
2014.0
2014.5
2015.0
2015.5

B.12 Lithuania







C Sweden

C.1 Correlation internally

Correlation between the Swedish regions

	SE1	SE2	SE3	SE4
SE1	1.0000	0.9999	0.9981	0.9943
SE2	0.9999	1.0000	0.9981	0.9943
SE3	0.9981	0.9981	1.0000	0.9964
SE4	0.9943	0.9943	0.9964	1.0000

C.2 Summary statistics Sweden

Summary statistics Sweden before and after split

	Spot price				
	Sweden (96-11)	SE1	SE2	SE3	SE4
Mean	247.200	273.300	273.400	276.700	283.400
Median	227.200	265.100	265.200	267.600	272.600
Maximum	4044.000	762.200	762.200	774.800	774.800
Minimum	21.170	31.650	31.650	31.650	31.650
Std. Dev	145.139	98.107	98.066	99.418	99.832
Skewness	5.244	0.705	0.703	0.709	0.628
Kurtosis	101.194	1.818	1.823	1.754	1.582
CV	0.587	0.359	0.359	0.359	0.352
JB test	2362900.000	403.000	403.410	386.850	310.420
JB p value	0.000	0.000	0.000	0.000	0.000
ADF test	-5.561	-4.627	-4.642	-4.973	-5.534
ADF p value	0.010	0.010	0.010	0.010	0.010
Nr. Of observations	5479	1826	1826	1826	1826
	Logarithm spot price				
	Sweden (96-11)	SE1	SE2	SE3	SE4
Mean	5.371	5.537	5.538	5.550	5.575
Median	5.426	5.580	5.581	5.590	5.608
Maximum	8.305	6.636	6.636	6.653	6.653
Minimum	3.053	3.455	3.455	3.455	3.455
Std. Dev	0.534	0.411	0.410	0.409	0.407
Skewness	-0.178	-1.229	-1.234	-1.211	-1.301
Kurtosis	0.188	3.001	3.012	3.010	3.341
CV	0.099	0.074	0.074	0.074	0.073
JB test	36.962	1145.400	1153.400	1135.500	1364.500
JB p value	0.000	0.000	0.000	0.000	0.000
ADF test	-4.526	-4.164	-4.180	-4.454	-5.090
ADF p value	0.010	0.010	0.010	0.010	0.010
Nr. Of observations	5479	1826	1826	1826	1826

D Results Autoregressive model

Summary of estimated AR coefficients Trondheim, Tromso and Sweden

	NOR_Trondheim			NOR_Tromso			Sweden		
	Estimate	Std.error	p value	Estimate	Std.error	p value	Estimate	Std.error	p value
α_0	-0.0126	0.0093	0.1758	-6.06E-03	8.74E-03	0.4879	-0.0012	0.0090	0.8931
γ_1	0.5369	0.0117	<2e-16	0.5311	0.0117	<2e-16	0.5082	0.0117	<2e-16
γ_2	0.0912	0.0132	0.0000	0.0503	0.0131	0.0001	0.0489	0.0131	0.0002
γ_3	0.0831	0.0133	0.0000	0.0907	0.0131	0.0000	0.0879	0.0131	0.0000
γ_4	0.0617	0.0133	0.0000	0.0303	0.0132	0.0215	0.0371	0.0131	0.0046
γ_5	0.0003	0.0133	0.9797	0.0036	0.0132	0.7819	0.0285	0.0131	0.0297
γ_6	0.0651	0.0133	0.0000	0.0831	0.0131	0.0000	0.0835	0.0131	0.0000
γ_7	0.1110	0.0132	<2e-16	0.1534	0.0131	<2e-16	0.1099	0.0131	<2e-16
γ_8	-0.0407	0.0117	0.0005	-0.0288	0.0117	0.0137	0.0014	0.0117	0.9044
β_0	0.9212	0.0087	<2e-16	0.8521	0.0083	<2e-16	1.1721	0.0085	<2e-16
β_1	-0.4522	0.0155	<2e-16	-0.4013	0.0145	<2e-16	-0.6245	0.0178	<2e-16
β_2	-0.1181	0.0161	0.0000	-0.0757	0.0150	0.0000	-0.1033	0.0191	0.0000
β_3	-0.0441	0.0162	0.0064	-0.0556	0.0149	0.0002	-0.0687	0.0191	0.0003
β_4	-0.0601	0.0162	0.0002	-0.0165	0.0150	0.2694	-0.0320	0.0192	0.0947
β_5	0.0096	0.0162	0.5520	0.0120	0.0150	0.4212	-0.0376	0.0192	0.0496
β_6	-0.0650	0.0162	0.0001	-0.0926	0.0150	0.0000	-0.0889	0.0192	0.0000
β_7	-0.1571	0.0163	<2e-16	-0.1899	0.0151	<2e-16	-0.1658	0.0192	<2e-16
β_8	0.0598	0.0140	0.0000	0.0544	0.0131	0.0000	0.0416	0.0161	0.0096
δ_{mon}	-0.0002	0.0035	0.9448	0.0081	0.0033	0.0134	0.0183	0.0034	0.0000
δ_{tue}	-0.0037	0.0034	0.2769	-0.0013	0.0033	0.7009	0.0096	0.0034	0.0048
δ_{wed}	-0.0014	0.0034	0.6772	0.0026	0.0032	0.4290	0.0165	0.0034	0.0000
δ_{thu}	0.0010	0.0034	0.7734	0.0047	0.0032	0.1504	0.0136	0.0034	0.0001
δ_{fri}	-0.0033	0.0034	0.3415	-0.0012	0.0033	0.7010	0.0081	0.0034	0.0168
δ_{sat}	-0.0082	0.0033	0.0120	-0.0083	0.0031	0.0076	0.0013	0.0032	0.6956
δ_{jan}	0.0015	0.0036	0.6805	0.0022	0.0034	0.5197	0.0050	0.0035	0.1597
δ_{feb}	0.0033	0.0037	0.3689	0.0024	0.0035	0.4998	0.0040	0.0036	0.2629
δ_{mar}	0.0003	0.0036	0.9238	0.0004	0.0034	0.8982	0.0013	0.0035	0.7023
δ_{apr}	0.0059	0.0036	0.1057	0.0059	0.0034	0.0858	0.0007	0.0036	0.8373
δ_{may}	0.0087	0.0037	0.0178	0.0090	0.0035	0.0092	0.0132	0.0036	0.0002
δ_{jun}	0.0030	0.0037	0.4156	0.0014	0.0035	0.6815	0.0054	0.0036	0.1316
δ_{jul}	0.0013	0.0037	0.7158	-0.0001	0.0035	0.9841	0.0049	0.0036	0.1741
δ_{aug}	0.0022	0.0037	0.5517	0.0046	0.0035	0.1845	0.0108	0.0036	0.0030
δ_{sep}	-0.0007	0.0036	0.8393	0.0015	0.0034	0.6699	0.0050	0.0036	0.1634
δ_{oct}	0.0048	0.0036	0.1836	0.0042	0.0034	0.2187	-0.0025	0.0035	0.4834
δ_{nov}	0.0008	0.0036	0.8204	0.0014	0.0034	0.6821	0.0032	0.0036	0.3635

α_0 is the intercept, γ_i is the coefficient for the regions lagged value, and β_i is the coefficient for the lagged values of the system price. δ is the coefficient for the dummy variable.

Summary of estimated AR coefficients Denmark West and East, and Finland

	Denmark West			Denmark East			Finland		
	Estimate	Std.error	p value	Estimate	Std.error	p value	Estimate	Std.error	p value
α_0	0.23327	0.05619	3.35E-05	0.17343	0.05329	0.00114	0.0208	0.0149	0.1633
γ_1	0.23968	0.01291	<2e-16	0.26686	0.01343	<2e-16	0.5879	0.0124	<2e-16
γ_2	0.11791	0.01326	<2e-16	0.11844	0.01389	<2e-16	0.0288	0.0143	0.0438
γ_3	0.04172	0.01331	0.001732	0.06482	0.01392	3.31E-06	0.0846	0.0143	3.06E-09
γ_4	0.05993	0.01331	6.85E-06	0.07001	0.01393	5.16E-07	0.0352	0.0143	0.0137
γ_5	0.04269	0.01331	0.001346	0.05829	0.01392	2.88E-05	0.0179	0.0143	0.2101
γ_6	0.06814	0.01331	3.14E-07	0.08004	0.01392	9.41E-09	0.0989	0.0143	4.48E-12
γ_7	0.04428	0.01326	0.000848	0.05433	0.01388	9.18E-05	0.1151	0.0143	1.07E-15
γ_8	0.0517	0.01293	6.44E-05	0.03892	0.01345	0.00383	-0.0461	0.0124	2.01E-04
β_0	1.10947	0.04383	<2e-16	1.14602	0.03742	<2e-16	1.0770	0.0134	<2e-16
β_1	-0.39821	0.05839	1.00E-11	-0.40363	0.05090	2.65E-15	-0.6863	0.0223	<2e-16
β_2	-0.18327	0.05819	0.001644	-0.20261	0.05084	6.83E-05	-0.0645	0.0238	0.0067
β_3	-0.08958	0.05834	0.124715	-0.09930	0.05102	0.05168	-0.0810	0.0238	6.76E-04
β_4	0.01173	0.05844	0.84091	-0.03949	0.05111	0.43977	-0.0202	0.0238	0.3960
β_5	0.02276	0.05842	0.696932	0.00778	0.05112	0.87903	-0.0447	0.0238	0.0605
β_6	-0.13944	0.0583	0.016789	-0.15993	0.05094	0.00170	-0.1064	0.0238	7.98E-06
β_7	-0.15804	0.05876	0.007176	-0.15110	0.05131	0.00325	-0.0822	0.0239	5.89E-04
β_8	0.08253	0.0461	0.073464	0.10633	0.04038	0.00848	0.0778	0.0188	3.62E-05
δ_{mon}	0.17502	0.01812	<2e-16	0.10558	0.01516	3.70E-12	0.0639	0.0055	<2e-16
δ_{tue}	0.15172	0.01814	<2e-16	0.05948	0.01512	8.42E-05	0.0254	0.0056	5.69E-06
δ_{wed}	0.1718	0.01808	<2e-16	0.09135	0.01501	1.23E-09	0.0360	0.0055	7.52E-11
δ_{thu}	0.17851	0.01808	<2e-16	0.09296	0.01502	6.55E-10	0.0286	0.0055	2.25E-07
δ_{fri}	0.13987	0.01803	1.01E-14	0.06736	0.01499	7.19E-06	0.0325	0.0055	4.91E-09
δ_{sat}	0.06746	0.0171	8.11E-05	0.00821	0.01432	0.56643	-0.0043	0.0053	0.4159
δ_{jan}	0.05035	0.01876	0.007303	0.03073	0.01561	0.04903	0.0046	0.0057	0.4177
δ_{feb}	0.05322	0.01915	0.005475	0.02690	0.01590	0.09079	0.0010	0.0058	0.8608
δ_{mar}	0.04877	0.01869	0.009101	0.01102	0.01551	0.47752	0.0001	0.0057	0.9853
δ_{apr}	0.07349	0.01895	0.000107	0.02161	0.01567	0.16796	-0.0045	0.0057	0.4316
δ_{may}	0.09602	0.0191	5.12E-07	0.03212	0.01562	0.03986	0.0091	0.0057	0.1099
δ_{jun}	0.11375	0.01949	5.57E-09	0.04510	0.01582	0.00438	0.0047	0.0057	0.4108
δ_{jul}	0.1018	0.01928	1.34E-07	0.04014	0.01577	0.01093	0.0120	0.0058	0.0382
δ_{aug}	0.10023	0.01919	1.81E-07	0.05442	0.01586	0.00061	0.0123	0.0059	0.0349
δ_{sep}	0.10779	0.01909	1.71E-08	0.05126	0.01577	0.00116	0.0064	0.0058	0.2701
δ_{oct}	0 0.07106	0.01877	0.000155	0.03295	0.01545	0.03297	-0.0024	0.0057	0.6785
δ_{nov}	1 0.05684	0.01862	0.002278	0.03252	0.01541	0.03486	0.0017	0.0057	0.7605

α_0 is the intercept, γ_i is the coefficient for the regions lagged value, and β_i is the coefficient for the lagged values of the system price. δ is the coefficient for the dummy variable.

Summary of estimated AR coefficients Estonia, Latvia and Lithuania

	Estonia			Latvia			Lithuania		
	Estimate	Std.error	p value	Estimate	Std.error	p value	Estimate	Std.error	p value
α_0	1.0927	0.1200	<2e-16	1.4405	0.2297	5.54E-10	0.9027	0.1615	2.79E-08
γ_1	0.4510	0.0221	<2e-16	0.5130	0.0334	<2e-16	0.5317	0.0283	<2e-16
γ_2	0.0284	0.0240	0.236258	0.0260	0.0375	0.487876	0.0391	0.0319	0.220292
γ_3	0.0930	0.0239	0.000105	0.0789	0.0374	0.035266	0.0764	0.0316	0.015889
γ_4	-0.0110	0.0240	0.64791	-0.0230	0.0374	0.538835	0.0225	0.0316	0.47812
γ_5	0.0166	0.0240	0.489493	0.0564	0.0375	0.133224	0.0369	0.0317	0.244221
γ_6	0.0531	0.0239	0.02653	0.0669	0.0375	0.074697	0.0608	0.0317	0.055161
γ_7	0.1459	0.0240	1.50E-09	0.0343	0.0377	0.362577	0.0718	0.0318	0.023911
γ_8	-0.0724	0.0222	0.001147	-0.0253	0.0337	0.45261	-0.0215	0.0281	0.444326
β_0	0.5183	0.0324	<2e-16	0.2929	0.0476	1.12E-09	0.2515	0.0439	1.24E-08
β_1	-0.2115	0.0453	3.26E-06	-0.0863	0.0626	0.168338	-0.0477	0.0589	0.418732
β_2	-0.0673	0.0455	0.139543	-0.0619	0.0627	0.323551	-0.0757	0.0591	0.200217
β_3	-0.1343	0.0457	0.003297	0.0023	0.0631	0.971517	-0.0237	0.0593	0.690114
β_4	0.0420	0.0458	0.359089	0.0131	0.0633	0.836081	0.0362	0.0596	0.543817
β_5	-0.0714	0.0459	0.119783	-0.1059	0.0635	0.095488	-0.1307	0.0597	0.028751
β_6	-0.0077	0.0458	0.866343	0.0275	0.0633	0.663938	0.0742	0.0596	0.213302
β_7	0.0295	0.0459	0.520348	-0.0822	0.0635	0.195836	-0.0877	0.0598	0.142535
β_8	-0.0010	0.0347	0.977359	0.0173	0.0494	0.726655	0.0239	0.0452	0.597239
δ_{mon}	0.0939	0.0150	4.13E-10	0.1598	0.0224	2.07E-12	0.1374	0.0195	3.23E-12
δ_{tue}	0.0513	0.0153	0.000788	0.1097	0.0233	2.94E-06	0.0713	0.0201	0.000394
δ_{wed}	0.0410	0.0149	0.00617	0.1000	0.0233	1.89E-05	0.0736	0.0199	0.000229
δ_{thu}	0.0483	0.0149	0.001193	0.0816	0.0234	0.000499	0.0499	0.0200	0.012601
δ_{fri}	0.0475	0.0151	0.001714	0.0695	0.0233	0.002904	0.0399	0.0200	0.045819
δ_{sat}	-0.0072	0.0143	0.616169	-0.0212	0.0216	0.325615	-0.0350	0.0187	0.061624
δ_{jan}	0.0139	0.0157	0.375993	0.0004	0.0232	0.987938	0.0019	0.0199	0.924248
δ_{feb}	0.0125	0.0161	0.438413	-0.0058	0.0236	0.807885	-0.0034	0.0203	0.868284
δ_{mar}	0.0100	0.0157	0.523812	-0.0455	0.0237	0.055201	-0.0138	0.0199	0.4904
δ_{apr}	-0.0166	0.0153	0.277422	-0.0105	0.0242	0.665511	-0.0021	0.0201	0.916047
δ_{may}	0.0104	0.0150	0.4879	0.0022	0.0231	0.922486	0.0069	0.0199	0.727199
δ_{jun}	0.0280	0.0152	0.066148	0.0579	0.0225	0.010333	0.0527	0.0204	0.00979
δ_{jul}	0.0538	0.0159	0.00071	0.0507	0.0216	0.018876	0.0456	0.0198	0.021679
δ_{aug}	0.0499	0.0158	0.001618	0.0351	0.0221	0.112281	0.0221	0.0202	0.274527
δ_{sep}	0.0584	0.0158	0.000217	0.0758	0.0217	0.000488	0.0512	0.0189	0.006857
δ_{oct}	0.0441	0.0156	0.004714	0.0714	0.0231	0.002055	0.0337	0.0193	0.080805
δ_{nov}	0.0204	0.0152	0.179175	0.0318	0.0210	0.131479	0.0139	0.0185	0.451878

α_0 is the intercept, γ_i is the coefficient for the regions lagged value, and β_i is the coefficient for the lagged values of the system price. δ is the coefficient for the dummy variable.