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Optimizing Hedging Strategies for Hydropower Producers Using Forwards

Investigating the Effects of Seasonality in the Price-Load Relationship for the Norwegian Electricity Market

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Oppgavens (foreløpige) tittel
Optimizing Hedging Strategies for Hydropower Producers Using Forwards **Investigating the Effects of Seasonality in the Price-Load Relation for the Norwegian Electricity Market and Evaluating Different Risk Metrics**

4. Bedømmelse

Kandidatene skal ha *individuell* bedømmelse ☐
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Oppgavetekst/Problembeskrivelse The thesis aims to analyse the price-load relationship in the Norwegian electricity market and its implications for optimal hedging strategies. Different risk metrics are to be evaluated and compared, and it will be discussed whether hydropower producers ought to take seasonality into account when developing hedging strategies.	
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Abstract

When there is seasonality in the price or volume of a commodity, risk management strategies ought to be adjusted accordingly. Using the Norwegian electricity market as a case, this thesis examines the gains from implementing seasonal varying hedge ratios. To complement the analysis, relevant risk metrics are evaluated and compared. Using data spanning over a decade, we find that a seasonal trend is apparent in the price-load relationship. A linear relation is confirmed for the winter with a weakening tendency when approaching summer from each side, where it is non-existent. The observed seasonality is explained by the characteristic supply stack and varying demand throughout the year, with the prices being more demand-driven during winter. A strong price-load correlation implies a more sensitive cash flow. This indicates that there is seasonality in the optimal hedging strategy, requiring higher hedge ratios during winter. Performing hedge ratio optimizations, CVaR is found to be the superior risk metric. The optimized hedge ratio exhibits a clear seasonal pattern. As expected, the ratio is highest during winter and lowest during summer, reflecting the trend of the price-load correlation. Our results show that a seasonal varying hedge ratio outperforms a more static strategy, reducing downside risk and simultaneously increasing profit. Consequently, this thesis clearly shows that seasonal varying hedge ratios ought to be implemented as a part of a hydropower producer's hedging strategy.

Sammendrag

Når det er sesongvariasjon i pris eller volum av en råvare, bør et selskaps sikringsstrategier justeres deretter. Ved å studere det norske kraftmarkedet, undersøker denne oppgaven fordelene med å implementere sesongvarierende sikringsgrader. For å komplementere denne analysen, evalueres og sammenlignes relevante risikomål. Ved å benytte data over et tiår, finner vi en tydelig sesongtrend i forholdet mellom pris og last. En lineær sammenheng er bekreftet for vinteren med en avtagende tendens når sommeren nærmer seg, hvor den lineære sammenhengen er ikke-eksisterende. De observerte sesongvariasjonene forklares ved hjelp av den karakteristiske tilbudskurven og varierende etterspørselen gjennom året, med mer etterspørselsdrevet priser om vinteren. En høy pris-last korrelasjon innebærer en mer sensitiv kontantstrøm. Dette indikerer at det bør være sesongvariasjoner i den optimale sikringsgraden, med høyere sikringsgrad for vinteren. Ved å utføre sikringsgradoptimaliseringer, er CVaR funnet å være det beste risikomålet. Den optimale sikringsgraden viser et klart sesongmønster. Som forventet, er sikringsgraden høyest om vinteren og lavest om sommeren, noe som reflekterer variasjonene i pris-last korrelasjonen. Våre resultater viser at en sesongvarierende sikringsgrad utkonkurrerer en mer statisk strategi ved å redusere nedsiderisikoen og samtidig øke fortjenesten. Følgelig bekrefter oppgaven at sesongvarierende sikringsgrader bør implementeres som en del av en vannkraftprodusents sikringsstrategi.

Optimizing Hedging Strategies for Hydropower Producers Using Forwards

- Investigating the Effects of Seasonality in the Price-Load Relationship for the Norwegian Electricity Market -

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Abstract

When there is seasonality in the price or volume of a commodity, risk management strategies ought to be adjusted accordingly. Using the Norwegian electricity market as a case, this thesis examines the gains from implementing seasonal varying hedge ratios. To complement the analysis, relevant risk metrics are evaluated and compared. Using data spanning over a decade, we find that a seasonal trend is apparent in the price-load relationship. A linear relation is confirmed for the winter with a weakening tendency when approaching summer from each side, where it is non-existent. The observed seasonality is explained by the characteristic supply stack and varying demand throughout the year, with the prices being more demand-driven during winter. A strong price-load correlation implies a more sensitive cash flow. This indicates that there is seasonality in the optimal hedging strategy, requiring higher hedge ratios during winter. Performing hedge ratio optimizations, CVaR is found to be the superior risk metric. The optimized hedge ratio exhibits a clear seasonal pattern. As expected, the ratio is highest during winter and lowest during summer, reflecting the trend of the price-load correlation. Our results show that a seasonal varying hedge ratio outperforms a more static strategy, reducing downside risk and simultaneously increasing profit. Consequently, this thesis clearly shows that seasonal varying hedge ratios ought to be implemented as a part of a hydropower producer's hedging strategy.

Keywords: Hedging, electricity price, load, seasonality, electricity market, hydropower, risk management, optimal hedge ratio, risk metrics, CVaR.

1 Introduction

Commodity producers often deal with volatile prices and volumes, which frequently exhibit seasonality. The significance of the seasonality may vary and it can occur with different time perspectives, ranging from daily to yearly basis. Risk management strategies ought to take such seasonality into account to better reflect the dynamics of the commodity. Further, when there is seasonality in the relation between price and volume, there is an enhanced need to adjust the strategy accordingly. A strong positive relation between price and volume will lead to a more volatile revenue, indicating a need to hedge a larger portion of the volume to achieve the same level of predictability. However, with a weaker connection, a smaller volume needs to be hedged as the revenue will be less sensitive. Thus, for a commodity producer, knowledge about the dynamics of the relation between price and volume is an important part of the risk management.

Electricity is a commodity with distinct characteristics. The presence of seasonality in electricity price and load dynamics on daily, weekly and yearly basis is frequently highlighted, and several studies suggest that both demand fluctuations and seasonality are among the factors that influence the electricity spot price the most (Cartea & Villaplana, 2008; Kanamura, 2009; Sáez, Pena, & Villaplana, 2011). Due to the characteristic supply stack structure with different power sources utilized during base and peak load, demand dynamics often transform into fluctuations in electricity price (Weron, 2006). As a consequence of this relation and the high price volatility, power producers experience considerable profit fluctuations throughout the year. This has resulted in an enlarged need to hedge, not only against volume risk but also against price movements. The costs of over- or under contracting have increased considerably, leading to a greater possibility of financial distress (Weron, 2006). Accordingly, finding optimal hedging strategies is particularly important, also to create more stable cash flows and reduce unwanted profit fluctuations.

In this thesis we will use the Norwegian electricity market as a case to emphasize the gains from considering seasonality in risk management. This market is strongly dominated by hydropower, and provides more than a third of the power production at the Nordic market. Further, there are several other factors that make this market particularly interesting, including the cold climate, high usage of electricity heating and characteristic governmental regulations. Hence, the hydropower producers face a variety of challenges when it comes to managing operations and financial risk. In addition to a high volatility of the electricity spot price, generation risk by inflow and load uncertainty, the hydropower companies in Norway also have to consider distinct taxes that affect their cash flow and create an asymmetric profit function.

Our results from the Norwegian case show a particularly strong correlation in the price-load relation during the winter, being almost zero during the summer. This seasonality is found to have implications on hydropower producers' hedging strategies. The optimal hedge ratio, or the proportion of future production to be sold through forward contracts, is found to be highest during the winter and lowest during the summer. The optimization is based on cash flow with respect to three different risk metrics, CVaR being the most appropriate as it reduces downside risk while maintaining the upside potential. Our results show that a seasonal varying hedge ratio outperforms a more static strategy, reducing unwanted risk and simultaneously increasing profit. Hence, our findings underline the importance of taking seasonality into account when developing a risk management strategy.

The remainder of this thesis is structured as follows. The rest of this section presents earlier literature on electricity price and load dynamics, the Norwegian electricity market and hedging from a hydropower producer's perspective. Section 2 describes the data applied in the analysis, and further presents descriptive statistics on the daily price-load data. Section 3 presents an empirical analysis of the seasonality in the weekly price and load dynamics. Further, section 4 optimizes seasonal hedge ratios with respect to different risk metrics. Section 5 discusses gains and issues regarding implementation of seasonal hedging strategies. Finally, section 6 concludes the thesis and summarizes the most important findings.

1.1 Literature Review

1.1.1 Electricity as a Commodity: Price and Load Dynamics

With the restructuring of the electricity power market, the traditional vertical integration gradually opened. Unbundling due to economy of scale divided the power system in two where transmission and distribution remained a monopoly, while generation and consumption were introduced to competition. For the electricity supply industry this meant that the stable price structure disappeared, and the producers now had to make their own pricing decisions. In a risk management perspective, this price risk exposure created a need for a more dynamic managerial practice.

As a part of the restructuring, Nord Pool was established and created a Nordic market for power trading. With the introduction of the power exchange, the participants in the power market were exposed to increased competition and the transparency improved. Today Nord Pool is divided into two parts: Nord Pool Spot and NASDAQ OMX Commodities. Nord Pool Spot is a physical market for short-term power trading, while NASDAQ OMX Commodities is the exchange of power derivatives, constituting the cash-settled financial market. Here risk associated with electricity can be hedged through a variety of derivatives. The system price derived at Nord Pool Spot is the reference price when evaluating derivatives at maturity. This price represents the equilibrium between expected and aggregated demand and supply in the day-ahead Nordic market (NordPoolSpot, 2014).

Electricity is a commodity strongly characterized by its non-storability as it is generated at the same time as it is consumed. Electricity is also characterized by its limited transportability due to restrictions in transmission lines and transportation losses. Thus, in the electricity market there must be an instant balance between generation and consumption, which also fulfills the transportation limitations. However, the price mechanism is not capable to reflect the real time balance (Wangensteen, 2012), and as a consequence the pricing mostly occurs ex-ante, ahead of real time, at the exchange to provide an efficient market. At the Nordic power exchange about half of the electricity is generated from hydropower. As a consequence of the above-mentioned system characteristics, there are some distinctive properties of the electricity spot price in the Nordic market. These are frequently mentioned in scientific literature.

First, the electricity price is highly volatile. Applying standard volatility measures, the annualized volatility of log price changes has been ranged from 80% to as high as 189% (Lucia & Schwartz, 2002). On a daily scale, electricity prices exhibit extreme volatilities up to 50%. This is much higher compared to commodities like crude oil and natural gas having daily volatilities of 2-4% (Weron, 2006). The price variance in the Nordic market is greatly affected by reservoir levels and variations in climate, with temperature and precipitation being the most important. The latter can vary as much as +/- 25 % from wet or dry years (Aune, Johnsen, & Sagen, 2001). Moreover, as the demand for electricity at short-term is considered to be quite inelastic (Vucetic, Tomsovic, & Obradovic, 2001; Wangensteen, 2012), this also contributes to increasing the variance of the electricity prices. In the longer run, however, a more elastic demand is evident, as it follows changes in business cycles, preferences, population growth and technological innovations (Sáez et al., 2011; Westgaard, 2013). For electricity, as most industrial commodities, the price is expected to have a positive correlation with the overall economy since strong economic growth creates greater demand and higher prices (Botterud, Kristiansen, & Ilic, 2010).

A second distinctive characteristic is the relatively frequent presence of extreme electricity prices and jumps. This is indicated by a large excess kurtosis, with the extremely high prices being most common (Lucia & Torró, 2011). Given the short-term inelastic demand, prices can soar when capacity limits are reached (Gaudard & Romerio, 2014). This was the case with the extreme price peaks during the winter of 2009/2010 (NordREG, 2011). After shocks like these, volatility clustering often occurs as prices have a tendency to become more volatile (Lucia & Torró, 2011). Yet, in the case of a sudden demand/supply shock, prices are less volatile in hydro dominated systems compared to thermal systems due to the flexibility (Botterud et al., 2010).

Third, there is a seasonal pattern in the average level of electricity prices over the year. A major reason for this is the distinct seasonal trend in prominent price factors like demand, inflow and reservoir levels. Electricity demand is highly affected by temperature fluctuations over the year, being highest in the winter and lowest in the summer. Characteristic of the Nordic region is the high usage of electricity for heating purposes during cold periods, and low usage of air-condition during the summer months. Inflow is also highly dependent on climate and weather conditions, as it mainly is a result of precipitation and melting of snow-pack. In dry years with low precipitation, the prices increase in the winter, and in wet years, the prices are low in the summer (Botterud et al., 2010). Furthermore, hydro storage levels peak in September-November and reach their lowest levels in April-May due to the high demand for electricity heating and limited inflow during the winter (Näsäkkälä & Keppo, 2005b; Westgaard, 2013). Low reservoir levels often lead to higher prices vice versa. Also, when reservoir levels are low, a net import may take place, and the electricity price becomes more sensitive to other power sources. Hence, access to nuclear power, renewable energy and other fuel prices also affect the electricity price (NordPoolSpot, 2014). As a result of the above-mentioned factors, the average price during the winter has been found to be 28% higher than the summer, their equality being rejected at any significance level (Lucia & Torró, 2011).

As Chan, Gray, and Van Campen (2008) state, the electricity dynamics present a number of challenges to modeling, and the approaches that have proven successful for traditional financial series have struggled to model electricity prices. Sáez et al. (2011) and Knittel and Roberts (2005) specify that mean reversion should be taken into account, and the latter also underlines the importance of modeling time varying volatility, volatility clustering, extreme values and seasonal effects. Load modeling, however, should be different than price modeling due to the prominent inelastic characteristic. The electricity load patterns are well understood, with an apparent seasonality on daily, weekly and yearly basis (Cartea & Villaplana, 2008; Lucia & Schwartz, 2002). As specified by Weron (2006), load dynamics often transform into fluctuations in electricity price, but an inverse relationship may also appear. Consequently load and price are partially co-determined, and ought to be treated as one complex task. When searching for possible price regimes in California's electricity market, Vucetic et al. (2001) assume the electricity load to be nearly perfect inelastic and as a first approximation unaffected by the price. Hence, the price-load relationship is considered as a standard linear regression problem. Kanamura (2009), finding that energy prices seemed to increase with demand, also incorporates demand into the price model. Cartea and Villaplana (2008) highlight the seasonality present in the load and price dynamics, and both Sáez et al. (2011) and Kanamura (2009) suggest that demand fluctuations and seasonality are among the factors that influence the electricity price the most.

1.1.2 The Norwegian Hydropower System

In Norway nearly all power production comes from hydropower, and the country provides 70% of the hydropower generated at the Nordic power exchange (NordPoolSpot, 2014; SSB, 2013). We distinguish between two types of hydro power plants: run-of-river plants, which are uncontrollable, and reservoir plants, which are controllable (Wangensteen, 2012). The latter is able to store an amount of water for a longer period of time, depending on the reservoir size, and provides the largest generation volume in Norway. Installations with storage are less vulnerable to short-term variations as the limitation of the non-storability of electricity becomes more distant (Gaudard & Romerio, 2014). Hence, a power system with a high share of hydro production has greater generation flexibility. The value of the water stored in the reservoirs is determined by the estimation of the water-value, representing the opportunity cost of using water immediately as opposed to storing it for future use (Botterud et al., 2010). Thus, hydro production requires dynamic operational management to take advantage of future price peaks. Furthermore, reservoir plants have greater flexibility in the short-term operating window due to shorter startup and shutdown periods than thermal power plants. Compared to thermal generation, hydropower production is also characterized by relatively high investment costs followed by low marginal costs. Hence, hydropower is frequently used to cover base load while conventional fuels cover peak load.

The Norwegian electricity market stands out from other markets on several areas, not only with hydropower domination, but also the cold climate and high usage of electricity heating. Furthermore, Norwegian hydropower producers are exposed to governmental regulations that greatly affect both operational and financial risk management. Firstly, to compensate counties and municipalities affected by the regulated electricity production, the producers are obliged to deliver up to 10% of the average physical production at low tariff or for free (Sanda, Olsen, & Fleten, 2013). Secondly, in addition to the standard corporate tax of 27%, the producers are imposed a natural resource tax of 31%, where the income base for calculation of the tax is the spot price. Consequently an asymmetric tendency is apparent, as the revenue from physical production of electricity is exposed to both natural resource tax and corporate tax, while revenue from financial contracts only is exposed to corporate tax. This asymmetry influences the hydropower producers' choice of strategy regarding the use of financial instruments and production hedging. That is, if a producer's production is exposed to the natural resource tax, it will be optimal to hedge a smaller volume than what would be optimal without this tax (OED, 2003-2004).

1.1.3 Hedging From a Hydropower Producer's Perspective

Compared to other commodity producers, hydropower producers have to consider some other factors when developing a financial risk management strategy. In addition to facing technical constraints and contractual obligations, the producers have to consider the different taxation of physical and financial revenue, as recently mentioned. Moreover, the non-storability of electricity implies that the no-arbitrage pricing of derivatives does not hold. For storable commodities, like oil and corn, arbitrage forces create a strong connection between the spot and forward prices (Collins, 2002). However, the cost-of-carry relation that links these prices as a no-arbitrage condition cannot be utilized in electricity markets (Bessembinder & Lemmon, 2002; Byström, 2003; Collins, 2002). This creates a weaker connection between the spot and forward prices, making the price risk management and hedging of electricity production much more complex. Another consequence of the non-storability is that delta hedging cannot be applied (Bessembinder & Lemmon, 2002). These implications, together with the high volatility of electricity prices, contribute to making hedging particularly important for electricity producers (Byström, 2003). Furthermore, the electricity market has some other limitations. Hydropower companies face both price and inflow risk simultaneously. However, given that not all risk factors can be perfectly hedged by available financial instruments, both Oum, Oren, and Deng (2005) and Näsäkkälä and Keppo (2005a) claim the electricity market to be incomplete. This is particularly the case for volumetric risk. As the financial derivatives at the exchange only deal with price, volumetric hedging is difficult. A commonly suggested alternative includes the application of weather derivatives, which utilizes the strong relation between electricity demand and temperature (Deng & Oren, 2006; Oum et al., 2005). Another issue is the limited liquidity of certain derivatives, especially future and forward contracts[1] with longer maturities. The lack of potential buyers and sellers of the contracts creates challenges and greater risk, both when initializing a hedging strategy and when desiring to close out a position (Tanlapco, Lawarrée, & Liu, 2002).

There are several motives for using financial derivatives for hedging purposes. The most fundamental is to make investments to reduce the risk of adverse price movements and thus reduce price volatility. This is supported by Tanlapco et al. (2002), stating that the decision to take a hedged position is to protect against price risks and not to profit from it. Stulz (1996) elaborates on this and states that the fundamental goal of hedging is to eliminate downside risk. The extreme lower outcomes in corporate cash flow and value should be eradicated, while the upside outcomes preserved. This is also supported by Sanda et al. (2013), who analyzed risk management trends in electricity commodity markets by studying

[1] At the Nordic exchange future contracts are offered with weekly and daily delivery, while DS (Deferred Settlement) future contracts are available with yearly, quarterly and monthly delivery (NASDAQOMX, 2014). As underlined by Sanda et al. (2013), DS futures can be seen as forward contracts, indicating that futures and forwards at the exchange are not in accordance with standard financial terminology. Moreover, these contracts provide a delivery over a period and not at an instant time, as would be the case for a storable commodity.

12 Norwegian hydropower companies. They argued that stakeholder risk aversion is highly relevant and as a consequence downside risk metrics should be applied to provide more stable dividends. Sanda et al. (2013) identified different hedging motives among the hydropower producers. One approach was to reduce risk associated with physical production, including securing predetermined price levels and hence reduce price volatility. Another approach focused on income smoothing, trying to provide a stable cash flow and reduce profit fluctuations. A third approach, also mentioned by Deng and Oren (2006), comprises profit and value maximization. Sanda et al. (2013) explain this by selective hedging, a more speculative form of hedging based on a firm's view on price and market movements. However, this hedging approach is more untraditional and opposes Tanlapco et al. (2002) and Stulz (1996)'s arguments of hedging without profit motives. Despite the different approaches, Sanda et al. (2013) conclude that the hydropower producers' desired results from hedging nevertheless are based on the elimination of extreme lower outcomes of the earnings function.

The capability of risk management to add value is highly discussed. Neoclassical economics state that hedging is not able to add value due to efficient markets and the ability of the investors to hedge on their own (Modigliani & Miller, 1958). Yet, the assumptions used are criticized for being idealized and for not holding in real situations, and theories of hedging based on market imperfections imply that hedging should indeed increase firm value (Jin & Jorion, 2006). Nowadays corporate managers seem to make an extensive use of derivatives. In 2003, Smithson and Simkins (2005) found that about 92% of the world's 500 largest companies used some kind of derivatives, and 25% to explicitly manage commodity price risk. This may indicate a belief of the derivatives capability of adding value, which usually is measured as increased firm value. As underlined by Smithson and Simkins (2005), cash flow volatility can be related to firm value. A reduction in cash flow volatility reduces the likelihood of financial distress and unwilling avoidance of investment opportunities, and thus provides a value enhancement. A negative relationship between cash flow volatility and shareholder value has been found by Allayannis and Weston (2001), which supports these results. Smithson and Simkins (2005) also emphasize the use of derivatives and its association with reduced risk, but not necessarily increased firm value. In the case of commodity price risk management, commodity users mostly experience increased value from hedging. Carter, Rogers, and Simkins (2004) discovered fuel price hedging by airlines to be associated with higher firm value. For commodity producers, however, there is no clear value-adding tendency. By studying hedging activities of 119 U.S. oil and gas producers, Jin and Jorion (2006) found that although hedging reduced stock price sensitivity to oil and gas prices, it did not affect firm value. These contradicting results were explained by the investors' ability to hedge on their own, as the commodity risk exposure was more easily identified. According to Smithson and Simkins (2005) also a negative equity effect was found when studying hedging in gold mining companies. However, when analyzing hydropower companies, Sanda et al. (2013) got some remarkable results. The majority of the companies obtained an increased profit from hedging without reducing cash flow volatility. In theory hedging should provide the opposite, with zero expected value and income smoothing. Sanda et al. (2013) highlight the extensive use of selective hedging combined with periods of high basis risk as possible explanations for these results.

Several analyses have been performed on the stand-alone electricity price and load, but there are fewer empirical studies on the relation between the two. The literature regarding seasonal variations in the price-load dependency is scarcer. There are studies on dynamic risk management in commodity markets, several focusing on continuously modifying the hedging strategy to reflect short-term dynamics. Many of these underline the importance of adjusting the optimal hedge ratio to factors like price and volatility fluctuations, where GARCH models are frequently utilized for modelling (see Baillie and Myers (1991) and Alizadeh, Nomikos, and Pouliasis (2008)). Despite this, literature on hedging strategies considering seasonality as present in the electricity market, is more limited. Accordingly, using the Norwegian market as a case, the purpose of this study is to emphasize the gains from implementing seasonality in a power producer's hedging strategy. Having a seasonal focus at a yearly basis, the first part of the analysis (sections 2 and 3) aims to investigate the dynamics of the relation between price and load. Being the main influencers on the cash flow and its volatility, the understanding of this relation lays the foundation for the hedge optimization, comprising the second part of the analysis (sections 4 and 5).

2 Data and Descriptive Statistics

2.1 Data Description

In this empirical analysis the relation between the electricity price and load is examined. The objective is not to build a price model, but to apply descriptive statistics and linear regressions to understand the dynamics in the price-load relationship. This lays the foundation for our further analysis, aiming to study the effects of seasonality in optimal hedging strategies for hydropower producers.

Being a part of a larger interconnected market, Norway exchanges power with other countries. This exchange can vary significantly, depending on the demand and production in different areas. However, when performing the analysis, the aim is to study Norway as an isolated market, thus disregarding import and export. To be able to study this market as an isolated case, load data is chosen over production.

The raw data is collected using the Montel database (MontelXLF, 2013), comprising time series of the daily spot price in EUR/MWh and load in MWh in the Norwegian price areas, NO1 to NO5. The data period ranges from 02.06.2003 to 31.10.2013. The different price areas are aggregated into two different regions, North and South Norway,[2] weighted by load.[3] The two regions are further aggregated into one price area representing the whole country, again weighted by load. This data lays the foundation for the empirical analysis.

2.2 Daily Time Series and Descriptive Statistics

To confirm that the data used is in accordance with the expected electricity characteristics, the stand-alone price and load are examined. Figure 1 shows the daily aggregated price and load over the sample period, whose descriptive statistics are displayed in table 1. Seen from both the wide price range and the standard deviation of 13,9 it is evident that the price is highly volatile. These findings concur with earlier literature, exemplified by Lucia and Schwartz (2002) and Weron (2006). The volatility of the load is also high, with a standard deviation of 71 931.

A mean reverting tendency of the price and load is apparent in figure 1. The volume series has a clear sinusoidal trend, being high in the winter and low in the summer. The price series do also exhibit some seasonal fluctuations, with higher prices during the winter. Some price peaks are also apparent. In general, price peaks are a result of limited capacity combined with the inelastic characteristic of the demand. Especially high peaks are evident during the winter 2009-2010, which were basically due to issues with Swedish nuclear production (NordREG, 2011).

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[2] The Norwegian price areas have undergone several changes during the years, determined by the transmission system operator, Statnett, in order to deal with major and long-term congestions in the regional and central grid system (NordPoolSpot, 2014). Hence, the information provided by a single price area over a longer historical period is not consistent. However, from 02.06.2003 a constant line is set between North and South Norway, see appendix [1]. Even though the price areas vary on each side of this line, the total price and load in the two regions are found by aggregating the price areas in the respective regions at a given time.

[3] We choose to aggregate the prices weighted by load instead of utilizing an unweighted arithmetic average. This to provide a more credible estimate, as the price based on the largest load ought to be weighted the most.

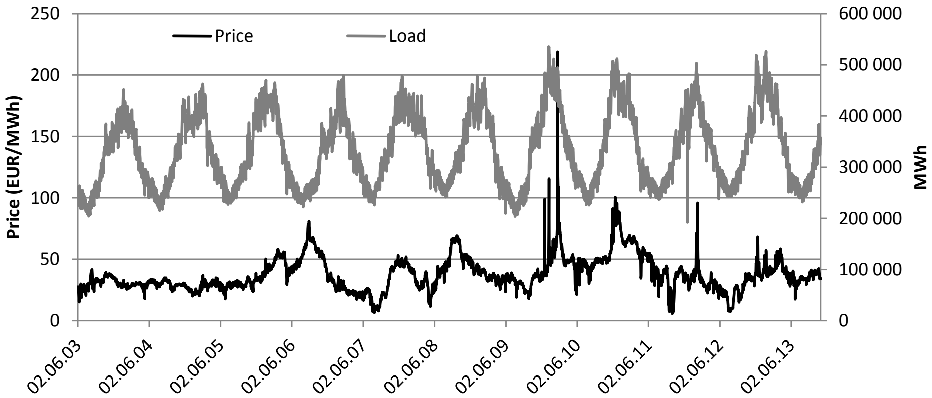

Figure 1: Daily aggregated price and load in Norway from 02.06.03 to 31.10.13

From the frequency plots of the daily aggregated load and price returns over the sample period, see appendix [6.1], the price return distribution looks more like a normal distribution compared to the volume distribution. The two have quite different characteristics. The price return distribution is leptokurtic with a kurtosis of 23,04, indicating heavy tails. The volume distribution is more platykurtic, having a kurtosis of -0,93. The significant difference in kurtosis indicates that extreme electricity prices appear quite often, while the load distribution is more flat with less outliers. A striking difference in kurtosis is also found by Cartea and Villaplana (2008), examining daily data at Nord Pool in the period 1999-2006. They estimate the price return kurtosis to be 26,5 and the volume kurtosis to be 1,47. Our data provides a similar trend. Furthermore, the price returns have an imperceptible negative skewness of -0,01, approximately zero. Hence, the return distribution exhibits an equally probability of having higher and lower returns compared to the mean. The volume distribution has a positive skewness of 0,35, which is higher than the skewness of the price return. Cartea and Villaplana (2008) on the other hand, found a return skewness of 1,72 and a volume skewness of 1,36. However, these findings were based on data from a different time period (2003-2006) for the system price at Nord Pool.

Table 1: Descriptive statistics for daily price series (EUR/MWh), price return and load (MWh) in Norway from 02.06.2003 to 31.10.2013

	Price	Return	Load
Mean	37,71	0,000	336 032
Standard Error	0,23	0,001	1 166
Median	34,87	-0,003	328 362
Standard Deviation	13,90	0,086	71 931
Kurtosis	9,22	23,043	-0,93
Skewness	1,52	-0,014	0,35
Range	212,91	1,800	343 108
Minimum	5,91	-0,900	192 454
Maximum	218,81	0,900	535 562
Count	3 805	3 804	3 805

3 Analysis of Seasonality in the Price and Load Dynamics

3.1 Empirical Analysis of Weekly Price and Load Series

Before analyzing the relationship between electricity price and load in more detail, the daily prices belonging to the Northern, Southern and aggregated area are scaled up to weekly prices,[4] this to filter out some of the noise apparent in the daily data. Further, the time series of the weekly data undergo a logarithmic transformation. Sáez et al. (2011) argue that such transformation tends to eliminate right skewness and outliers, which are recognized as a part of the main source of uncertainty. However, we choose to perform a logarithmic transformation when examining the price-load relationship. There are two advantages of doing this. Firstly, the application of a linear regression becomes more accurate as the data is linearized. The data becomes smoother and the errors more normally distributed. Secondly, the regression coefficient, β, may be interpreted as elasticity. If the dependent variable increases with 1%, the explanatory variable increases with β%.

To obtain a significant data transformation, the data must contain stationary series meaning that the price, and also load, should be mean reverting. In general few price series are stationary, but as underlined in previous literature, Weron (2006) and Knittel and Roberts (2005) among others, electricity spot prices tend to be mean reverting, which is also indicated by figure 1. However, a test for stationarity ought to be applied to confirm this for the data used in the analysis, see appendix [3.5]. By utilizing an ADF(2) test, stationarity is verified for the prices and loads, as the test statistics are more negative than the critical value at a 1% significance level (-3,90), see appendix [4].

After performing a logarithmic transformation on the weekly data, the weekly prices and loads are grouped together as a replication of months.[5] To better understand the dynamics of both the price and load individually and the relation between them, the same week groups in each year, from 2003-2013, are analyzed together. Evaluating both the descriptive statistics (see tables 2 and 3) and the scatter plots (appendix [8.1]) for the aggregated data, a seasonal pattern for the price and load dynamics appears.

It is evident that prices have a seasonal trend being higher in the winter and lower in the summer. As shown in table 2, the mean price is highest for the period ranging from week 42 through week 9, and reaches its lowest levels in week 26 to 33. Regarding load, the same trends are observed, with the mean levels being clearly higher in the winter weeks. Furthermore, the variance of the price is higher during the summer and early fall, where it reaches its highest levels during weeks 30-41. This is consistent with the findings of Lucia and Schwartz (2002), who found the warm seasons to be significantly more volatile than the cold seasons. However, as the data here is logarithmic transformed, these results should be interpreted carefully. The transformation is expected to comparatively increase the volatility during periods with lower prices, which is the case for the summer months. Compared to the variance of the price, the trend for the variance of the load is different as the standard deviation is slightly lower during the summer weeks. However, worth noting is that the variance of the logarithmic load always is lower than the variance of the logarithmic price, see table A2 in appendix [7.1] and appendix [7.4].

As mentioned, extreme electricity prices appear relatively frequent, as illustrated by the high kurtosis value (9,22) in table 1. When analyzing weekly prices at Nord Pool from 1998-2007 on a seasonal basis, Lucia and Torró (2011) found the kurtosis to be significantly higher in the winter and lowest during the spring. In our case, the kurtosis values are also lowest for the weeks during early spring and summer (week 10-25). Although, for the rest of

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[4] The daily prices are aggregated into weekly prices weighted by load.

[5] To get a better understanding of the seasonality and trends in the sample period, the data from four and four weeks are grouped together as a replication of months. Weeks 2-5 make up the first month, giving a total of 40 data points for this period (four weeks times ten years). Further, weeks 6-9 form the second group, 10-13 the third etc. Week 1 and week 53 are not included, as the number of days in these weeks varies, and hence their respective loads are incomparable.

the year, a seasonal trend is not as clear. During the period from week 26 to 41 the kurtosis is consistently positive, but during the winter months the kurtosis varies between positive and negative values. This may indicate a varying appearance of extreme values during the winter months, which deviates somewhat from the findings of Lucia and Torró (2011). This, however, may be explained by the use of logarithmic transformed data reducing outliers. In addition, our sample period begins after the extreme price spikes in the winter 2002-2003.

Moreover, it seems to be some seasonality present in the skewness of the price. The summer weeks 26-33 yield a negative skewness below -1,2. The winter period, however, exhibits positive skewness, thus indicating a larger probability of high extreme values. This is as expected given that extreme electricity price peaks mainly occur during cold winter months, a result of the characteristic supply stack structure and almost inelastic short-term demand. Lucia and Torró (2011) also found the skewness to be more positive during the winter than the rest of the year. The calculated skewness values in their case were positive for all seasons. However, in our case, the skewness is expected to be somewhat lower due to the logarithmic transformed data, which also tend to reduce right skewness. Regarding load, the most positive skewness values are also observed during the winter. Yet, the seasonal trend is not as evident as for the price.

Table 2: Descriptive statistics for the grouped weekly logarithmic transformed price in Norway from 02.06.2003 to 31.10.2013

	Mean	St. Dev.	Kurtosis	Skewness	Min	Max	Count
W2-5	3,669	0,331	-0,430	0,134	3,095	4,423	40
W6-9	3,675	0,362	0,579	0,766	3,132	4,759	40
W10-13	3,622	0,357	-1,204	0,445	3,120	4,319	40
W14-17	3,612	0,299	-1,146	0,090	3,091	4,155	40
W18-21	3,480	0,314	-0,602	-0,037	2,850	4,033	40
W22-25	3,488	0,265	-0,928	0,135	2,976	3,967	43
W26-29	3,447	0,374	2,760	-1,368	2,133	3,931	44
W30-33	3,388	0,516	0,852	-1,213	2,097	4,145	44
W34-37	3,557	0,423	0,925	-0,365	2,286	4,325	44
W38-41	3,480	0,455	0,919	-0,379	2,060	4,221	44
W42-45	3,667	0,211	-0,714	0,097	3,196	4,031	43
W46-49	3,681	0,227	0,002	0,488	3,297	4,300	40
W50-52	3,683	0,310	1,522	1,216	3,222	4,468	30

Table 3: Descriptive statistics for the grouped weekly logarithmic transformed load in Norway from 02.06.2003 to 31.10.2013

	Mean	St. Dev.	Kurtosis	Skewness	Min	Max	Count
W2-5	14,920	0,073	0,111	0,657	14,804	15,095	40
W6-9	14,913	0,063	-1,034	-0,033	14,792	15,025	40
W10-13	14,830	0,070	-0,395	-0,122	14,686	14,959	40
W14-17	14,682	0,073	-0,224	-0,344	14,505	14,804	40
W18-21	14,546	0,061	-0,148	0,270	14,427	14,706	40
W22-25	14,452	0,058	4,323	-1,623	14,224	14,528	43
W26-29	14,390	0,054	-0,068	-0,430	14,261	14,498	44
W30-33	14,365	0,056	-0,254	-0,582	14,236	14,457	44
W34-37	14,453	0,052	-0,558	0,154	14,355	14,558	44
W38-41	14,559	0,069	-0,523	-0,177	14,423	14,705	44
W42-45	14,701	0,080	6,396	-1,750	14,364	14,830	43
W46-49	14,818	0,094	0,499	0,741	14,665	15,068	40
W50-52	14,881	0,092	-0,981	0,277	14,731	15,050	30

Examining the price-load relationship, seasonality becomes more prominent when studying the scatter plots of the price and load for the different week groups. The difference between winter and summer is highly apparent and is illustrated by the plots of weeks 50-52 (December) and weeks 26-29 (July), figures 2 and 3 respectively. Examining the scatter plot for weeks 50-52, it seems to be a linear dependency between the logarithmic transformed price and load. For weeks 26-29, however, no such trend is prominent. The tendency of a more linear relationship is also observed for the other winter months, see appendix [8.1]. Overall, the linear trend seems to be strongest in December through March, and weakening when approaching summer from each side, where the linearity seemingly is non-existent. Analyzing the correlation, an equal trend is apparent, as seen from figure 4.

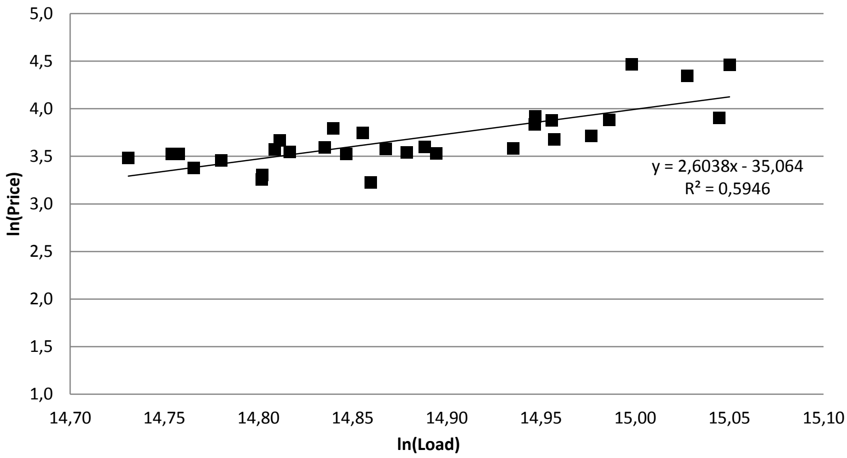

Figure 2: Scatter plot for the grouped weekly logarithmic transformed price and load in Norway for weeks 50-52 from 02.06.2003 to 31.10.2013

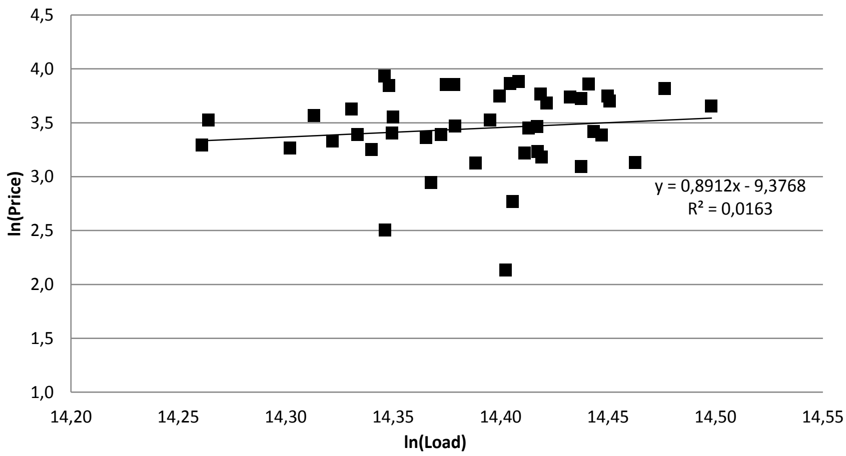

Figure 3: Scatter plot for the grouped weekly logarithmic transformed price and load in Norway for weeks 26-29 from 02.06.2003 to 31.10.2013

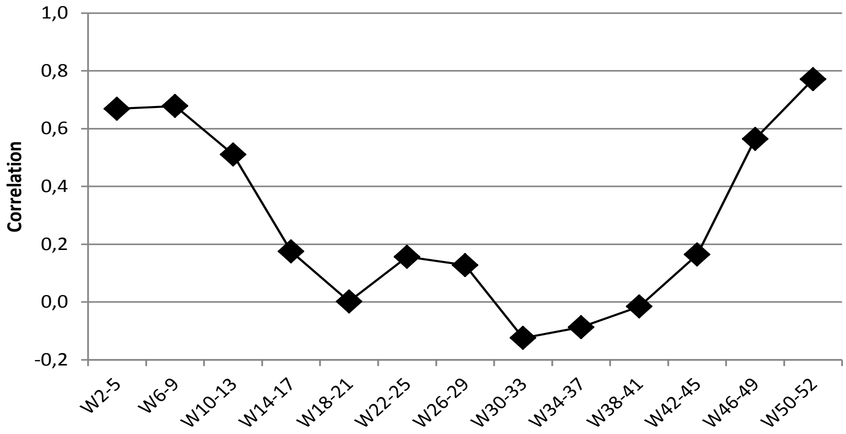

Figure 4: Correlation for the grouped weekly logarithmic transformed price and load in Norway from 02.06.2003 to 31.10.2013

3.2 Linear Regression

Cartea and Villaplana (2008) allege that price increases with demand. This is ostensible in figure 1 during parts of the sample period, particularly in winter periods with high load. However, to be able to presume something more explicit about the price-load relationship, a more detailed analysis has to be derived. From the scatter plots, a tendency of a linear relationship in the winter months is observed. To further examine this trend, a regression is run on the different week groups using ANOVA software, see appendices [3.1] and [9.1]. The logarithmic price is the dependent variable and the logarithmic load is the explanatory variable. Examining both the beta coefficient and the R^2 value from the estimated regression models (figures 5 and 6), a clear seasonal trend is apparent. As underlined earlier, the beta coefficient is interpreted as the price elasticity. Moving from late summer towards winter, the price elasticity increases and peaks around February (weeks 6-9), before it declines as spring is approached. For the rest of the year, the beta coefficient is much lower and even negative in some periods. Consequently, the sensitivity of the price to load is largest in the winter.

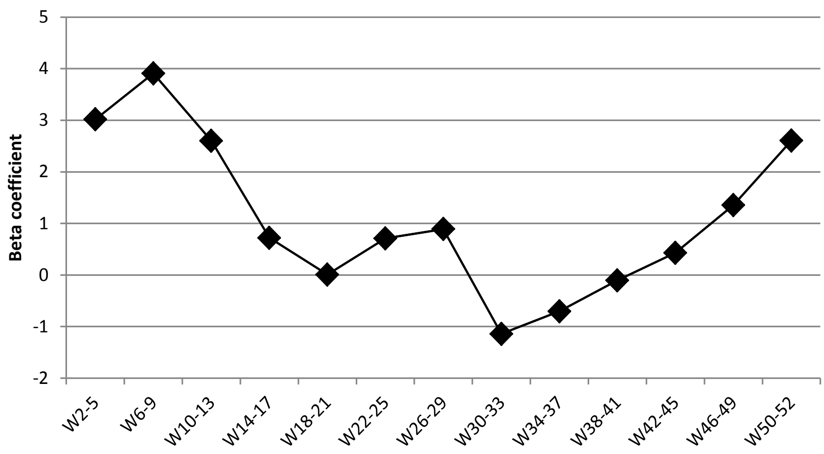

Figure 5: Beta coefficients for the grouped weekly logarithmic transformed price and load in Norway from 02.06.2003 to 31.10.2013

A similar trend is again found when evaluating R^2. The fit of the regression in the winter is very good, especially for week groups 2-5, 6-9 and 50-52. For the rest of the year, however, the fit of the regression is really poor and approximately zero. This further underlines the presence of a seasonal trend; with a linear dependency during the winter and a weak to non-existing linearity for the rest of the year.

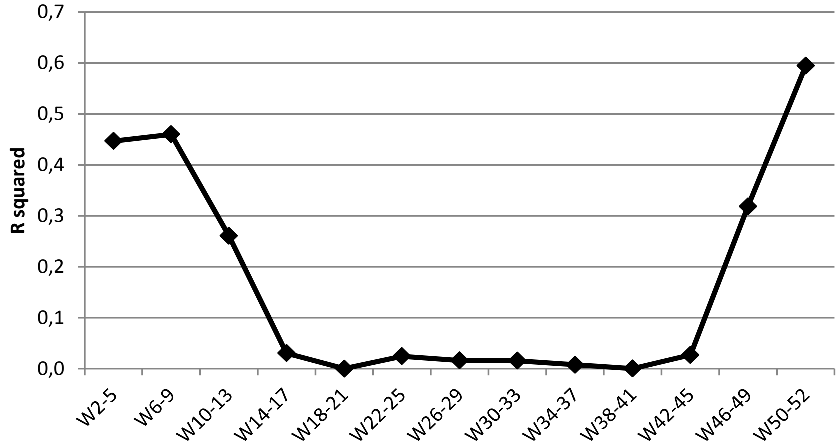

Figure 6: R^2 values for the grouped weekly logarithmic transformed price and load in Norway from 02.06.2003 to 31.10.2013

3.3 Significance Tests

Before drawing any conclusions, the significance of the regression models (beta coefficient and R^2 value) needs to be evaluated. The significance of the beta coefficient is examined by applying a t-test, which indicates whether the coefficient should be included in the model or not, see appendix [3.2].[6] For the winter week groups (weeks 46 through 13), the t-statistics for all the beta coefficients are significant at a 1% level as their test statistics exceed the two-sided critical value (2,70), see table A10 in appendix [9.1] for further details. The beta coefficients for the rest of the year are not significant, as also indicated by the scatter plots. The significance of the R^2 value is evaluated by an F-test, see appendix [3.3]. The same seasonal pattern as for R^2 is discovered, which is rational as we only deal with one explanatory variable. The F values in the winter months exceed the critical value at a 1% significant level (7,31), while the null hypothesis are not rejected for the rest of the year, see appendix [9.1]. Hence, the test results support both the observed trend of a linear dependency during the winter, and the weak to non-existing linear relation for the rest of the year.

To examine whether the hypothesis testing and model evaluation formerly prescribed are reliable or not, the accuracy of the estimated t-statistics and F values has to be tested. The accuracy is evaluated by performing five tests on the regression residuals: (1) a Jarque-Bera test for normality, (2) a hetero-X test for cross-correlation, (3) an AR test for autocorrelation, (4) an ARCH test for heteroscedasticity, and (5) a RESET test for non-linearity, see appendix [3.4]. From the discussion performed in appendix [9.3.1], we conclude that the assumptions about the residuals are satisfied for most week groups. All the residuals satisfy tests (1), (2) and (5), while tests (3) and (4) are mostly satisfied. Heteroscedasticity and autocorrelation are only evident in the summer, where the F values, and also t-statistics, are far from being significant. Thus the conclusions drawn are not affected, even though some of the residual tests are violated. To sum up, the residual specification tests verify that the estimated t-statistics and F values of the regression models are reliable, thus supporting the seasonality found in 3.2.

[6] The intercept coefficient, alpha, is not evaluated. This is a regression constant, which does not provide critical information about the price-load relationship.

3.4 Explaining the Seasonality in the Price-Load Relation

There are several factors that might contribute to explain the seasonal dependency between price and load. As for the case of the linear trend during the cold winter months, the market for this period has a tendency of being more *demand-driven*. Short-term inelasticity of demand and a rise in load combined with constraints in the system capacity, may lead to an increased usage of conventional fuels in electricity production, as exemplified by the import of electricity from gas or coal. As illustrated by the supply stack curve in figure 7, the fuels with lower marginal costs are utilized first. The use of conventional fuels with higher marginal costs than hydropower will therefore lead to a rise in the electricity price. Furthermore, the increased consumption in the winter results in a shift in the demand curve to the right. This leads to an equilibrium point further to the right at the steeper side of the supply stack curve, compared to the summer months with lower load. Hence, an increase in the load will lead to an increase in the price (and vice versa), as underlined by the higher price elasticity for the winter months.

During the summer, however, the equilibrium point is placed further to the left at the horizontal part of the supply curve due to the lower load. Thus, a change in demand will not affect the price as much as it would during the winter months, as underlined by the lower price elasticity. Contradictory to the winter, the system is more *supply-driven* during the summer. As hydropower producers want to sell their production at the highest possible price, they prefer to store water in the reservoirs during summer and fall, and produce at high prices during winter. The summer production is thus more dependent on precipitation and inflow. In wet years, larger amounts ought to be produced to avoid reservoir overflow. The opposite occurs in dry years, as producers then will save as much water as possible for the winter. Thus, these two cases may influence the price in opposite direction.

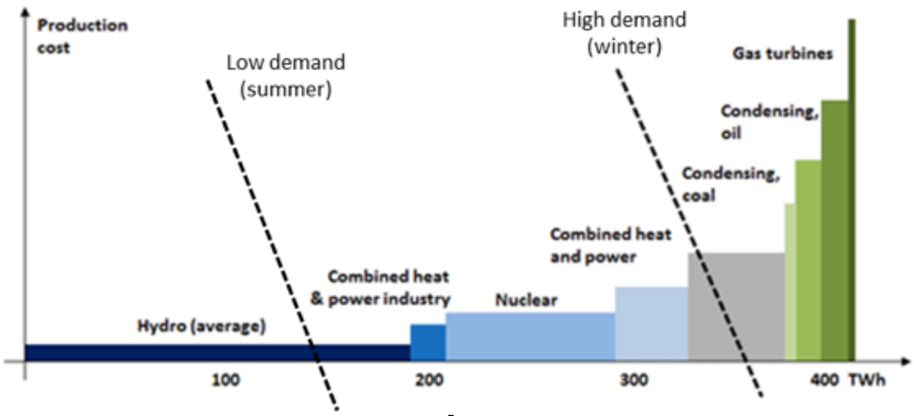

Figure 7: The supply stack curve at Nord Pool[7] together with the approximately inelastic demand curve varying with seasons.

Nevertheless, the Norwegian price and load dynamics should not be analyzed without considering the rest of the European power system, which are highly interconnected. Import and export between different regions occur on a regular basis to balance out the demand. Hence, the price, production and demand in one system influence the other interconnected systems. This includes prices of other energy sources as coal, oil and renewable energy. In periods where a system is close to its capacity limits, as can happen during cold winters, import could be necessary to cover demand and prevent undesirable price peaks. The opposite

[7] Source: Nord Pool, downloaded from http://www.nordpoolspot.com/How-does-it-work/The-market-members/Producers/

may occur with export. Consequently the price and load dynamics in Norway are not only a result of the Norwegian system characteristics, and this should be kept in mind when further considering the findings of this analysis.

3.5 Dividing into North and South Norway

The Norwegian electricity market is now separated into two areas that are to be further analyzed: North and South Norway, see appendix [1]. Performing the same analysis as for the aggregated system, a seasonal trend is also present in these two areas; with a linear dependency during the winter and a weak to non-existing linearity for the rest of the year, see appendices [7]-[9]. However, there are some remarkable differences between the two areas.

The price and load series for the two areas are plotted in figure A5, appendix [5.2], and figure A8, appendix [5.3]. The load in the South is more than the double of the load in North, due to that most of the population and industry are placed in this area. Besides, the North experiences both higher average prices, almost 7% higher than in South, in addition to a higher standard deviation, see appendices [7.2] and [7.3]. This could be explained by the fact that the Northern part of Norway usually experience colder weather and longer winters. In addition, given the geographical structure with long distances and a more dispersed consumption, there are limitations in the transmission and flexibility. Given the inelastic demand, this could lead to both higher and more volatile prices.

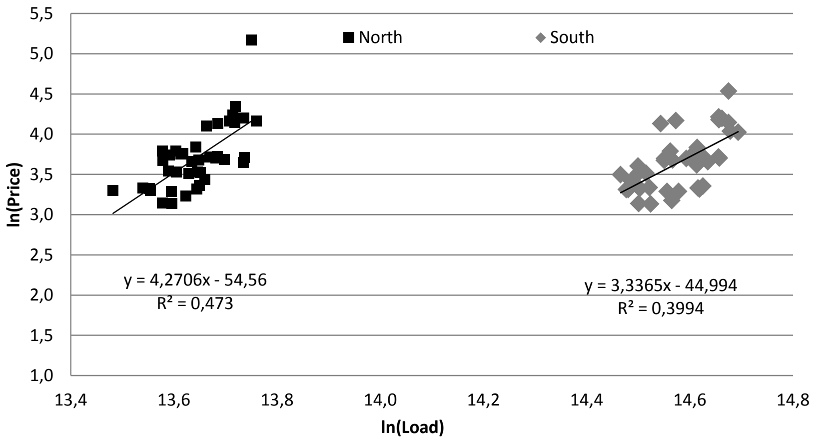

Figure 8: Scatter plots for the grouped weekly logarithmic transformed price and load in North and South Norway for weeks 6-9 from 02.06.2003 to 31.10.2013

Further, when examining the scatter plots and the linear regression models, a clear pattern evolves. The regression betas, representing the price elasticity, are found to be higher in the North than in the South. This trend is consistent, except for weeks 26-29, as seen from figure A20 in appendix [9.2]. The tendency is also shown by the steeper regression lines in the North, particularly during the winter, as illustrated by the scatter plot in figure 8 (see appendix [8.2] for further details). The regression fit for the winter months, specified by the R^2 value, is also calculated to be better in the North, as seen from figure A21 in appendix [9.2]. Thus there are indications of a stronger linear relationship in the winter months in the North compared to the South. This can be explained by the well-known supply stack structure. Due to the colder climate, a more dispersed load and transmission limitations, the system in the North is less flexible. Hence, the equilibrium is located more to the right at the steeper side of the supply stack curve, leading to a more demand-sensitive system.

4 Optimizing Seasonal Hedge Ratios

4.1 Hydropower Producer Cash Flow

Hydropower producers sell electricity, thus wanting the price to be as high as possible. Revenue is dependent on price and production, and a significant decrease in either can greatly reduce cash flow. With the particularly strong correlation found between price and load during the winter, the cash flow could be even more sensitive in this period compared to the rest of the year. Hence, the seasonal tendencies found in the price-load relation may implicate that there also are seasonal variations in the optimal hedging strategy, requiring different hedge ratios for summer and winter.

To account for potential price falls, hydropower producers can compose a hedging portfolio of short positions through derivatives and long positions from expected sold production volume. Power producers in Norway prominently use futures and forwards at the Nordic exchange (Sanda et al., 2013). The analysis in this thesis is limited to forwards as we choose to have a long-term perspective. The total revenue from the hedged portfolio with forward contracts and sold volume[8] can be formulated as

$$Revenue = S_T \cdot Q - h(S_T - F_t) \cdot Q, \qquad (1)$$

where h is the optimal hedge ratio, representing the proportion of volume sold through financial derivatives, Q the volume sold, F_t the forward price at time t and S_T the spot price at maturity.

The Norwegian hydropower producers are exposed to governmental regulations that affect both operational and financial risk management. As mentioned, these include license power and the natural resource tax of 31% in addition to the standard corporate tax of 27%, creating an asymmetry. However, license power can be excluded in this analysis, as this power is not exposed to market uncertainty. Assuming taxation represents the only cost,[9] the total costs can be formulated as

$$Costs = revenue \cdot tax_c + S_T \cdot Q \cdot tax_n, \qquad (2)$$

where tax_c is the corporate tax of 27% and tax_n the natural resource tax of 31%.

In this analysis cash flow represents the difference between revenue and costs, and is the foundation when optimizing hedging strategies.[10]

4.2 Risk Metrics

This study focuses on the cash flow function derived, and attempts to optimize the hedge ratio h with respect to three predetermined risk metrics: mean-variance, semivariance and Conditional Value at Risk (CVaR). These risk metrics are considered for several reasons. Mean-variance[11] measures the dispersion of cash flow from the mean, and is well established and widely used in practice due to its plainness (Zenios, 2008). A drawback is that downside and upside potential are equally weighted. As mentioned, according to Stulz (1996) the goal of hedging is to eliminate downside risk. Sanda et al. (2013) also argue that downside risk

[8] As explained in section 2.1, load data is used. Hence, this is considered as the sold volume.

[9] Variable costs are approximately zero for hydropower producers. For the purpose of simplicity, all other costs including transaction costs are disregarded. Moreover, as prices at the Nordic exchange are noted in Euros, a Norwegian producer will be exposed to currency risk from the NOK-EUR exchange rate. However, this analysis is carried out in Euros, and thus the currency risk is not considered.

[10] In this analysis cash flow is equivalent to profit.

[11] Optimization model for mean-variance: $minimize\ \sigma^2 = \frac{1}{N} \cdot \sum_{t=1}^{N}(x_t - \bar{x})^2$, where x is the cash flow function in 4.1 containing the hedge ratio h as a variable.

metrics are preferred because of risk aversion among stakeholders. Semivariance[12] is thus a better risk metric as it measures the dispersion of cash flow that falls below the mean. Hence, by minimizing semivariance the likelihood of a large loss is reduced, while the upper potential is more preserved, as opposed to minimizing mean-variance. CVaR is the final risk metric, being the weighted average of VaR[13] and losses exceeding VaR. Nowadays VaR is one of the most popular and accepted risk measures. Still, it has some serious mathematical limitations (non-convex, non-smooth and multiple local minima), which makes it hard to optimize and control (Larsen, Mausser, & Uryasev, 2002; Zenios, 2008). Besides, VaR does not reveal anything about the magnitude of the losses outside the given confidence level. CVaR is a more coherent risk measure (elaborately described in Rockafellar and Uryasev (2000)), and primarily due to its convexity it can be efficiently optimized using linear programming techniques. Optimizing CVaR may provide a portfolio that is less exposed to extreme losses than merely optimizing VaR (Dahlgren, Liu, & Lawarree, 2003). Moreover, it accounts for downside risk in a more comprehensive way than semivariance as it considers the expected maximum loss instead of the cash flow below the mean. Hence, CVaR describes the tail risk better and is considered to be the most reasonable metric from a risk management perspective. According to Larsen et al. (2002), CVaR can be reduced by minimizing the following function (the minimum of $F_\alpha(x,\zeta)$ equals to the minimum of CVaR)

$$F_\alpha(x,\zeta) = \zeta + \frac{1}{1-\alpha} E\{[f(x,y) - \zeta]^+\}, \qquad (3)$$

where $a^+ = max\{0, a\}$, α represents the predetermined significance level, ζ the VaR, x the electricity price data, y the corresponding load data and f(x,y) the cash flow loss function. Thus considering the right tail risk. However, in this analysis we are dealing with producers having long positions through physical sale. Hence, we consider the left tail of the profit distribution and want to maximize CVaR, which now is a concave function. Therefore we minimize $-F_\alpha(x,\zeta)$. In this context CVaR represents the lower bound for VaR. Thus a maximization of CVaR also increases VaR, which means that the expected downside profit is enlarged.

4.3 Optimizing Hedge Ratios

4.3.1 The Decision Problem

Given that price and load are main factors in the revenue function, the strong correlation found in the price-load relationship during the winter provides a more sensitive cash flow. Consequently it is natural to expect an increased hedge ratio in this period compared to the rest of the year to achieve the same level of predictability. The hypothesis, however, has to be verified by a thorough analysis. This section aims to do this by studying optimal hedge ratios, emphasizing seasonal variations.

There are a variety of financial contracts available, which differ in many ways as in type, size and time horizon. Producers use combinations of several different contracts, and there are a number of ways to combine these. To be able to perform the optimization, simplifications are necessary. Hence, we choose to utilize one type of contract throughout the analysis. As we are analyzing weekly prices and loads in week groups, weekly forwards are seemingly optimal to use. However, weekly contracts are only traded 6 weeks ahead of delivery (NASDAQOMX, 2014). In such short-term perspective, the correlation between the forward and the spot is quite strong, and thus the hedging effect is reduced. This is also the

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[12]Optimization model for semivariance: $minimize\ \sigma_{semi}^2 = \frac{1}{n} \cdot \sum_{x_t<\bar{x}}^{n} (x_t - \bar{x})^2$, where x is the cash flow function in 4.1 containing the hedge ratio h as a variable.

[13] Value at Risk (VaR) is an estimate of the maximum loss during a standardized period that would be exceeded with a small probability α (elaborately described in Alexander (2008c) and Zenios (2008)).

case for the shortest monthly contracts, trading only a few months ahead. However, monthly contracts are considered to be among the more liquid contracts and are frequently used by Norwegian hydropower producers (Sanda et al., 2013). Consequently, to preserve a more long-term perspective and attain a greater hedging effect while still using a liquid contract, the monthly forward trading 6 months ahead is chosen. Quarterly and yearly contracts of shorter term are also considered to be liquid and are often utilized, but given their time resolution they do not capture the seasonality as well as monthly contracts. Hence, the input to the analysis is the prices of rolling monthly forwards (6-pos) at Nord Pool[14] (ReutersEcoWin, 2014), together with the previously studied weekly prices and loads in Norway.[15]

The decision problem faced by the hydropower producer in this analysis is to find the optimal hedge ratio for future production. Six months ahead of the physical sale, the producer has to estimate the proportion of production to be hedged through sale of forwards.[16] Cash flow (revenue minus costs) lays the foundation for the optimization of hedge ratios. For each week group, the cash flow from the physical sale and hedging activities is calculated. By using the hedge ratio as a variable, the three risk metrics (mean-variance, semivariance and CVaR) are optimized using the Excel Solver. In the following, the most important findings are presented.

4.3.2 Optimal Hedge Ratios for Different Risk Metrics

Studying the optimal hedge ratio from the CVaR optimization[17] in figure 9, seasonality is apparent. As expected, the hedge ratio is significantly higher for the winter months than for the rest of the year.

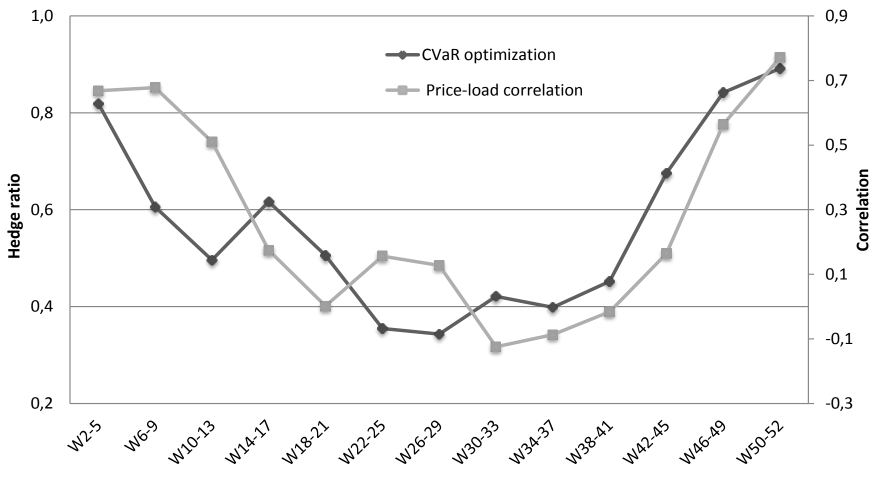

Figure 9: Price-load correlation (from figure 4) vs. optimized hedge ratios based on CVaR from 01.03.2004 to 31.10.2013

The seasonal trend clearly resembles the one found for the price-load correlation. The values are highest during December and January, and decline when approaching summer from each side. Hence, as claimed earlier, the price-load correlation seems to influence the

[14] The forward prices are converted into weekly prices using arithmetic average. However, as data for the monthly contract is not available for the first four months, this part of the analysis starts 01.03.2004 (week 10).
[15] The data is analysed using the same week groups as described in section 3.1.
[16] With reference to the revenue function, the producer receives the predetermined forward price for the hedged production, while the physical production is priced at the week's average spot price. E.g. when a producer hedge the production in week 27, the production sold is priced at the spot price for week 27, while the price of the hedged production equals the forward price in week 1, six months earlier.
[17] 10% CVaR is used in the optimization.

optimal hedge ratio. Due to the strong correlation between price and load in the winter, cash flow becomes more sensitive to changes in either. This increased sensitivity implies a need for a higher hedge ratio. However, when the correlation approximates zero, as for summer months, there is a reduced need to hedge through financial instruments, and consequently the hedge ratio is lower.

However, the hedge ratios from the optimization of mean-variance and semivariance (figures A24 and A25 in appendix [11.1]) do not exhibit a seasonality as clear as for the CVaR optimization. These risk metrics experience just a small decline in hedge ratio from winter to summer, and the ratio during summer and early fall is less stable with an increasing tendency. Yet, the hedge ratio generated from semivariance is more similar to the CVaR ratio compared to the mean-variance ratio. With a higher hedge ratio during the winter compared to mean-variance, semivariance provides a more apparent decline from winter to summer.

It is to be expected that the three risk metrics provide somewhat different results, as they consider different parts of the cash flow distribution. CVaR only deals with the lower tail of the distribution, as opposed to semivariance and mean-variance considering the lower half and whole distribution respectively. Hence, it is reasonable to assume that the hedge ratio generated from CVaR is more sensitive to the seasonality in the price and load dynamics compared to semivariance and mean-variance, the latter being the least sensitive. Consequently, changes in measures of variability like skewness and kurtosis are better reflected by CVaR, and may be used to explain the difference in the optimization results, together with price-load correlation.[18] Price skewness is particularly interesting, exhibiting a prominent seasonality highlighted in 3.1. This skewness was found to be more positive during winter while declining and being negative during summer. The increased probability of high extreme prices during winter combined with the high correlation in this period, result in a more sensitive cash flow. This is better captured by the CVaR optimization, which may explain the higher optimal hedge ratio compared to the other risk metrics. Another possible explanation is the tendency of the monthly forward price to exceed the average spot price, particularly during winter, see figure A23 in appendix [10.2]. This could be a result of the fact that many consumers, particularly industrial companies, want to hedge against price peaks during winter, thus being willing to pay a premium to reduce the risk.[19] In the CVaR optimization, expected downside profit is maximized. Thus, if the forward price exceeds the spot price, the optimal hedge ratio increases. The hedge ratios generated from the other risk metrics, however, are not affected in the same way as the optimizations aim to reduce the variance of the profit distribution, not to increase the profit itself.

The cash flow corresponding to the optimal hedge ratio is highest during winter and lowest during summer, see figure A33 in appendix [11.3]. This is expected as most hydropower is produced at high prices during winter. Worth noting, however, is that the CVaR optimization yields a 3,5% and 2,8% higher cash flow than the optimization of mean-variance and semivariance respectively. This is a result of CVaR's ability to reduce downside risk the most, while allowing for upside potential, which is advantageous from a profit perspective. Consequently, in addition to being a more reasonable risk metric as underlined in 4.2, CVaR outperforms the other risk metrics with respect to overall profit. Despite this, simpler risk metrics like mean-variance may be preferred as they are easier to deal with. Nevertheless, as highlighted here, there are strong incentives for choosing CVaR as a risk metric.

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[18] For mean-variance and semivariance the optimal hedge ratio suddenly decreases from weeks 38-41 to weeks 42-45, see figures A24 and A25 in appendix [11.1]. An explanation for this might be that these two are less sensitive to the increase in correlation (from -0,02 to 0,16) together with the decrease in price kurtosis (from 0,92 to -0,71).

[19] This tendency, however, diminish as the maturity of the contracts increases. The liquidity decreases with maturity, and for the longest yearly forwards the producer may have to pay a premium to hedge.

4.3.3 Sensitivity Analysis

To better understand the behavior of the hedge ratio optimization, a sensitivity analysis is performed on the different risk metrics. Studying the sensitivity of the average weekly cash flow to the hedge ratio based on CVaR, see figure 10, seasonality is apparent. A positive relation is evident in the winter (W50-9), while the slope is almost flat in the summer (W22-33). Figure A31 in appendix [11.2] shows that the positive relation during the winter weakens when approaching summer from each side, illustrated by less steeper curves. This seasonal trend is similar for all risk metrics, see appendix [11.2].

The positive cash flow relation may again be explained by the tendency of the monthly forward price to exceed the average spot price, particularly during winter. Accordingly, the cash flow increases with hedge ratio, and the producer seemingly gains on undertaking hedging. This is amplified in the winter by the larger and more correlated prices and loads, resulting in substantial cash flows. These results are in accordance with Sanda et al. (2013), finding that hedging may add value for hydropower producers. Although the results are consistent, the explanations are somewhat different due to dissimilar approaches. As our analysis is based on optimizing historical data on an aggregated level, and not individual producers' actual hedging activities, selective hedging and basis risk are not among the factors present.

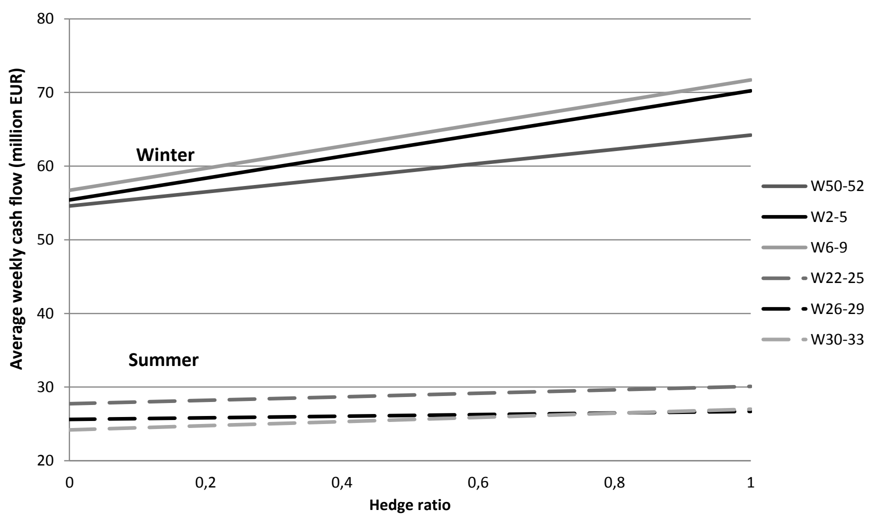

Figure 10: Average weekly cash flow for summer and winter weeks with varying hedge ratio based on CVaR optimization, from 01.03.2004 to 31.10.2013

Even though a high hedge ratio may seem like a better strategy, this is not the full truth. Taking the cash flow variance into account, the decision problem gets a new dimension. The sensitivity of the mean-variance to the hedge ratio is shown in figure 11. Here the optimal hedge ratio is found at the curve's lower point, yielding the minimum cash flow variance, which increases the predictability of the cash flows and adds value by relaxing stakeholder risk aversion. Again the seasonality is prominent, the winter months being significantly more sensitive to changes in hedge ratio compared to the summer months. In the winter the variance strongly increases when the hedge ratio is lower or higher than the optimal ratio. In the summer, however, altering the hedge ratio will not affect the cash flow variance as much. The same tendencies are found with respect to semivariance and CVaR, the latter having an optimal strategy at the summit, see appendix [11.2]. The higher sensitivity in the winter is caused by larger absolute values and changes in cash flow during this period, which again is a result of the larger and more correlated prices and loads. This as opposed to the summer with lower and uncorrelated prices and loads.

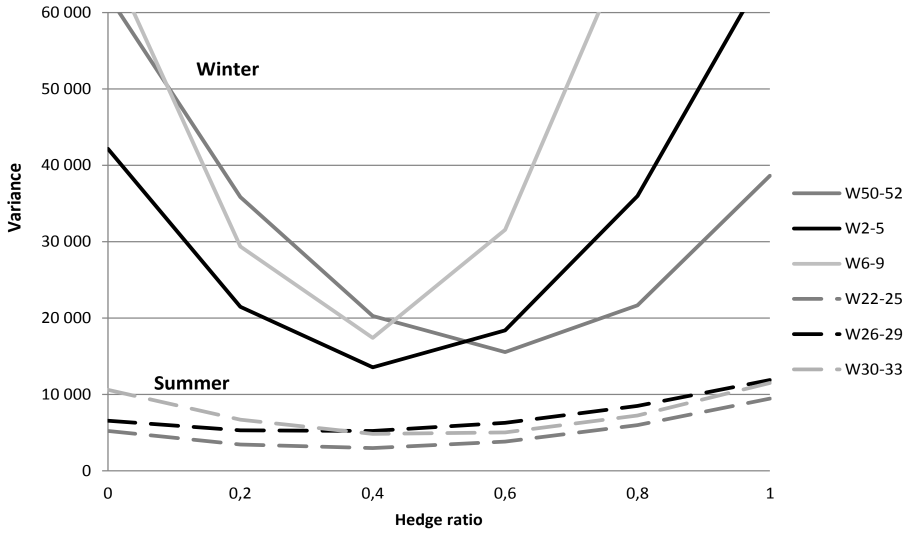

Figure 11: Cash flow variance for summer and winter weeks with varying hedge ratio based on mean-variance optimization, from 01.03.2004 to 31.10.2013

As emphasized, the ideal strategy is to attain the exact optimal hedge ratio. However, due to the positive relation between cash flow and hedge ratio, the producer may be better off by over-hedging than under-hedging, this effect being strongest during winter and weakest during summer. However, for risk-averse producers, altering the hedge ratio can be risky as the cash flow volatility may increase, particularly during the winter. The choice of hedge ratio during summer has less influence on cash flow volatility, and consequently the cash flow gained will not vary as significantly.

4.3.4 North and South Analysis

The analysis is extended by again separating into North and South Norway. The CVaR optimization done on the aggregated system is also performed on the two areas using the same forward prices. The optimal hedge ratios for the two areas exhibit a similar seasonal trend, being highest during winter and lowest during summer, see figure A34 in appendix [11.4]. The hedge ratio in the South follows the aggregated ratio closely for all week groups, while North deviates with lower ratios in some week groups. The fact that the hedge ratios in the South are more similar to the aggregated ratios is expected as South makes up approximately two-thirds of the aggregated volume. The somewhat differing ratios in the North may be explained by two factors: correlation and spot prices. As seen from figure A17 in appendix [8.3], the Northern area exhibits a higher price-load correlation for most of the year. Hence, it is reasonable to assume higher optimal hedge ratios in the North. On the other hand, the average price in the North is almost 7% higher than in South. The higher spot price together with the constant forward price, imply a lower hedge ratio as less is earned from hedging. This contributes to lowering the optimal ratios in the North compared to the South. Consequently, the differences in correlation and spot price work in opposite directions; the higher correlation in the North forces the hedge ratio up, while the higher spot prices drive the ratio down. As the Northern ratio is lower for several week groups, weeks 50-5 and 30-41 being most prominent, this may indicate that the price difference has a stronger influence on the optimal hedge ratio than the difference in correlation in these periods.

5 Seasonal Hedging Strategies

5.1 Gains From Seasonal Hedging Strategies

The majority of the Norwegian hydropower companies tend to apply a hedge ratio range or a specific hedge ratio target. According to Sanda et al. (2013), all but one of the hydropower companies studied did not specify the hedge ratio to vary with seasons in their hedging policies. There may be several reasons for this. Firstly, the producers may not have seen the need to take seasonality into account and adjust their hedge ratio accordingly. Secondly, a constant range or target may be easier to deal with, making the implementation simpler. Moreover, transaction costs and liquidity concerns can make the use of dynamic hedging strategies more complex (Näsäkkälä & Keppo, 2005a).

Having a static hedging strategy, however, does not necessarily result in a constant hedge ratio throughout the year. Due to the seasonal varying electricity consumption, hedging of a fixed power size throughout the year may result in a varying hedge ratio. With higher production during winter, the hedge ratio becomes considerably lower compared to the summer with lower production. Consequently, hedging of a fixed volume can result in a seasonal varying hedge ratio completely opposite of what we find to be optimal.

To underline the gain from implementing a more dynamic hedging strategy, the optimal hedge ratios presented in figure 9 are compared to a constant hedge ratio, which is optimized based on the entire data set. With respect to CVaR, being the superior risk metric, the constant hedge ratio is found to be 0,49, see figure 12.

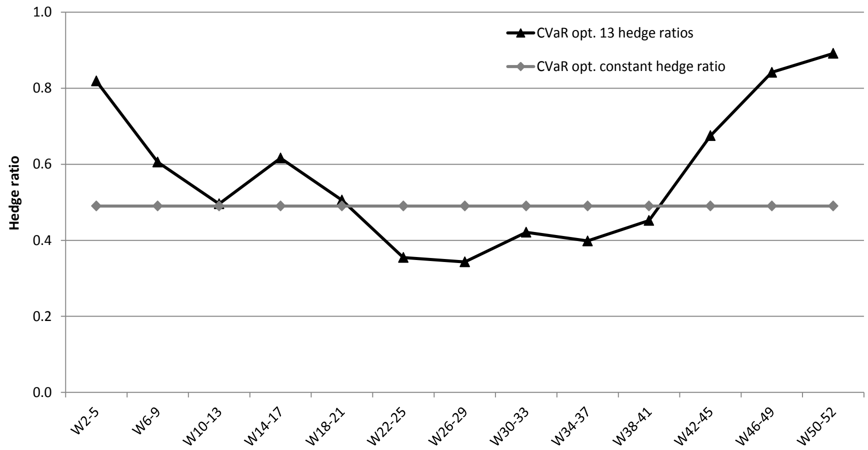

Figure 12: Constant hedge ratio vs. 13 seasonal hedge ratios based on CVaR optimization in Norway from 01.03.2004 to 31.10.2013

Compared to the constant hedge ratio, the seasonal varying hedge ratio yields an increase of 6,5% of the expected downside cash flow and 2,5% of the overall profit. Moreover, the total variance is higher with the dynamic CVaR optimization, even though downside risk is more reduced. This may be explained by a better preservation of the upside potential. A dynamic strategy proves advantageous also for the other risk metrics. Utilizing a constant hedge ratio increases both semivariance with 27% and mean-variance with 11%, as well as reducing the profit, see table A16 in appendix [11.5]. Consequently, there are strong incentives for hydropower producers to take seasonality into account when developing hedging strategies. In this way unwanted risk is reduced and profit simultaneously increased.

5.2 Implementing Seasonal Hedging Strategies

5.2.1 Merging into Four Seasonal Hedge Ratios

As concluded in the previous section, seasonal hedging strategies ought to be implemented. The remaining question is how this should be done. So far 13 optimal hedge ratios have been estimated, corresponding to the different week groups. However, such comprehensive division may be difficult to implement from a producer's perspective. Thus, to get a more holistic picture of the optimal hedge ratio dynamics, the analysis is extended for the CVaR optimization by utilizing seasons instead of week groups. Consequently the weeks are merged into four groups as a replication of seasons. Each group comprises weeks of similar correlation.[20]

Figure 13 presents the optimal hedge ratio based on the merged week groups, and there is a clear seasonal trend. The hedge ratio from the CVaR optimization is highest during winter (0,63) and lowest during summer (0,38). The ratios for spring and fall are in-between these values, with spring (0,48) being somewhat higher than fall (0,43), explained by a slightly higher correlation during spring. Hence, these results further support the argument of a higher hedge ratio during the winter months. When comparing the effect on both expected downside cash flow and overall cash flow, the results of the hedging strategy with four seasonal hedge ratios exceed the results of the constant hedge ratio from 5.1, see tables A17 and A18 in appendix [11.5]. Again, this emphasizes the possible gain from utilizing a seasonal varying hedge ratio throughout the year. However, compared to the original seasonal hedge ratios corresponding to each week group, the four seasonal hedge ratios perform slightly poorer, with 1,6% reduction in profit and 3,0% lower CVaR. Clearly, a more fine-tuned hedge ratio may result in increased gain. However, there should be a trade-off between this gain and the intricacy of implementation and execution of the desired hedging strategy.

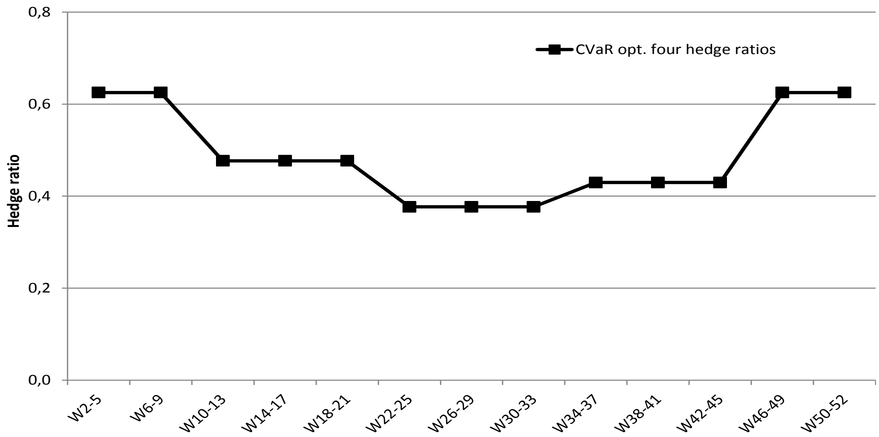

Figure 13: Four seasonal hedge ratios based on CVaR optimization in Norway from 01.03.2004 to 31.10.2013

5.2.2 Individual Considerations

In this study historical data from the Norwegian market is used as a case to emphasize the gains from considering seasonality in risk management. However, to assume that our findings are directly applicable for all hydropower producers today is not realistic. The producers are exposed to other risk factors not considered in this analysis. Inflow,

[20] The weeks are merged as follows. Winter: W46-13, spring: W14-21, summer: 22-33, fall: 34-45.

reservoir capacity and generation capacity vary from producer to producer. Further, price may differ between price areas due to congestion and differences in production capacity and demand. The physical production is given the area price, while the system price serves as the underlying in the financial market. This basis risk could be hedged through Contracts for Difference (CfDs), but as Sanda et al. (2013) highlight, these contracts are rarely used as they suffer from low liquidity. Moreover, volume risk is present. As future production is uncertain, it may be difficult to achieve the hedge ratio desired when hedging a long time ahead of maturity. Usually the producers utilize a combination of different contracts (yearly, quarterly and monthly being the most common) and begin the hedging process a couple of years ahead by hedging a part of the volume using yearly contracts. Then the hedge ratio is fine-tuned using contracts of shorter term as maturity approaches. Long-term contracts are less correlated with the spot price and also tend to be less liquid, which often leads to an increased premium. This may result in a lower optimal hedge ratio in reality compared to what is found to be optimal in this analysis, where only a (6-pos) monthly contract is used.

Nevertheless, although this study does not comprise the above-mentioned risk factors, it still contributes by showing that seasonal varying hedge ratios ought to be implemented in a hydropower producer's hedging strategy. The optimal hedge ratios should however be estimated by the individual producers according to their capacities, overall business strategy and operational plans. With such individual fine-tuning, a producer could gain even more from implementing a seasonal hedging strategy than what is yielded in this analysis.

6 Conclusion

This thesis examines optimal hedging strategies for hydropower producers in the Norwegian electricity market, emphasizing seasonality in the price-load relationship and risk metric evaluations.

Analyzing data spanning over a decade, the stand-alone characteristics of the electricity price and load are found to coincide with the usual characteristics. A mean reverting seasonal trend is clear, with price and load being highest during winter and lowest during summer. The price is particularly volatile, and the daily price returns are leptokurtic, which is in accordance with the relatively frequent appearance of extreme electricity prices. Positive price skewness is evident during winter, implying an enlarged probability of high extreme values in this period.

Whilst there are many studies on the stand-alone price and load, there are fewer studies on the relationship between the two. Investigating the price-load relation, a prominent seasonal trend is found. Scatter plots of the logarithmic transformed weekly price and load indicate a linear dependency during the winter months. This linearity weakens when approaching summer from each side, where the linearity is non-existent. These findings are supported by linear regression models, which are verified by statistical tests to be significant and reliable. The correlation and the beta coefficient from the regressions, which here can be interpreted as the price elasticity, follow the same seasonal trend. The observed seasonality is explained by the characteristic supply stack and varying demand throughout the year. The increased consumption in the winter results in a shift in demand to the right, where the supply curve is steeper. Thus, the price is demand-driven, and an increase in load results in an increase in price. Due to the lower load during summer, the equilibrium point settles more to the left, at the horizontal part of the supply curve. Hence, a change in demand will not affect the price as much as in the winter, resulting in a more supply-driven price. Comparing North and South Norway, the North experiences both higher average prices and a higher standard deviation. The linear dependency in the price-load relation for the winter months is also stronger in this region with consistently larger beta coefficients. This is due to the colder climate and limited flexibility in the North, leading to a more demand-sensitive system as the equilibrium is located more to the right side of the supply stack.

A strong price-load correlation implies a more sensitive cash flow. This indicates that there is seasonality in the optimal hedging strategy, requiring higher hedge ratios during winter. The hedge ratio is optimized based on different risk metrics. CVaR is regarded as the superior metric in a risk management perspective, as it reduces downside risk while preserving the upside potential. Dealing with the lower tail of the profit distribution, as opposed to semivariance and mean-variance considering the lower half and whole distribution respectively, CVaR better reflects the tail risk. Thus, the hedge ratio generated from CVaR is more sensitive to the seasonality in the price-load dynamics (as changes in correlation, skewness and kurtosis) and should be applied to capture unwanted risk more accurately. In fact, our analysis confirms that CVaR outperforms mean-variance and semivariance with respect to both a reduction of unwanted risk and an increase in profit.

The hedge ratio based on the CVaR optimization, exhibits a clear seasonal trend. As expected, the ratio is highest during winter and lowest during summer, reflecting the seasonal trend of the price-load correlation. A similar tendency is found when dividing into North and South Norway. However, the higher average price in the North contributes to lower hedge ratios in this region despite of the higher correlation. Furthermore, the sensitivity analysis shows a positive relation between the average weekly profit and the hedge ratio for the winter months, the slope being almost flat for the summer months. Thus over-hedging may be preferred to under-hedging, particularly during winter. However, as the cash flow volatility is highly sensitive to the hedge ratio in this period, deviating the hedge ratio from the optimal can be risky. Comparing the results of a constant hedge ratio with a seasonal varying hedge ratio, the gains from implementing a more dynamic strategy are evident. The varying hedge ratio based on CVaR increases both the expected downside cash flow and the overall profit.

Previous studies have shown that most producers do not take seasonality into account when formulating a hedging strategy. However, this study clearly shows that seasonal varying hedge ratios ought to be implemented as a part of a hydropower producer's hedging strategy. This to better manage the risks associated with the highly volatile electricity prices, as well as to optimize cash flow and reduce profit fluctuations throughout the year. Our results indicate that the more fine-tuned the hedge ratio is, the better the results are. However, the gain has to be balanced with the intricacy of implementing and executing the strategy. We emphasize that the hedging strategies should be adjusted to the individual producers' capacities and operational plans. In this way the gains from realizing a seasonally adjusted hedging strategy could exceed what was achieved in this analysis.

Future Research

As highlighted, there are clear seasonal tendencies in the optimal hedging strategies for hydropower producers, primarily explained by the seasonality in the price-load relation. Being a hydro dominated system, the Norwegian market exhibits some clear distinct characteristics. Other markets, like EEX and ENDEX, have a different input mix with larger proportions of energy sources as coal and gas. Hence, future research should take our findings further and examine if the same seasonal tendencies are present in other power markets. This knowledge could be advantageous not only for power producers, but also contribute to operational and financial risk management for other market participants, as retailers and consumers.

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References

Alexander, C. (2008a). *Practical Financial Econometrics, Market Risk Analysis* (Vol. 2). England: John Wiley & Sons, Ltd.

Alexander, C. (2008b). *Quantitative Methods in Finance, Market Risk Analysis* (Vol. 1). England: John Wiley & Sons, Ltd.

Alexander, C. (2008c). *Value at Risk Models, Market Risk Analysis* (Vol. 4). England: John Wiley & Sons, Ltd.

Alizadeh, A. H., Nomikos, N. K., & Pouliasis, P. K. (2008). A Markov regime switching approach for hedging energy commodities. *Journal of Banking & Finance, 32*(9), 1970-1983.

Allayannis, G., & Weston, J. P. (2001). The use of foreign currency derivatives and firm market value. *Review of Financial Studies, 14*(1), 243-276.

Aune, F. R., Johnsen, T. A., & Sagen, E. L. (2001). Regional og nasjonal utvikling i elektrisitetsforbruket til 2010. SSB.

Baillie, R. T., & Myers, R. J. (1991). Bivariate GARCH estimation of the optimal commodity futures hedge. *Journal of Applied Econometrics, 6*(2), 109-124.

Bessembinder, H., & Lemmon, M. L. (2002). Equilibrium pricing and optimal hedging in electricity forward markets. *The Journal of Finance, 57*(3), 1347-1382.

Botterud, A., Kristiansen, T., & Ilic, M. D. (2010). The relationship between spot and futures prices in the Nord Pool electricity market. *Energy Economics, 32*(5), 967-978.

Byström, H. N. (2003). The hedging performance of electricity futures on the Nordic power exchange. *Applied Economics, 35*(1), 1-11.

Cartea, Á., & Villaplana, P. (2008). Spot price modeling and the valuation of electricity forward contracts: The role of demand and capacity. *Journal of Banking & Finance, 32*(12), 2502-2519.

Carter, D., Rogers, D. A., & Simkins, B. J. (2004). *Does Fuel Hedging Make Economics Sense? The Case of the U.S. Airline Industry*. Working paper. Oklahoma State University and Portland State University.

Chan, K. F., Gray, P., & Van Campen, B. (2008). A new approach to characterizing and forecasting electricity price volatility. *International Journal of Forecasting, 24*(4), 728-743.

Collins, R. A. (2002). The economics of electricity hedging and a proposed modification for the futures contract for electricity. *IEEE Transactions on Power Systems, 17*(1), 100-107.

Dahlgren, R., Liu, C.-C., & Lawarree, J. (2003). Risk assessment in energy trading. *Power Systems, IEEE Transactions on, 18*(2), 503-511.

Deng, S., & Oren, S. (2006). Electricity derivatives and risk management. *Energy, 31*(6), 940-953.

Gaudard, L., & Romerio, F. (2014). The future of hydropower in Europe: Interconnecting climate, markets and policies. *Environmental Science & Policy, 37*, 172-181.

Jin, Y., & Jorion, P. (2006). Firm value and hedging: Evidence from U.S. oil and gas producers. *The Journal of Finance, 61*(2), 893-919.

Kanamura, T. (2009). A supply and demand based volatility model for energy prices. *Energy Economics, 31*(5), 736-747.

Knittel, C. R., & Roberts, M. R. (2005). An empirical examination of restructured electricity prices. *Energy Economics, 27*(5), 791-817.

Larsen, N., Mausser, H., & Uryasev, S. (2002). *Algorithms for optimization of value-at-risk*: Springer.

Lucia, J. J., & Schwartz, E. S. (2002). Electricity prices and power derivatives: Evidence from the Nordic power exchange. *Review of Derivatives Research, 5*(1), 5-50.

Lucia, J. J., & Torró, H. (2011). On the risk premium in Nordic electricity futures prices. *International Review of Economics & Finance, 20*(4), 750-763.

Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review*, 261-297.
MontelXLF. (2013). Montel XLF Database, Montel AS.
NASDAQOMX. (2014). Product Specifications. from http://www.nasdaqomx.com
NordPoolSpot. (2014). The Leading Power Market. from http://www.nordpoolspot.com
NordREG. (2011). NordREG report on the price peaks in the Nordic wholesale market during winter 2009-2010.
Näsäkkälä, E., & Keppo, J. (2005a). Electricity load pattern hedging with static forward strategies. *Managerial Finance, 31*(6), 116-137.
Näsäkkälä, E., & Keppo, J. (2005b). Hydropower production planning and hedging under inflow and forward uncertainty. *Applied Mathematical Finance, 15*, 503-529.
OED. (2003-2004). St.meld. nr. 18: Om forsyningssikkerheten for strøm mv. (kap 8).
Oum, Y., Oren, S., & Deng, S. (2005). *Volumetric hedging in electricity procurement.* Paper presented at the Power Tech, 2005 IEEE Russia.
ReutersEcoWin. (2014). Nord Pool Monthly Forwards, 6-pos.
Rockafellar, R. T., & Uryasev, S. (2000). Optimization of conditional value-at-risk. *Journal of Risk, 2*, 21-42.
Sáez, Á. E., Pena, J. I., & Villaplana, P. (2011). Modelling Electricity Prices: International Evidence. *Oxford Bulletin of Economics and Statistics, 73*(5), 622-650.
Sanda, G. E., Olsen, E. T., & Fleten, S.-E. (2013). Selective hedging in hydro-based electricity companies. *Energy Economics, 40*(1), 326-338.
Smithson, C., & Simkins, B. J. (2005). Does risk management add value? A survey of the evidence. *Journal of Applied Corporate Finance, 17*(3), 8-17.
SSB. (2013). Elektrisitet, månedstall. from http://www.ssb.no
Stulz, R. M. (1996). Rethinking risk management. *Journal of Applied Corporate Finance, 9*(3), 8-25.
Tanlapco, E., Lawarrée, J., & Liu, C.-C. (2002). Hedging with futures contracts in a deregulated electricity industry. *Power Systems, IEEE Transactions on, 17*(3), 577-582.
Vucetic, S., Tomsovic, K., & Obradovic, Z. (2001). Discovering Price-Load Relationships in California's Electricity Market. *Power Systems, IEEE Transactions on, 16*(2), 280-286.
Wangensteen, I. (2012). *Power System Economics - the Nordic Electricity Market* (2 ed.). Trondheim: Tapir Academic Press.
Weron, R. (2006). *Modeling and forecasting electricity loads and prices*. England: John Wiley & Sons Ltd.
Westgaard, S. (2013). *Energy Risk Modeling*. Montel Course Material, Stockholm 14-15 November.
Zenios, S. A. (2008). *Practical Financial Optimization: Decision Making for Financial Engineers*. Chicester: Wiley-Blackwell.

Appendix 1

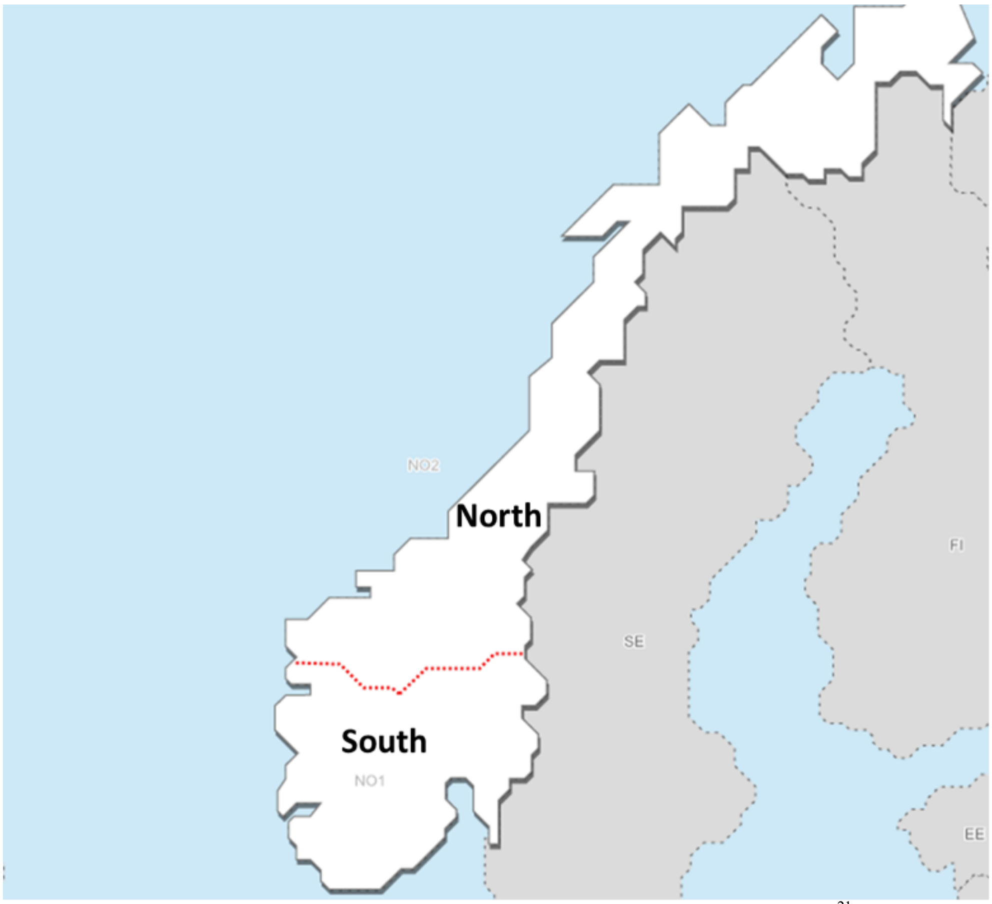


Figure A1: The Norwegian price regions analyzed: North and South Norway.[21]

[21] Source: Statnett, downloaded from http://www.statnett.no/Drift-og-marked/Kraftmarkedet/Prisomrader-historisk-elspot/

Appendix 2

2.1 Descriptive Statistics

Descriptive Statistics provide important information about the central tendency and variability in the sample data. In the following the most common descriptive statistics are presented.

Measures of central tendencies:

- Mean
  The first moment of the probability distribution, representing the center of location. It is calculated as the arithmetic average of the observations in the sample.

  Mean: $\bar{x} = \frac{1}{T}\sum_{t=1}^{T} x_t$

- Median
  Splits the sample data such that 50% of the data is below and above the observation.

Measures of variability:

- Variance
  The second moment of the probability distribution, being the mathematical expectation of the average squared deviation from the mean.

  Variance: $s^2 = \frac{1}{T-1}\sum_{t=1}^{T}(x_t - \bar{x})^2$

- Standard deviation
  The square root of the variance, representing the dispersion from the mean. The annualized standard deviation represents the volatility and risk of the sample data.

  Standard deviation: $s = \sqrt{s^2}$

- Min/max
  Measures the range of the sample data.

- Skewness
  The third moment of the probability distribution, describing the asymmetry from the normal distribution having zero skewness. Deviation of the mean from the median indicates skewness, which gives a signal of whether a data point will be more or less than the mean:

  Mean = Median implies symmetric data
  Mean > Median implies positive/right skewness
  Mean < Median implies negative/left skewness

  Skewness: $\hat{\tau} = \frac{1}{T-1}\sum_{t=1}^{T}(\frac{x_t - \bar{x}}{s})^3$

- Kurtosis
  The fourth moment of the probability distribution, describing the concentration of data in the center against the data in the tails compared to a normal distribution. A normal distribution has a kurtosis of 3 and an excess kurtosis of zero; by subtracting 3 from the kurtosis, excess kurtosis is obtained.

  Leptokurtic data with positive excess kurtosis tend to have a peak close to the mean and heavier tails (more extreme values) than the normal distribution. *Platykurtic* data with negative excess kurtosis tend to be more flat close to the mean and have thinner tails (less extreme values) than the normal distribution.

Kurtosis: $\hat{\kappa} = \frac{1}{T-1}\sum_{t=1}^{T}(\frac{x_t-\bar{x}}{s})^4$

2.2 Measure of Dependency

Correlation is frequently used as a measure of dependency, revealing a possible linear relationship between two variables, ranging between -1 and +1. We distinguish between two types of correlation:

- Cross-correlation: The correlation between two different time series. Often referred to as just correlation.
  Correlation: $\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{1}{T-1}\frac{\sum_{t=1}^{T}(X_t-\bar{X})(Y_t-\bar{Y}))}{\sqrt{\sum_{t=1}^{T}(X_t-\bar{X})^2 \sum_{i=1}^{T}(Y_t-\bar{Y})^2}}$

- Autocorrelation: The cross-correlation between a time series and a lagged version of itself. Also referred to as lagged correlation or serial correlation.
  Autocorrelation: $\rho_j = \frac{\sum_{t=j+1}^{T}(X_t-\bar{X})(X_{t-j}-\bar{X}))}{\sum_{t=1}^{T}(X_t-\bar{X})^2}$

Appendix 3

3.1 Simple Linear Regression Model

Ordinary least squares (OLS) represent the standard linear regression method. The model is expressed as $Y_t = \alpha + \beta X_t + \varepsilon_t,\ t = 1, \dots, T$, where Y is the dependent variable, X the independent variable/explanatory variable, α the intercept coefficient, β the regression coefficient, and ε the residual, all at a given time t (Alexander, 2008b). In our analysis, Y denotes the logarithmic electricity spot price, and X the logarithmic load. For OLS the objective is to find the OLS estimators $\hat{\alpha}$ and $\hat{\beta}$ by minimizing the residual sum of squares

$$RSS = \min_{\alpha, \beta} \sum_{t=1}^{T} (Y_t - (\alpha + \beta X_t))^2.$$

3.2 Hypothesis Tests on Regression Coefficients

$\hat{\alpha}$ and particularly $\hat{\beta}$ explain how much the load affects the electricity spot price. The test statistics for the coefficients in a linear regression are assumed to have a Student t distribution. Using the t-statistics on the respective parameters, we can determine whether the regression constant $\hat{\alpha}$ and the explanatory variable $\hat{\beta}$ are significant enough to be included in the regression model. According to Alexander (2008b), the hypothesis tests are formulated as

i) H_0: $\alpha = 0$ against H_1: $\alpha > 0$
ii) H_0: $\beta = 0$ against H_1: $\beta \neq 0$

If the test statistics given by the regression exceed the critical value $t_{\alpha,T-k}$, H_0 is rejected and the respective coefficients should be included in the model. Here α represents the significance level and T-k the degrees of freedom; T is the sample size and k the number of regression coefficients including the intercept coefficient. Thus, in a simple linear regression model the critical value becomes $t_{\alpha,T-2}$. If the sample size is sufficiently large, the distribution converges towards a normal distribution.

3.3 ANOVA and Goodness of Fit

Analysis of variance (ANOVA) decomposes the total variance of the dependent variable into the variance explained by the model and the residual variance. The regression R^2 summarises the results, being the squared correlation between the price and the explained part of the model. R^2 takes a value between 0 and 1, and a large value indicates a good fit of the model.

Using the F-statistic, the significance of the R^2 from a simple linear regression model is examined. According to Alexander (2008b), the hypothesis test is formulated as

iii) H_0: R^2 is not significant against H_1: R^2 is significant

If the test statistic given by the regression exceed the critical value $F_{k-1,T-k}$, H_0 is rejected indicating a highly significant overall fit of the regression. Here $k - 1$ represents the number of regression coefficients, not including the intercept constant, and $T - k = \nu$ represents the degrees of freedom, being $T - 2$ in a simple regression model.

3.4 Residual Specification Tests

According to Westgaard (2013), the linear regression model is optimal only when the residuals in the regression are:

1. Normally distributed
2. Not correlated with the explanatory variables (not cross-correlated)
3. Not correlated over time (not serial correlated/autocorrelated)
4. Have a constant variance (not heteroscedastic but homoscedastic)
5. Also, the model should be linear

If some of these assumptions are violated, the model estimates of the t-statistics and F value are less precise. This may affect the hypothesis testing and model evaluation.

1. We can test whether the residuals are normally distributed with a Jarque Bera test. Test H_0: Residuals are normally distributed against H_1: residuals are not normally distributed. If $JB = \frac{T}{6}(Skewness^2 + \frac{Excess\ Kurtosis^2}{4}) > \chi^2(2)$, H_0 is rejected, implying non-normality.

2. We can test whether the residuals are uncorrelated with the explanatory variables or not with a hetero-X test. Run the following regression: $\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1 X_1^2 + \cdots + \gamma_k X_k^2 + \alpha_1 X_1 X_2 + \cdots + \alpha_{k(k-1)} X_k X_{k-1} + \xi_t$. Test H_0: $\gamma_1 = \cdots = \gamma_k = \alpha_1 = \cdots = \alpha_{k(k-1)} = 0$ against H_1: $\gamma_1 \neq 0$ or ... $\alpha_{k(k-1)} \neq 0$. H_0 is rejected if F exceeds the critical value, implying cross-correlation.

3. We can test whether the residuals are uncorrelated over time or not with an AR test. Run the following regression: $\hat{\varepsilon}_t = \gamma_0 + \gamma_1 \widehat{\varepsilon_{t-1}} + \cdots + \gamma_q \widehat{\varepsilon_{t-q}} + \vartheta_t$. Test H_0: $\gamma_1 = \cdots = \gamma_q = 0$ against H_1: at least one $\gamma_i \neq 0$. Reject H_0 if F exceeds the critical value, implying autocorrelation.

4. We can test whether the residuals have a constant variance or not with an ARCH test. Run the following regression on the squared residuals: $\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1 \hat{\varepsilon}_{t-1}^2 + \cdots + \gamma_q \hat{\varepsilon}_{q-1}^2 + \xi_t$. Test H_0: $\gamma_1 = \cdots = \gamma_q = 0$ against H_1: at least one $\gamma_i \neq 0$. Reject H_0 if F exceeds the critical value, implying a dynamic variance.

5. We can test whether we have a linear model with a RESET test. Run the following regression: $\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1 \hat{y}_t^2 + \gamma_2 \hat{y}_t^3 + \cdots + \gamma_{m-1} \hat{y}_m^m + \xi_t$. Test H_0: $\gamma_1 = \cdots = \gamma_{m-1} = 0$ against H_1: at least one $\gamma_i \neq 0$. Reject H_0 if F exceeds the critical value, implying non-linearity.

3.5 Test for Stationarity

To test for stationarity, a unit root test called augmented Dickey-Fuller, ADF(q), is applied. According to Alexander (2008a), this test is based on the following regression model, testing H_0: $\beta = 0$ against H_1: $\beta < 0$,

$$\Delta X_t = \alpha + \beta X_{t-1} + \gamma_1 \Delta X_{t-1} + \cdots + \gamma_q \Delta X_{t-q} + \varepsilon_t.$$

Here q represents the number of lagged dependent variables, this to remove any autocorrelation in the residuals. According to Westgaard (2013), 2 lags are adequate. If the augmented Dickey-Fuller test statistic, i.e. the t ratio on beta, is more negative than the critical value at some significance level, the null hypothesis is rejected implying stationarity.

Appendix 4

4.1 Test for Stationarity: Price Time Series

SUMMARY OUTPUT	
Regression Statistics	
Multiple R	0,312448732
R Square	0,09762421
Adjusted R Square	0,096911246
Standard Error	4,012290305
Observations	3801

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	6612,952	2204,317	136,9271	3,09E-84
Residual	3797	61125,9	16,09847		
Total	3800	67738,86			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	1,132701483	0,19128	5,921678	3,47E-09
Agg Spot $_{t-1}$	-0,029939226	0,004769	**-6,27748**	3,83E-10
Δ Agg Spot$_{t-1}$	-0,263135358	0,01612	-16,3233	6,07E-58
Δ Agg Spot$_{t-2}$	-0,171914278	0,015985	-10,755	1,35E-26

4.2 Test for Stationarity: Load Time Series

SUMMARY OUTPUT	
Regression Statistics	
Multiple R	0,280839293
R Square	0,078870709
Adjusted R Square	0,078142927
Standard Error	16838,61759
Observations	3801

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	9,22E+10	3,07E+10	108,3714	2,54E-67
Residual	3797	1,08E+12	2,84E+08		
Total	3800	1,17E+12			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	6777,016451	1322,205	5,125543	3,11E-07
Agg Spot $_{t-1}$	-0,020339612	0,003849	**-5,28404**	1,33E-07
Δ Agg Spot$_{t-1}$	0,027093188	0,016636	1,628628	0,103475
Δ Agg Spot$_{t-2}$	-0,274381637	0,016642	-16,4871	4,89E-59

Appendix 5

5.1 Time Series Plot of Price and Load for Norway

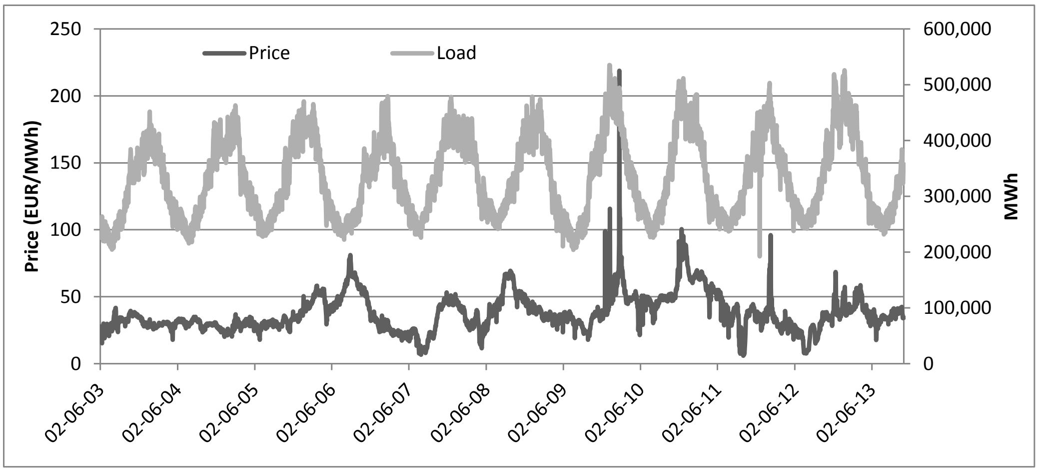


Figure A2: Daily aggregated price and load in Norway from 02.06.2003 to 31.10.2013

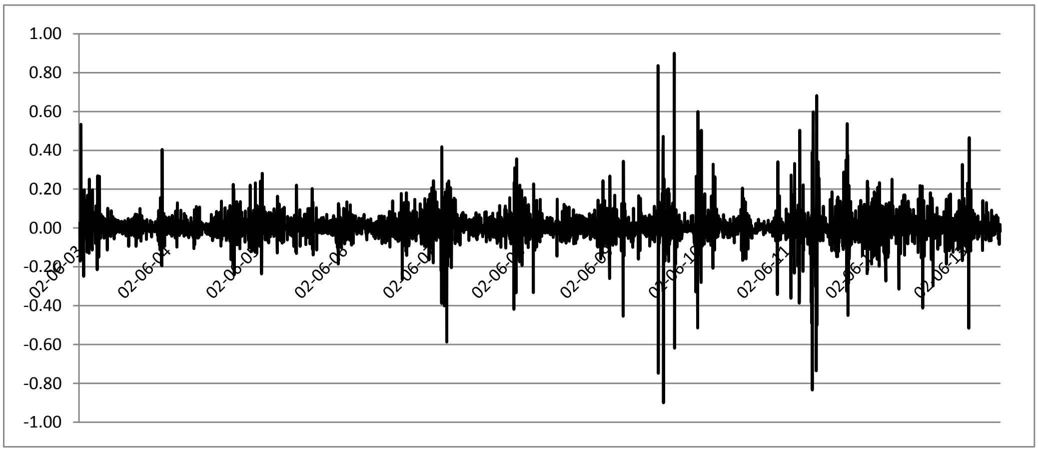


Figure A3: Daily price return in Norway from 02.06.2003 to 31.10.2013

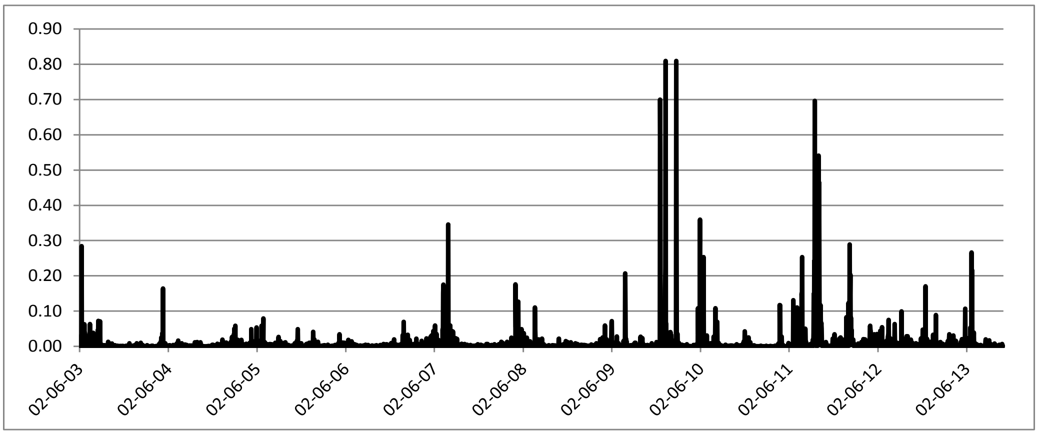


Figure A4: Daily price squared return in Norway from 02.06.2003 to 31.10.2013

5.2 Time Series Plot of Price and Load for North Norway

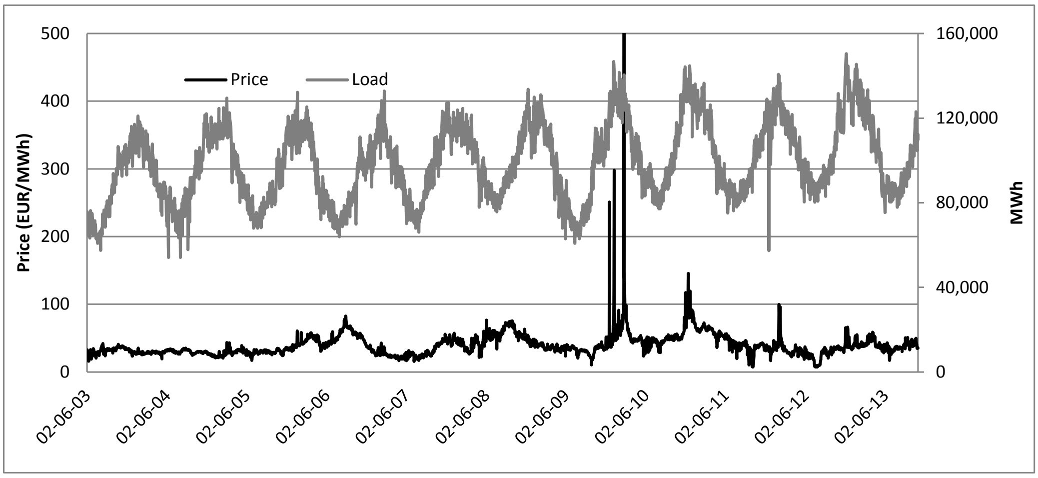


Figure A5: Daily price and load in North Norway from 02.06.2003 to 31.10.2013

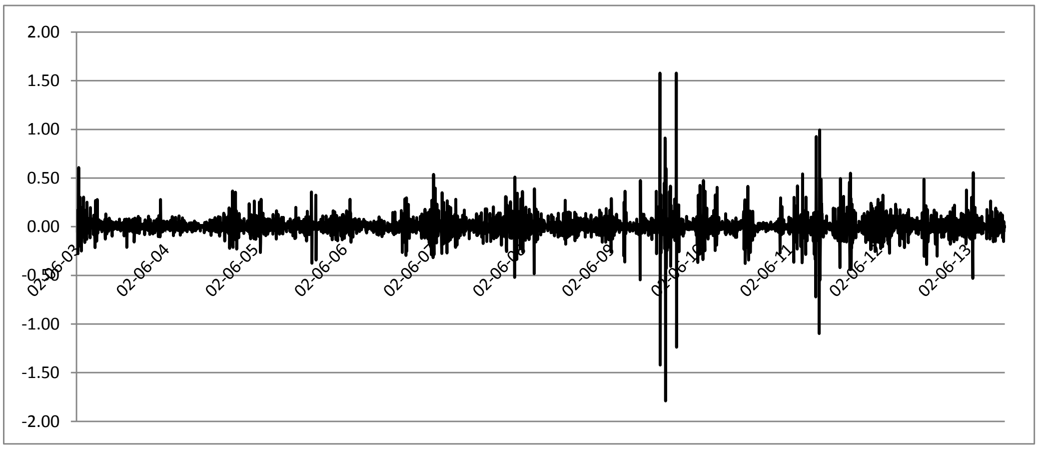


Figure A6: Daily price return in North Norway from 02.06.2003 to 31.10.2013

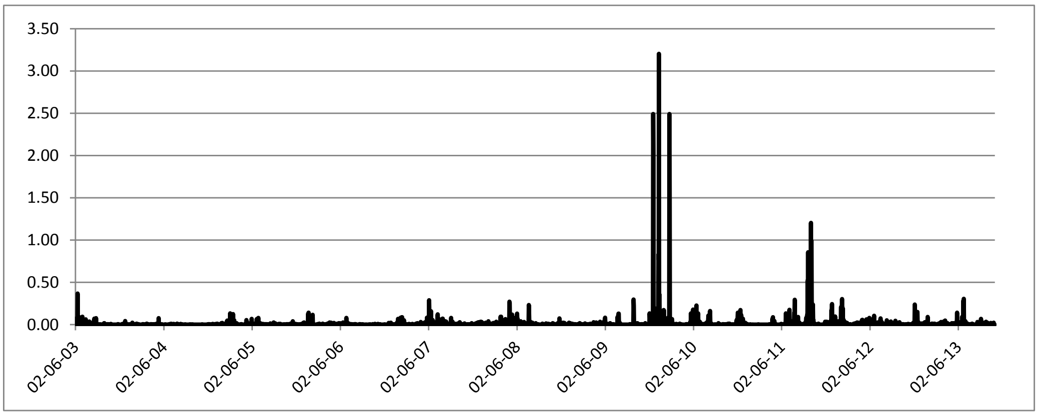


Figure A7: Daily price squared return in North Norway from 02.06.2003 to 31.10.2013

5.3 Time Series Plot of Price and Load for South Norway

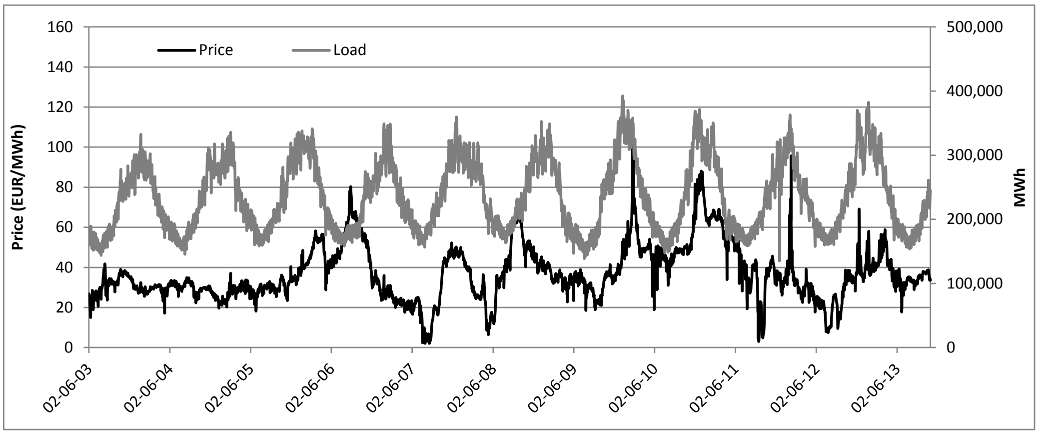


Figure A8: Daily price and load in South Norway from 02.06.2003 to 31.10.2013

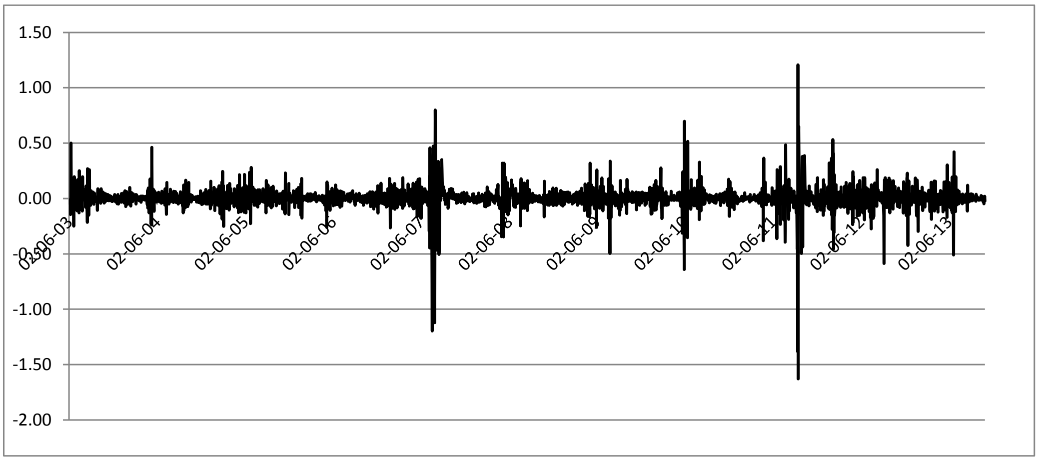


Figure A9: Daily price return in South Norway from 02.06.2003 to 31.10.2013

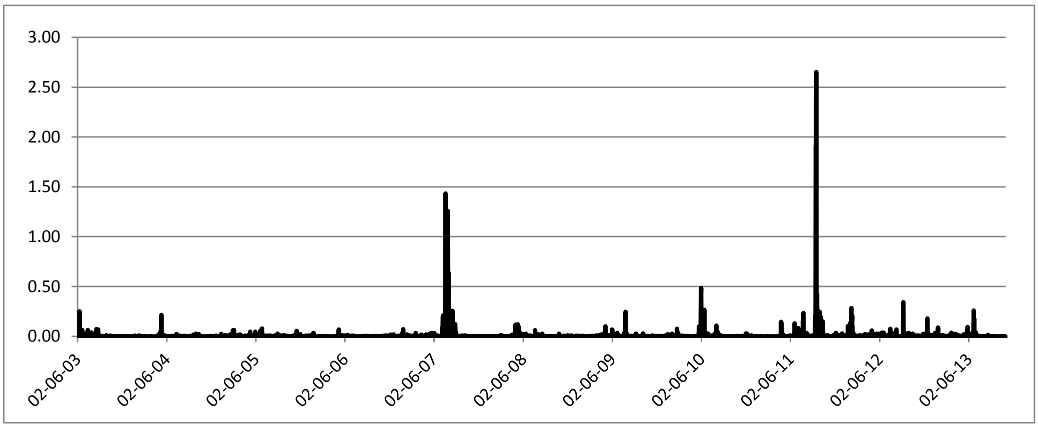


Figure A10: Daily price squared return in South Norway from 02.06.2003 to 31.10.2013

Appendix 6

6.1 Frequency Distribution Plots for Norway

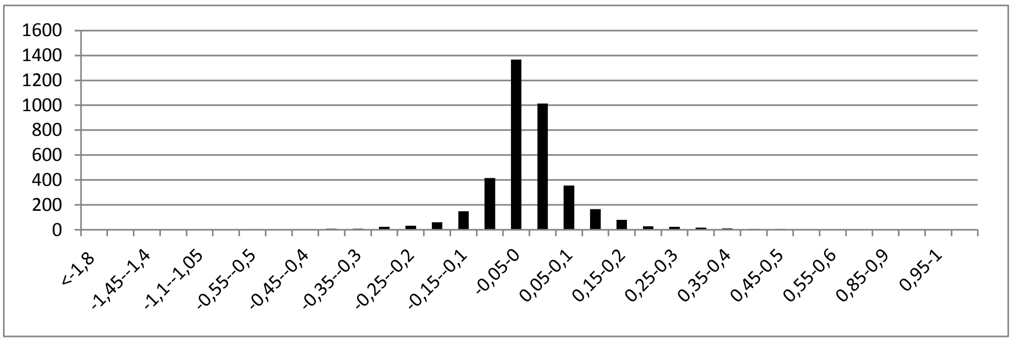


Figure A11: Distribution plot for daily price return in Norway from 02.06.2003 to 31.10.2013

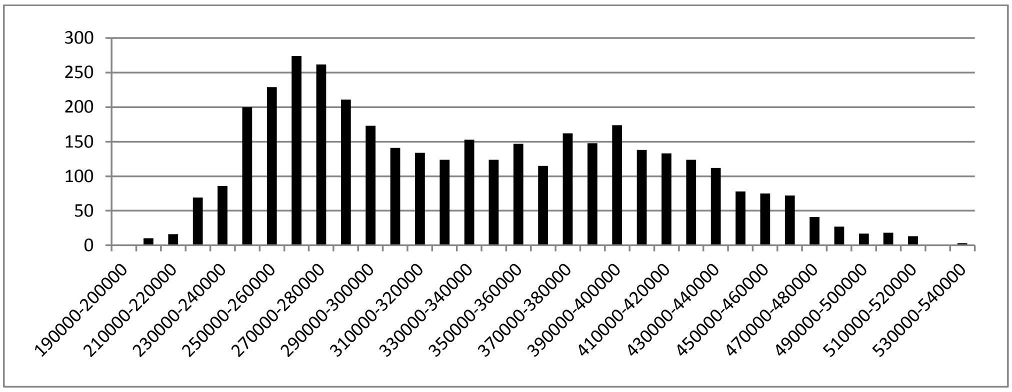


Figure A12: Distribution plot for daily load (MWh) in Norway from 02.06.2003 to 31.10.2013

6.2 Frequency Distribution Plots for North Norway

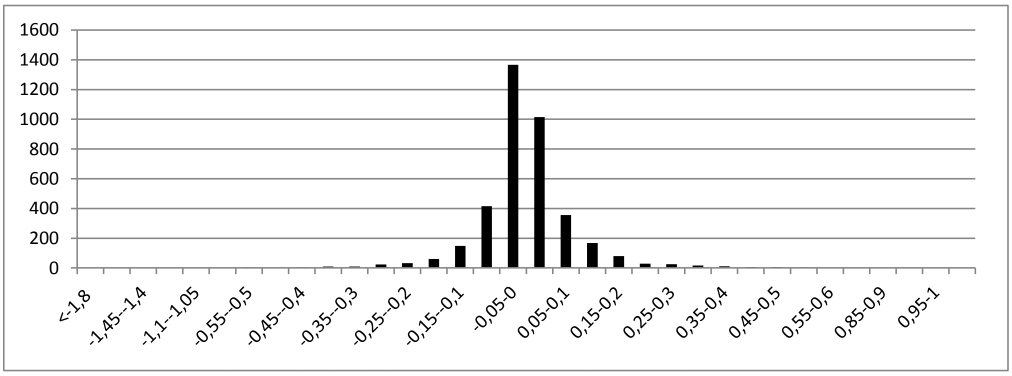


Figure A13: Distribution plot for daily price return in North Norway from 02.06.2003 to 31.10.2013

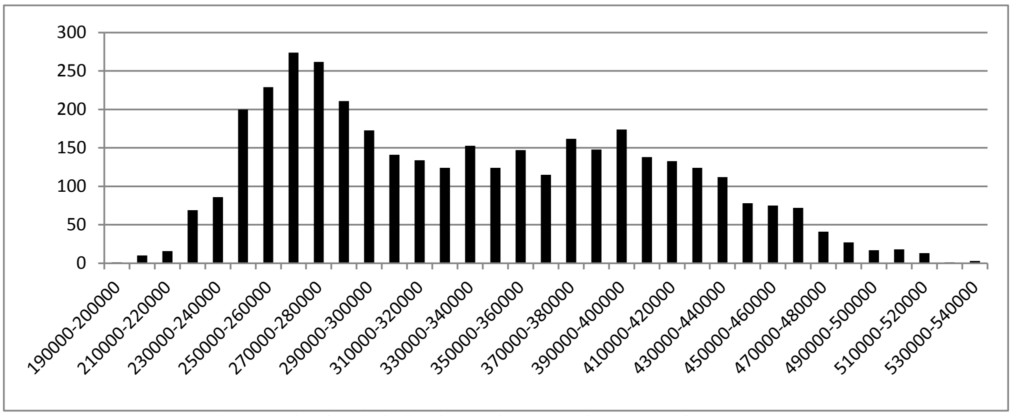


Figure A14: Distribution plot for daily load (MWh) in North Norway from 02.06.2003 to 31.10.2013

6.3 Frequency Distribution Plots for South Norway

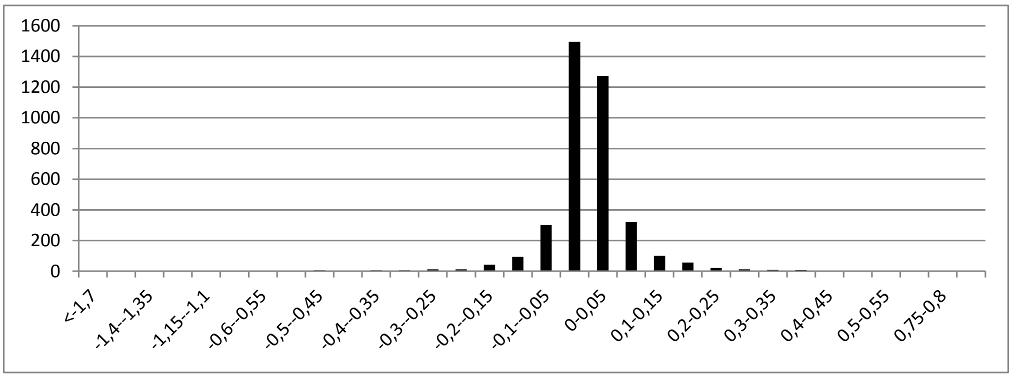


Figure A15: Distribution plot for daily price return in South Norway from 02.06.2003 to 31.10.2013

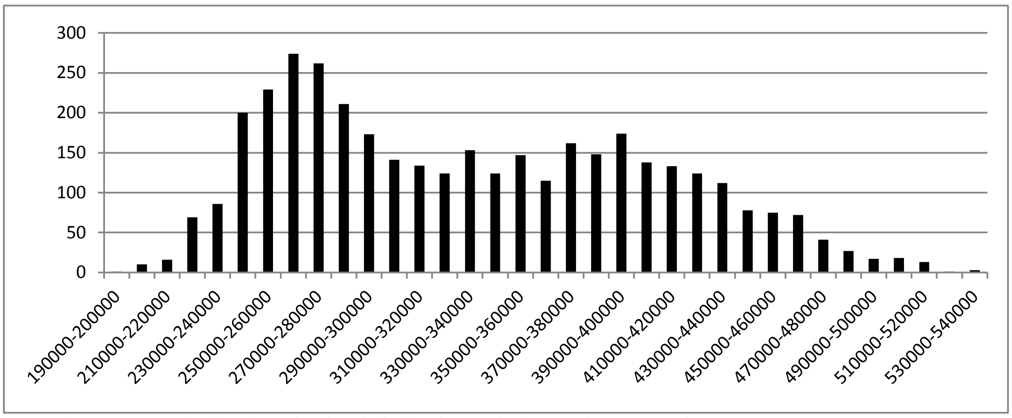


Figure A16: Distribution plot for daily load (MWh) in South Norway from 02.06.2003 to 31.10.2013

Appendix 7

7.1 Descriptive Statistics for Price and Load Series in Norway

Table A1: Descriptive statistics for daily price series (EUR/MWh), price return, price squared return and load (MWh) in Norway from 02.06.2003 to 31.10.2013

Daily data	Agg_price	Agg_return	Agg__sq_return	Agg_load
Mean	37,7065	6,2322E-05	0,0073	336031,6042
St. Error	0,2254	0,0014	0,0006	1166,1097
Median	34,8735	-0,0034	0,0007	328362
St. Dev.	13,9038	0,0856	0,0367	71931,1083
Samp.Var.	193,3143	0,0073	0,0013	5174084336
Kurtosis	9,2187	23,0433	233,4264	-0,9295
Skewness	1,5186	-0,0136	13,5707	0,3535
Minimum	5,9058	-0,9001	2,4639E-10	192454
Maximum	218,8142	0,9001	0,8102	535562
Count	3805	3804	3804	3805

Table A2: Descriptive statistics for weekly price series (EUR/MWh), ln(weekly price), weekly price return, weekly load (MWh) and ln(weekly load) in Norway from 02.06.2003 to 31.10.2013

Weekly data	Agg_price	ln(Agg_price)	Agg_return	Agg_load	ln(Agg_load)
Mean	37,8216	3,5697	5,7077E-05	2317366,692	14,6265
St. Error	0,5783	0,0155	0,0010	22316,6646	0,0110
Median	34,8292	3,5504	0,0002	2251112	14,6269
St. Dev.	13,5736	0,3643	0,0246	523847,754	0,2591
Samp.Var.	184,2422	0,1327	0,0006	2,7442E+11	0,0671
Kurtosis	2,7487	2,0959	25,5120	0,0369	11,5265
Skewness	1,1287	-0,5443	-0,4141	-0,0297	-1,9636
Minimum	7,8459	2,0600	-0,1976	345782	12,7536
Maximum	116,6236	4,7590	0,1990	3595130	15,0950
Count	551	551	551	551	551

7.2 Descriptive Statistics for Price and Load Series in North Norway

Table A3: Descriptive statistics for daily price series (EUR/MWh), price return, price squared return and load (MWh) in North Norway from 02.06.2003 to 31.10.2013

Daily data	N_price	N_return	N__sq_return	N_load
Mean	39,4756	6,3585E-05	0,0132	99372,9130
St. Error	0,2754	0,0019	0,0016	293,0058
Median	35,98	-0,0055	0,0012	98586
St. Dev.	16,9897	0,1149	0,0976	18073,9718
Samp.Var.	288,6507	0,0132	0,0095	326668455
Kurtosis	170,6386	52,6691	591,8745	-0,7332
Skewness	7,7221	0,0923	22,4425	0,1587
Minimum	7,3766	-1,7892	2,1205E-10	54055
Maximum	505,68	1,5785	3,2012	150473
Count	3805	3804	3804	3805

Table A4: Descriptive statistics for weekly price series (EUR/MWh), ln(weekly price), weekly price return, weekly load (MWh) and ln(weekly load) in North Norway from 02.06.2003 to 31.10.2013

Weekly data	N_price	ln(N_price)	N_return	N_load	ln(N_load)
Mean	39,5628	3,6181	-6,3142E-05	685226,0614	13,4129
St. Error	0,6338	0,0146	0,0010	5799,6637	0,0103
Median	36,0902	3,5860	-5,6667E-06	679558	13,4291
St. Dev.	14,8765	0,3430	0,0243	136137,763	0,2427
Samp.Var.	221,3115	0,1177	0,0006	18533490513	0,0589
Kurtosis	13,4921	2,1580	16,4536	1,1456	18,1394
Skewness	2,3032	-0,0057	-0,4507	-0,4344	-2,8487
Minimum	7,8761	2,0638	-0,1694	94693	11,4584
Maximum	175,4028	5,1671	0,1677	1018661	13,8340
Count	551	551	551	551	551

7.3 Descriptive Statistics for Price and Load Series in South Norway

Table A5: Descriptive statistics for daily price series (EUR/MWh), price return, price squared return and load (MWh) in South Norway from 02.06.2003 to 31.10.2013

Daily data	S_price	S_return	S_sq_return	S_load
Mean	36,9489	6,1460E-05	0,0088	236658,6913
St. Error	0,2224	0,0015	0,0012	888,8349
Median	34,3908	-0,0015	0,0060	229460
St. Dev.	13,7184	0,0940	0,0711	54827,4961
Samp.Var.	188,1955	0,0088	0,0051	3006054328
Kurtosis	1,3769	62,9349	749,1967	-0,9341
Skewness	0,7428	-2,3317	24,8831	0,4025
Minimum	2,0695	-1,6282	0	135106
Maximum	109,4425	1,2071	2,6510	392632
Count	3805	3804	3804	3805

Table A6: Descriptive statistics for weekly price series (EUR/MWh), ln(weekly price), weekly price return, weekly load (MWh) and ln(weekly load) in South Norway from 02.06.2003 to 31.10.2013

Weekly data	S_price	ln(S_price)	S_return	S_load	ln(S_load)
Mean	37,0731	3,5381	9,5079E-05	1632140,63	14,2728
St. Error	0,5760	0,0177	0,0013	16770,8531	0,0115
Median	34,5256	3,5417	0,0002	1569001	14,2659
St. Dev.	13,6047	0,4166	0,0294	393668,7627	0,2699
Samp.Var.	185,0865	0,1735	0,0009	1,5498E+11	0,0729
Kurtosis	1,3191	5,5086	24,9272	-0,2713	8,8816
Skewness	0,7713	-1,4218	-0,5684	0,0971	-1,6002
Minimum	3,3254	1,2016	-0,2190	251089	12,4336
Maximum	93,3223	4,5361	0,2202	2630228	14,7826
Count	551	551	551	551	551

7.4 Descriptive Statistics for Grouped Weekly Logarithmic Price and Load in Norway

Table A7: Descriptive statistics for the grouped weekly logarithmic transformed price in Norway from 02.06.2003 to 31.10.2013

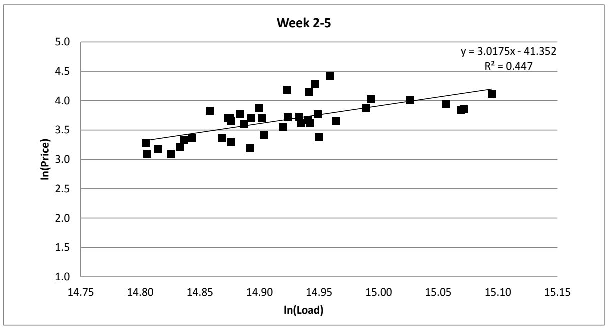
ln(Price)	Mean	St. Error	Median	St. Dev.	Variance	Kurtosis	Skewness	Min	Max	Count
W2-5	3,669	0,052	3,698	0,331	0,110	-0,430	0,134	3,095	4,423	40
W6-9	3,675	0,057	3,690	0,362	0,131	0,579	0,766	3,132	4,759	40
W10-13	3,622	0,056	3,478	0,357	0,128	-1,204	0,445	3,120	4,319	40
W14-17	3,612	0,047	3,540	0,299	0,090	-1,146	0,090	3,091	4,155	40
W18-21	3,480	0,050	3,461	0,314	0,099	-0,602	-0,037	2,850	4,033	40
W22-25	3,488	0,040	3,470	0,265	0,070	-0,928	0,135	2,976	3,967	43
W26-29	3,447	0,056	3,467	0,374	0,140	2,760	-1,368	2,133	3,931	44
W30-33	3,388	0,078	3,474	0,516	0,267	0,852	-1,213	2,097	4,145	44
W34-37	3,557	0,064	3,503	0,423	0,179	0,925	-0,365	2,286	4,325	44
W38-41	3,480	0,069	3,429	0,455	0,207	0,919	-0,379	2,060	4,221	44
W42-45	3,667	0,032	3,618	0,211	0,045	-0,714	0,097	3,196	4,031	43
W46-49	3,681	0,036	3,635	0,227	0,051	0,002	0,488	3,297	4,300	40
W50-52	3,683	0,057	3,586	0,310	0,096	1,522	1,216	3,222	4,468	30

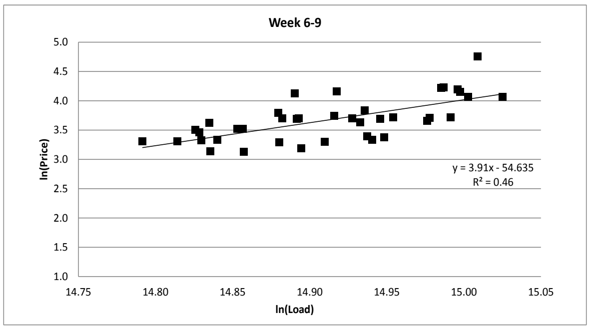
Table A8: Descriptive statistics for the grouped weekly logarithmic transformed load in Norway from 02.06.2003 to 31.10.2013

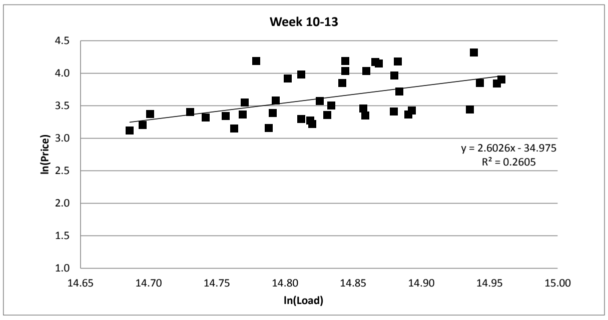
ln(Load)	Mean	St. Error	Median	St. Dev.	Variance	Kurtosis	Skewness	Min	Max	Count
W2-5	14,920	0,012	14,912	0,073	0,005	0,111	0,657	14,804	15,095	40
W6-9	14,913	0,010	14,916	0,063	0,004	-1,034	-0,033	14,792	15,025	40
W10-13	14,830	0,011	14,833	0,070	0,005	-0,395	-0,122	14,686	14,959	40
W14-17	14,682	0,012	14,684	0,073	0,005	-0,224	-0,344	14,505	14,804	40
W18-21	14,546	0,010	14,543	0,061	0,004	-0,148	0,270	14,427	14,706	40
W22-25	14,452	0,009	14,468	0,058	0,003	4,323	-1,623	14,224	14,528	43
W26-29	14,390	0,008	14,401	0,054	0,003	-0,068	-0,430	14,261	14,498	44
W30-33	14,365	0,008	14,375	0,056	0,003	-0,254	-0,582	14,236	14,457	44
W34-37	14,453	0,008	14,455	0,052	0,003	-0,558	0,154	14,355	14,558	44
W38-41	14,559	0,010	14,554	0,069	0,005	-0,523	-0,177	14,423	14,705	44
W42-45	14,701	0,012	14,708	0,080	0,006	6,396	-1,750	14,364	14,830	43
W46-49	14,818	0,015	14,803	0,094	0,009	0,499	0,741	14,665	15,068	40
W50-52	14,881	0,017	14,864	0,092	0,008	-0,981	0,277	14,731	15,050	30

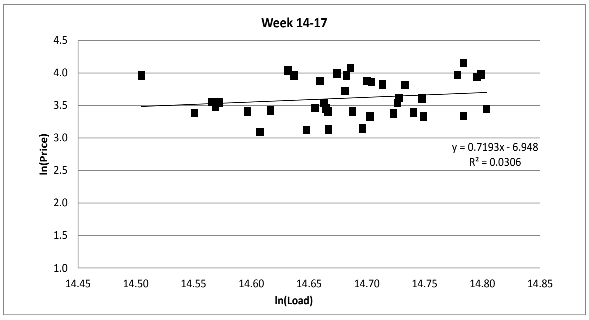
Appendix 8

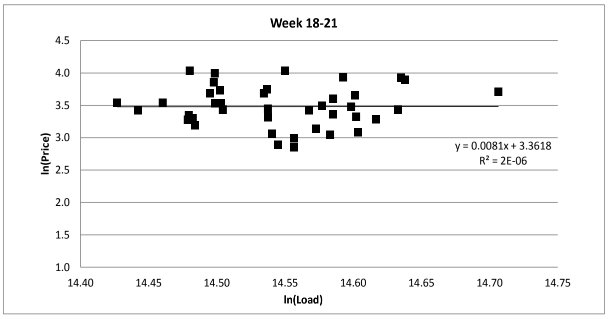
8.1 Scatter Plots for Grouped Weekly Logarithmic Price and Load in Norway

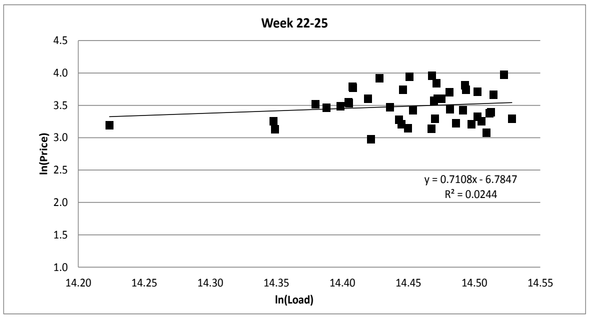


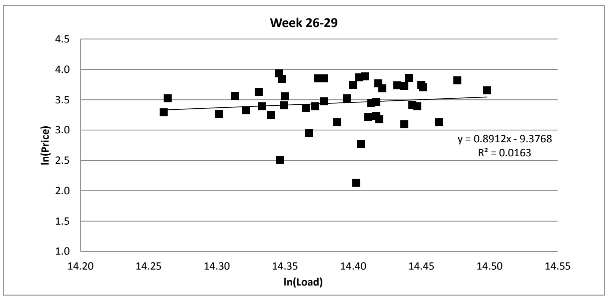


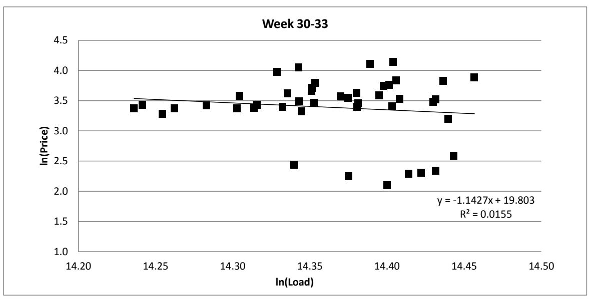


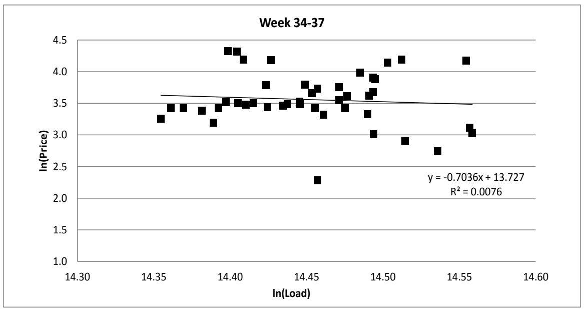


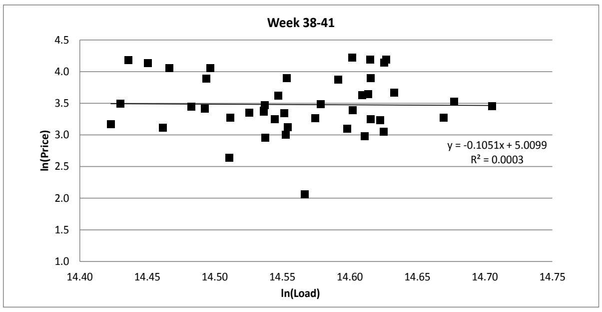


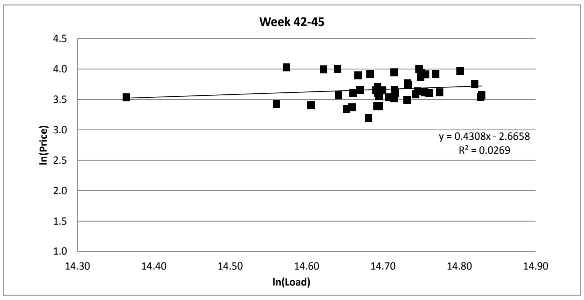


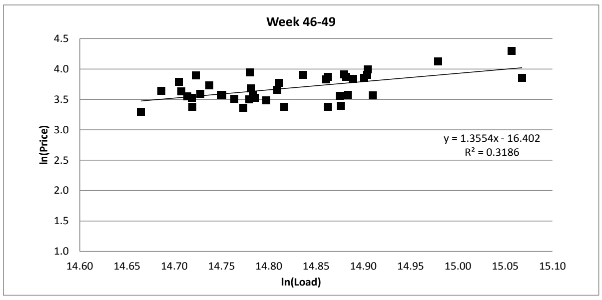


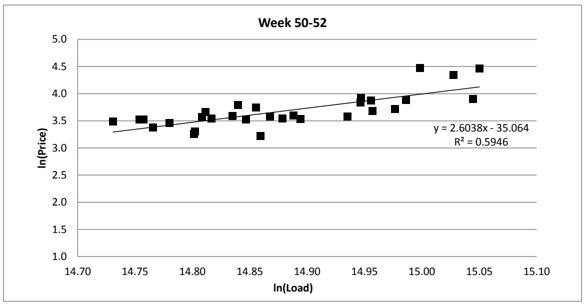




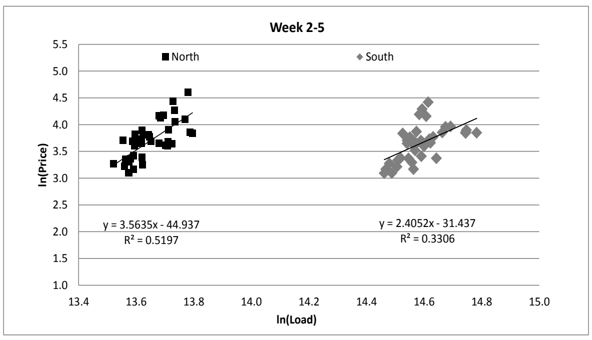


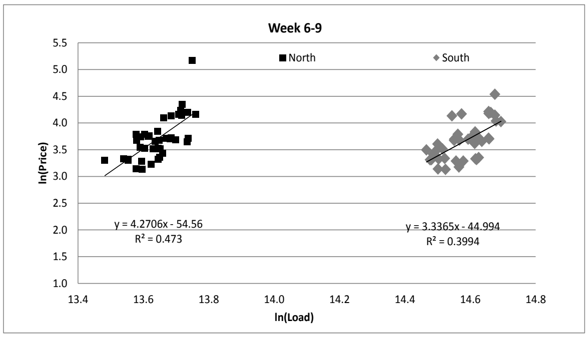


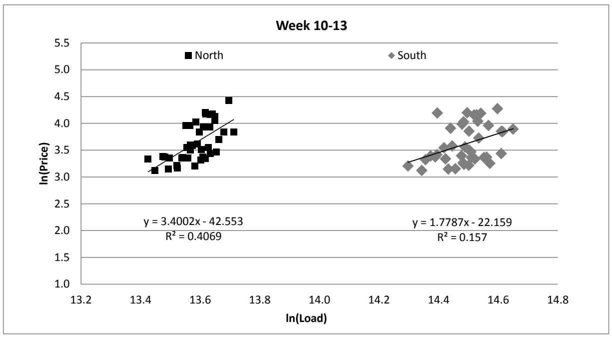


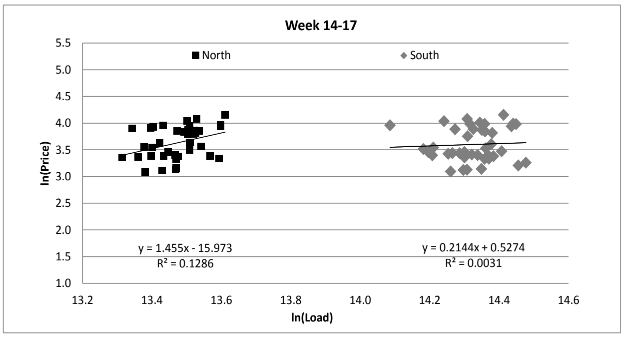


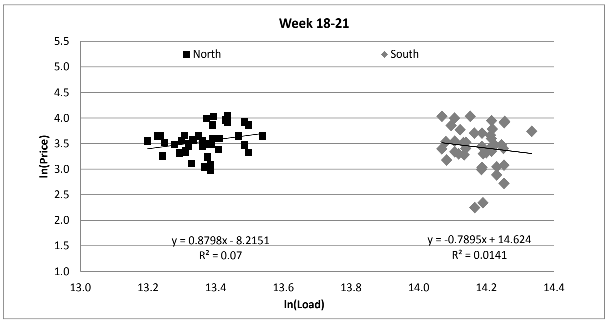
8.2 Scatter Plots for Grouped Weekly Logarithmic Price and Load in North and South Norway

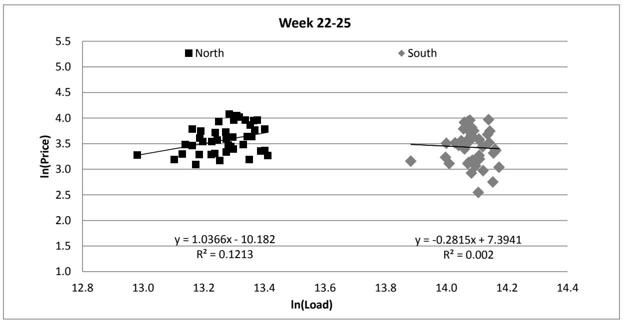


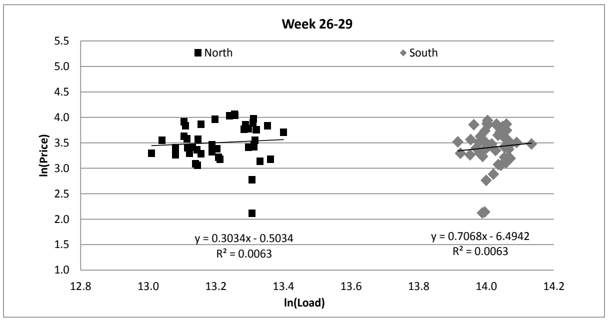


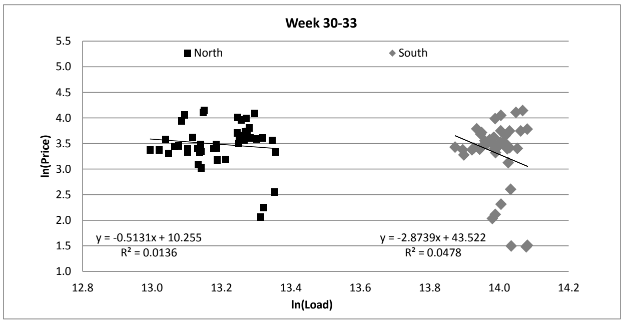

Week 10-13
North
South
y = 3.4002x - 42.553
R² = 0.4069
y = 1.7787x - 22.159
R² = 0.157
ln(Price)
ln(Load)

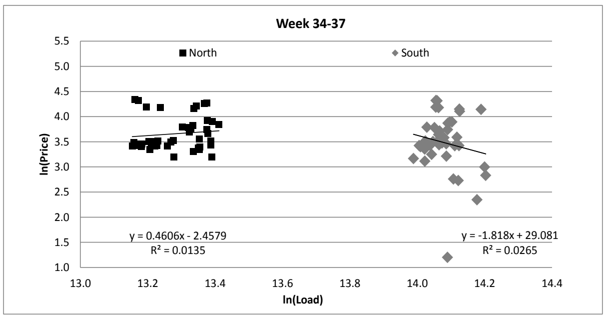

Week 14-17
North
South
y = 1.455x - 15.973
R² = 0.1286
y = 0.2144x + 0.5274
R² = 0.0031
ln(Price)
ln(Load)

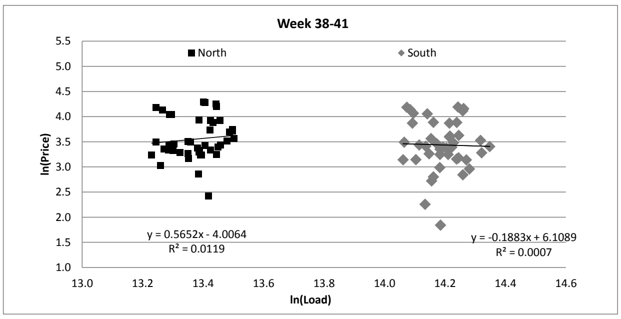

Week 18-21
North
South
y = 0.8798x - 8.2151
R² = 0.07
y = -0.7895x + 14.624
R² = 0.0141
ln(Price)
ln(Load)

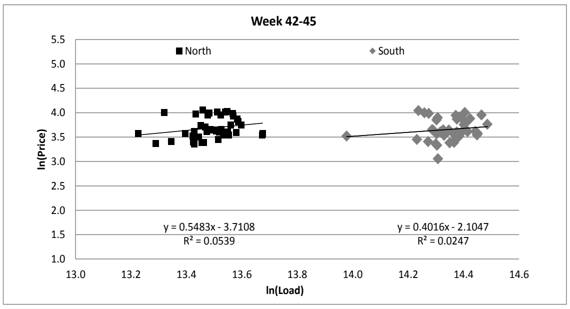

Week 22-25
North
South
y = 1.0366x - 10.182
R² = 0.1213
y = -0.2815x + 7.3941
R² = 0.002
ln(Price)
ln(Load)

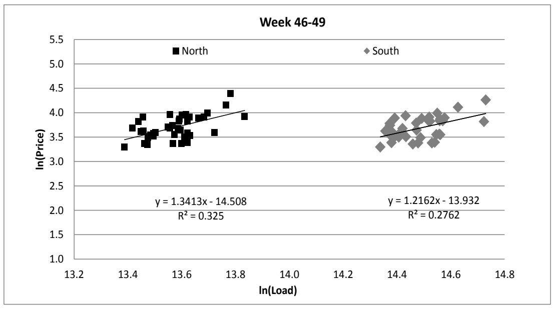

Week 26-29
North
South
y = 0.3034x - 0.5034
R² = 0.0063
y = 0.7068x - 6.4942
R² = 0.0063
ln(Price)
ln(Load)

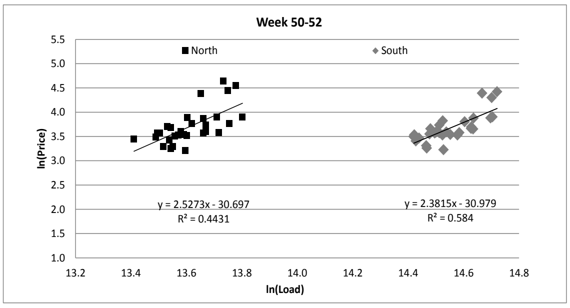

Week 30-33
North
South
y = -0.5131x + 10.255
R² = 0.0136
y = -2.8739x + 43.522
R² = 0.0478
ln(Price)
ln(Load)


Week 34-37
North
South
y = 0.4606x - 2.4579
R² = 0.0135
y = -1.818x + 29.081
R² = 0.0265
ln(Price)
ln(Load)


Week 38-41
North
South
y = 0.5652x - 4.0064
R² = 0.0119
y = -0.1883x + 6.1089
R² = 0.0007
ln(Price)
ln(Load)







8.3 Correlation for Grouped Weekly Logarithmic Price and Load

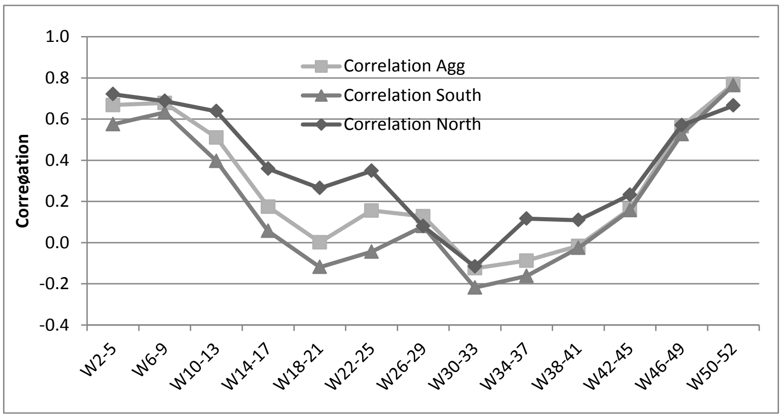


Figure A17: Correlation for the grouped weekly logarithmic transformed price and load from 02.06.2003 to 31.10.2013

Table A9: Correlation values for the grouped weekly logarithmic transformed price and load from 02.06.2003 to 31.10.2013

Correlation	Norway	North	South
W2-5	0,67	0,72	0,58
W6-9	0,68	0,69	0,63
W10-13	0,51	0,64	0,40
W14-17	0,17	0,36	0,06
W18-21	0,00	0,26	-0,12
W22-25	0,16	0,35	-0,04
W26-29	0,13	0,08	0,08
W30-33	-0,12	-0,12	-0,22
W34-37	-0,09	0,12	-0,16
W38-41	-0,02	0,11	-0,03
W42-45	0,16	0,23	0,16
W46-49	0,56	0,57	0,53
W50-52	0,77	0,67	0,76

Appendix 9

9.1 Regression Results for Norway

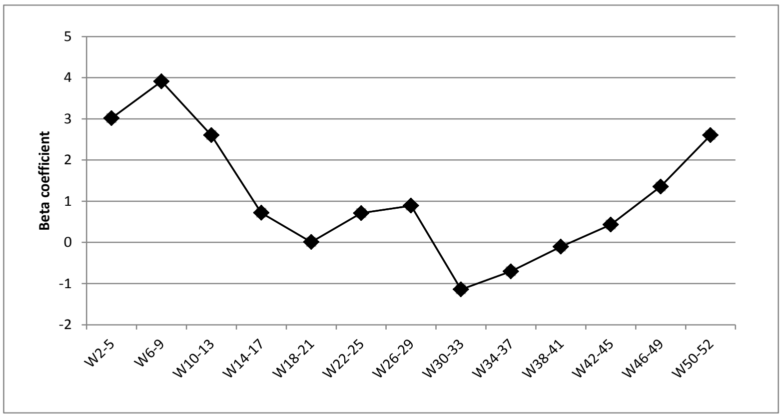


Figure A18: Beta coefficients for the grouped weekly logarithmic transformed price and load in Norway from 02.06.2003 to 31.10.2013

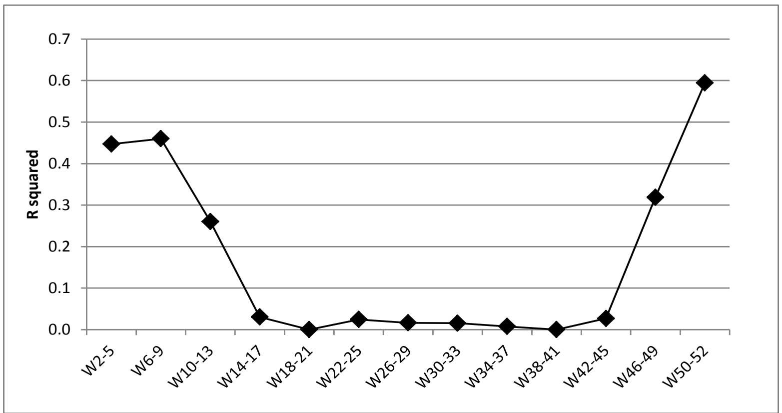


Figure A19: R^2 values for the grouped weekly logarithmic transformed price and load in Norway from 02.06.2003 to 31.10.2013

Table A10: Regression results for the grouped weekly logarithmic transformed price and load in Norway from 02.06.2003 to 31.10.2013

Weekly data	R^2	F	β	t-stat (β)	α	t-stat (α)
W2-5	0,447	30,711	3,018	5,542	-41,352	-5,090
W6-9	0,460	32,365	3,910	5,689	-54,635	-5,330
W10-13	0,261	13,386	2,603	3,659	-34,975	-3,315
W14-17	0,031	1,197	0,719	1,094	-6,948	-0,720
W18-21	0,000	0,000	0,008	0,010	3,362	0,276
W22-25	0,024	1,026	0,711	1,013	-6,785	-0,669
W26-29	0,016	0,696	0,891	0,834	-9,377	-0,610
W30-33	0,016	0,663	-1,143	-0,814	19,803	0,982
W34-37	0,008	0,323	-0,704	-0,568	13,727	0,767
W38-41	0,000	0,011	-0,105	-0,103	5,010	0,336
W42-45	0,027	1,133	0,431	1,065	-2,666	-0,448
W46-49	0,319	17,766	1,355	4,215	-16,402	-3,442
W50-52	0,595	41,074	2,604	6,409	-35,064	-5,800

9.2 Regression Results for North and South Norway

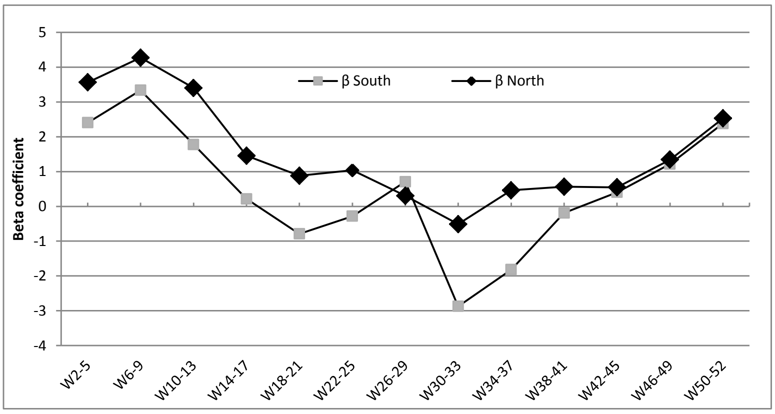


Figure A20: Beta coefficients for the grouped weekly logarithmic transformed price and load in North and South Norway from 02.06.2003 to 31.10.2013

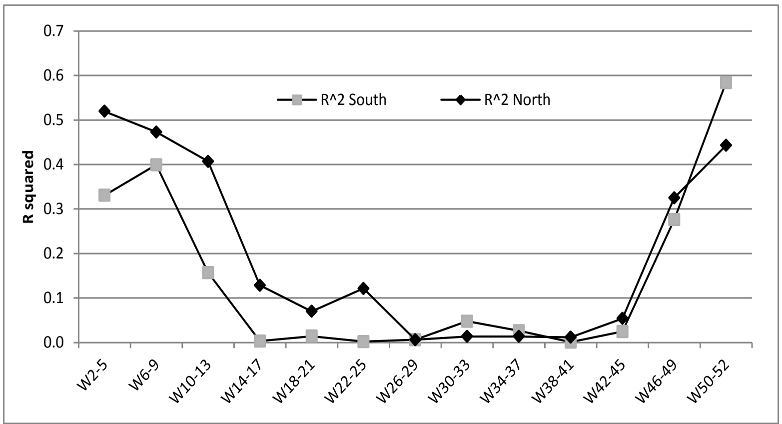


Figure A21: R^2 values for the grouped weekly logarithmic transformed price and load in North and South Norway from 02.06.2003 to 31.10.2013

Table A11: Regression results for the grouped weekly logarithmic transformed price and load in North Norway from 02.06.2003 to 31.10.2013

North Norway	R^2	F	β	t-stat (β)	α	t-stat (α)
W2-5	0,520	41,114	3,563	6,412	-44,937	-5,925
W6-9	0,473	34,110	4,271	5,840	-54,560	-5,469
W10-13	0,407	26,073	3,400	5,106	-42,553	-4,704
W14-17	0,129	5,609	1,455	2,368	-15,973	-1,929
W18-21	0,070	2,861	0,880	1,691	-8,215	-1,182
W22-25	0,121	5,662	1,037	2,379	-10,182	-1,761
W26-29	0,006	0,266	0,303	0,515	-0,503	-0,065
W30-33	0,014	0,579	-0,513	-0,761	10,255	1,153
W34-37	0,013	0,574	0,461	0,757	-2,458	-0,304
W38-41	0,012	0,505	0,565	0,711	-4,006	-0,377
W42-45	0,054	2,338	0,548	1,529	-3,711	-0,767
W46-49	0,325	18,297	1,341	4,277	-14,508	-3,409
W50-52	0,443	22,279	2,527	4,720	-30,697	-4,211

Table A12: Regression results for the grouped weekly logarithmic transformed price and load in South Norway from 02.06.2003 to 31.10.2013

South Norway	R^2	F	β	t-stat (β)	α	t-stat (α)
W2-5	0,331	18,771	2,405	4,333	-31,437	-3,881
W6-9	0,399	25,267	3,337	5,027	-44,994	-4,648
W10-13	0,157	7,076	1,779	2,660	-22,159	-2,287
W14-17	0,003	0,120	0,214	0,346	0,527	0,059
W18-21	0,014	0,545	-0,790	-0,738	14,624	0,965
W22-25	0,002	0,082	-0,282	-0,287	7,394	0,535
W26-29	0,006	0,265	0,707	0,515	-6,494	-0,338
W30-33	0,048	2,107	-2,874	-1,452	43,522	1,571
W34-37	0,026	1,142	-1,818	-1,069	29,081	1,214
W38-41	0,001	0,029	-0,188	-0,171	6,109	0,390
W42-45	0,025	1,037	0,402	1,018	-2,105	-0,372
W46-49	0,276	14,500	1,216	3,808	-13,932	-3,013
W50-52	0,584	39,306	2,381	6,269	-30,979	-5,605

9.3 Residual Specification Test Results for Norway

Table A13: Residual specification test results for the grouped weekly logarithmic transformed price and load in Norway from 02.06.2003 to 31.10.2013

Weekly data	Test 1: JB-test	Test 2: Cross correlation	Test 3: Autocorrelation	Test 4: Heteroscedasticity	Test 5: Linearity test
W2-5	4,53	0,18	0,37	1,74	0,86
W6-9	0,76	2,43	1,49	2,06	0,92
W10-13	2,63	1,59	0,73	1,07	1,95
W14-17	2,23	0,01	0,61	11,52	0,13
W18-21	0,61	0,42	2,23	1,69	1,29
W22-25	1,38	0,86	2,10	6,53	0,40
W26-29	5,04	0,02	2,58	0,23	0,56
W30-33	5,81	6,06	5,80	3,04	2,26
W34-37	1,73	1,56	11,66	1,72	0,62
W38-41	1,69	0,10	4,53	0,44	0,32
W42-45	0,90	1,58	1,10	1,99	2,91
W46-49	1,02	1,42	0,03	1,97	0,47
W50-52	0,50	4,27	0,30	0,72	1,80

9.3.1 Discussion of Residual Specification Tests

The residuals from the regressions are examined by applying the specification tests described in appendix [3.4]. Firstly, the residuals are highly normal, as all the JB statistics are lower than the chi squared critical value at a significance level of 5%. Secondly, cross-correlation is not evident in the residuals. All week groups but two have null hypotheses that are not rejected at a significance level of 10%. W30-33 and W50-52 have a higher tendency of cross correlation, but their null hypotheses are not rejected at a significance level of 1%. Thirdly, autocorrelation is evident in three of the week groups, W30-33, W34-37 and W38-41. W34-37 has a test statistic of 11,66, which is considerably higher compared to the other test statistics. Thus the problem of autocorrelation is more apparent in this period. There is no indication of correlation over time in the other week groups, as all the null hypotheses are not rejected at a significance level of 10%, except for W26-29 whose null hypothesis is not rejected at a level of 5%. Fourthly, the ARCH test indicates homoscedasticity in the majority of the week groups at a significance level of 10%. W30-33 has a higher tendency of heteroscedasticity, but the null hypothesis is not rejected at a significance level of 1%. W14-17 has a test statistic of 11,52, which is considerably higher compared to the others. Thus a more dynamic variance is apparent in this period. Heteroscedasticity is also evident in W22-25. Finally, all the residuals satisfy a linear model, the majority at a significance level of 10%. W22-25 satisfies a linear model at a level of 5% and W42-45 at a level of 1%.

From the analysis of the residuals, we conclude that the assumptions about the residuals are satisfied for most week groups. All the residuals satisfy tests (1), (2) and (5). Test (4) about heteroscedasticity is also satisfied, except for two week groups (W14-17 and W22-25). It can be argued that the test for autocorrelation, test (3), is among the most critical. In three week groups (W30-33, W34-37 and W38-41) such correlation is evident, the highest in W34-37. This may result in less precise t-statistics and F values in the respective regression models, which may affect the hypothesis testing and model evaluation.

9.4 Residual Specification Test Results for North and South Norway

Table A14: Residual specification test results for the grouped weekly logarithmic transformed price and load in North Norway from 02.06.2003 to 31.10.2013

North Norway	Test 1: JB-test	Test 2: Cross correlation	Test 3: Autocorrelation	Test 4: Heteroscedasticity	Test 5: Linearity test
W2-5	2,32	6,90	0,54	0,02	2,71
W6-9	12,62	3,50	1,97	0,38	2,75
W10-13	2,45	5,88	2,24	4,75	2,81
W14-17	1,63	0,17	5,63	8,68	0,84
W18-21	0,57	1,64	0,38	4,36	2,50
W22-25	1,16	3,76	3,50	2,67	1,21
W26-29	0,39	2,11	0,78	0,81	1,10
W30-33	11,41	5,42	2,80	1,47	2,32
W34-37	6,52	0,40	8,26	2,38	0,72
W38-41	3,21	0,01	5,22	0,19	1,46
W42-45	3,19	0,79	0,97	7,69	1,26
W46-49	0,44	1,63	0,25	3,80	0,94
W50-52	1,81	6,60	1,21	0,42	2,70

Table A15: Residual specification test results for the grouped weekly logarithmic transformed price and load in South Norway from 02.06.2003 to 31.10.2013

South Norway	Test 1: JB-test	Test 2: Cross correlation	Test 3: Autocorrelation	Test 4: Heteroscedasticity	Test 5: Linearity test
W2-5	7,18	0,00	0,41	1,65	0,38
W6-9	0,32	0,74	1,52	4,71	0,78
W10-13	2,55	0,43	0,99	1,47	1,04
W14-17	3,00	0,75	0,37	5,35	0,56
W18-21	7,99	0,31	3,18	0,21	0,26
W22-25	1,35	0,61	4,06	0,74	0,71
W26-29	29,56	0,81	4,01	0,08	1,26
W30-33	9,76	13,08	5,74	2,01	6,48
W34-37	76,60	1,02	5,56	0,28	0,56
W38-41	0,10	0,51	3,29	0,37	0,34
W42-45	0,04	1,29	1,10	0,51	2,10
W46-49	1,39	2,13	0,04	1,99	0,72
W50-52	0,53	4,97	0,36	0,29	1,75

Appendix 10

10.1 Time Series Plot of Forward Price

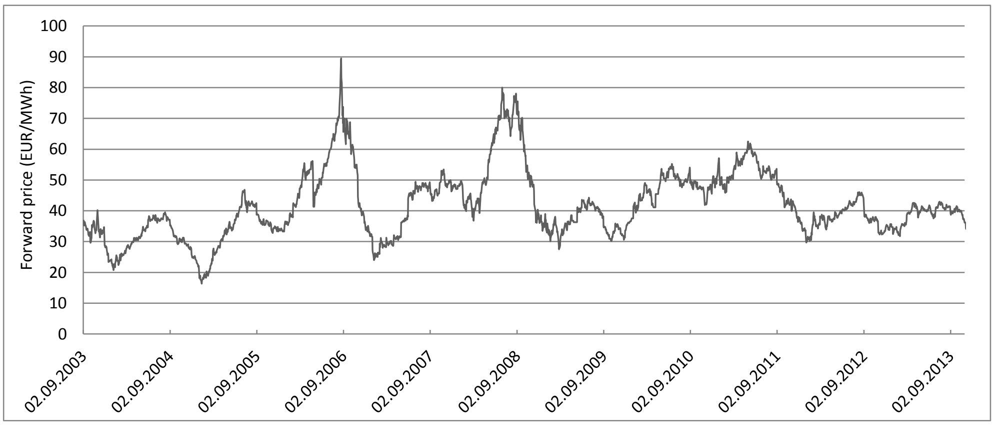


Figure A22: Daily forward price of the monthly 6-pos contract at Nord Pool from 02.09.2003 to 31.10.2013

10.2 Average Forward Price vs. Electricity Spot Price

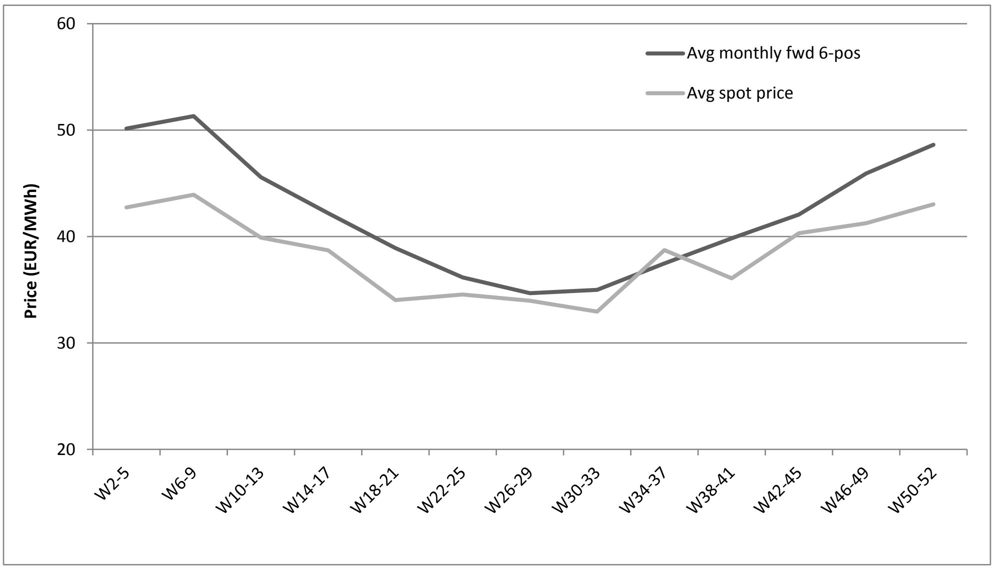


Figure A23: Average weekly spot price and forward price of the monthly 6-pos contract at Nord Pool from 01.03.2004 to 31.10.2013

Appendix 11

11.1 Optimized Hedge Ratios

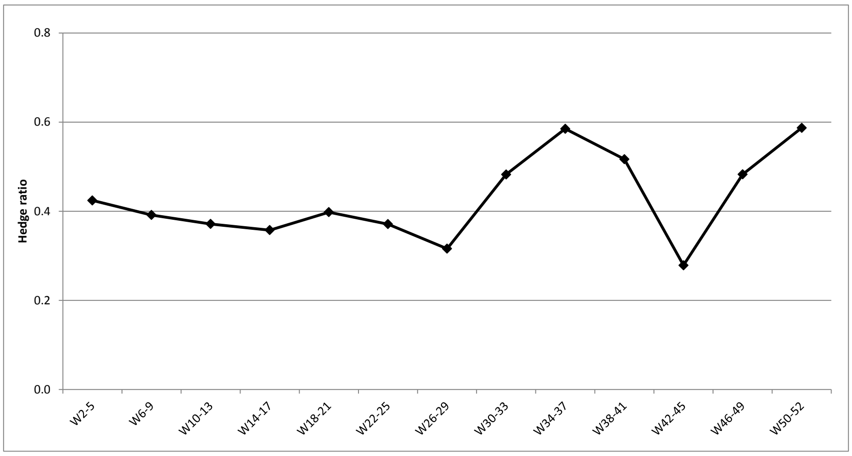


Figure A24: Optimized hedge ratios based on mean-variance from 01.03.2004 to 31.10.2013

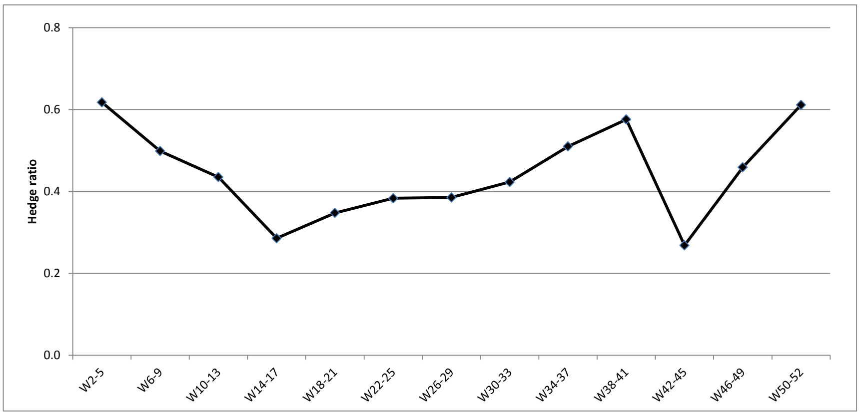


Figure A25: Optimized hedge ratios based on semivariance from 01.03.2004 to 31.10.2013

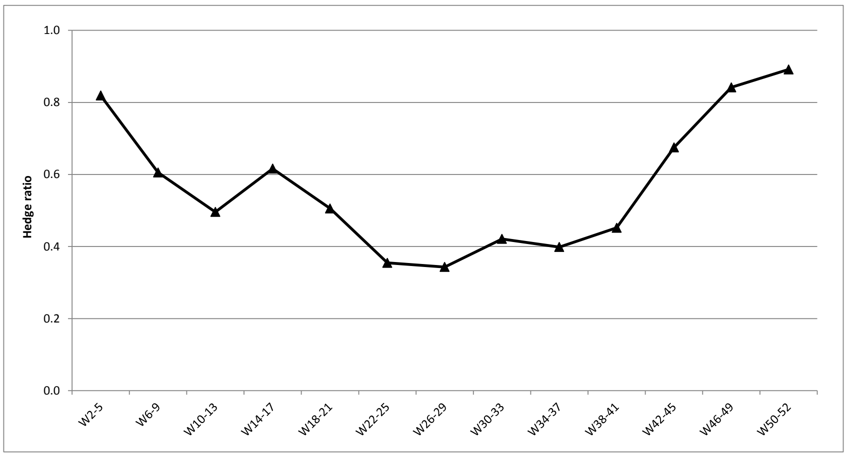


Figure A26: Optimized hedge ratios based on CVaR from 01.03.2004 to 31.10.2013

11.2 Sensitivity Analysis of Optimized Hedge Ratios

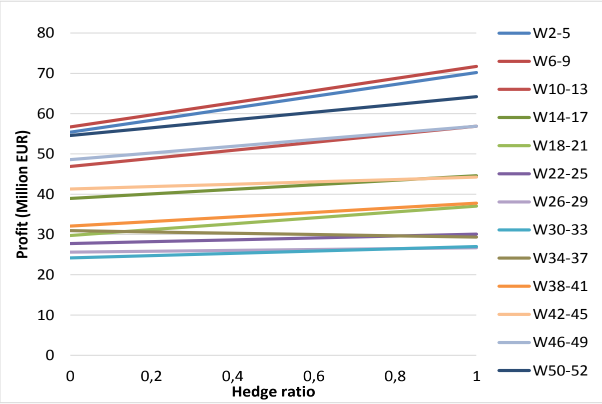


Figure A27: Average weekly profit for the week groups with varying hedge ratio based on mean-variance optimization, from 01.03.2004 to 31.10.2013

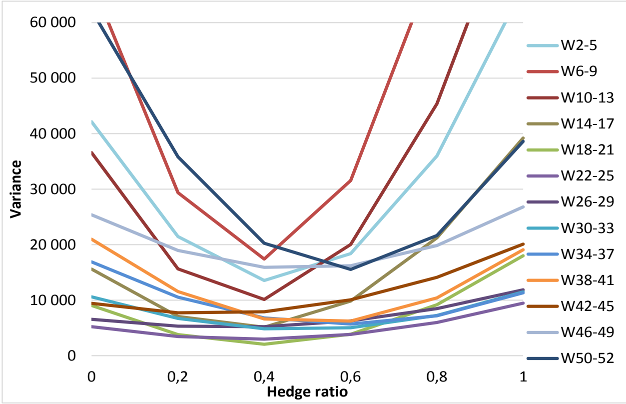


Figure A28: Cash flow variance for the week groups with varying hedge ratio based on mean-variance optimization, from 01.03.2004 to 31.10.2013

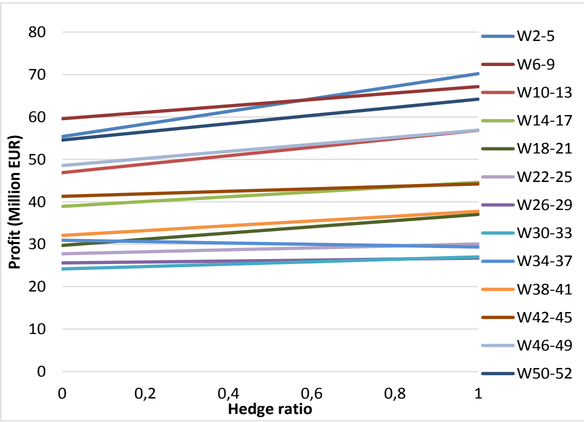


Figure A29: Average weekly profit for the week groups with varying hedge ratio based on semivariance optimization, from 01.03.2004 to 31.10.2013

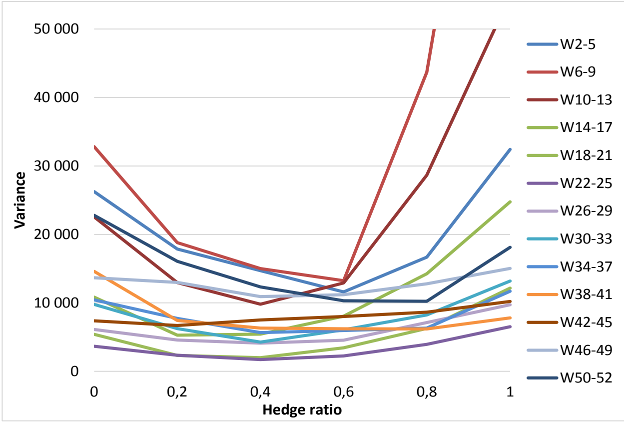


Figure A30: Cash flow variance for the week groups with varying hedge ratio based on semivariance optimization, from 01.03.2004 to 31.10.2013

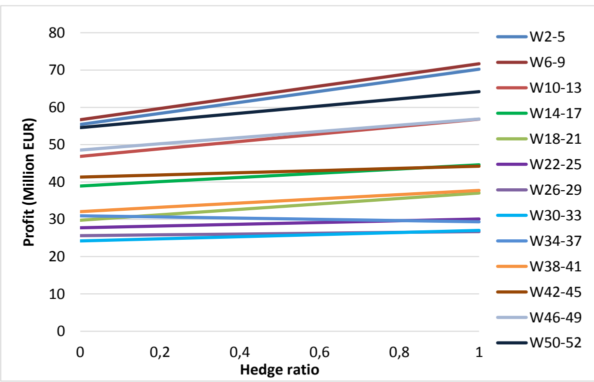


Figure A31: Average weekly profit for the week groups with varying hedge ratio based on CVaR optimization, from 01.03.2004 to 31.10.2013

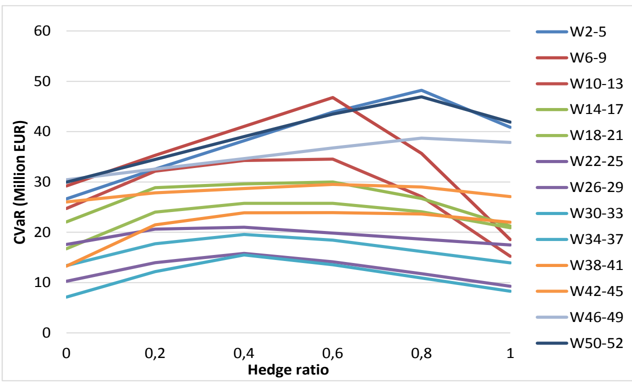


Figure A32: CVaR for the week groups with varying hedge ratio based on CVaR optimization, from 01.03.2004 to 31.10.2013

11.3 Average Weekly Cash Flow Corresponding to the Optimized Hedge Ratios

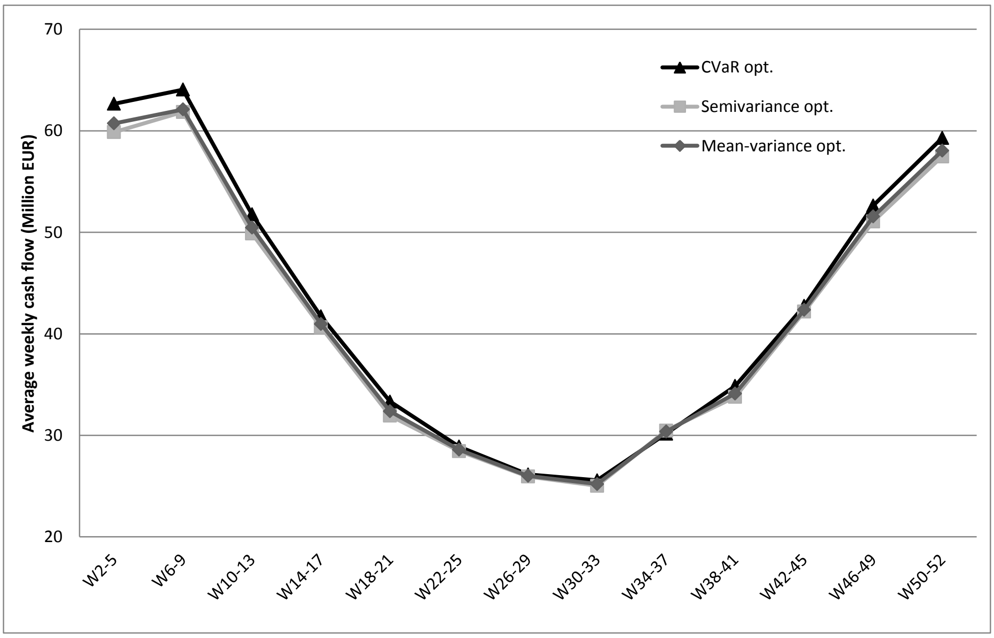


Figure A33: Average weekly cash flow corresponding to the optimized hedge ratios based on different risk metrics, from 01.03.2004 to 31.10.2013

11.4 Optimized Hedge Ratios in North and South Norway

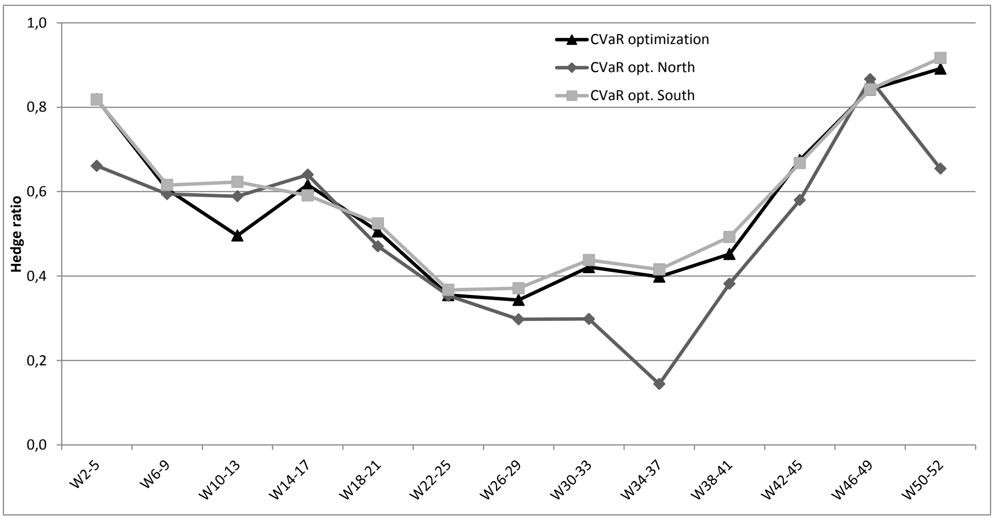


Figure A34: Optimized hedge ratios in North and South Norway based on CVaR (together with figure A26) from 01.03.2004 to 31.10.2013

11.5 Constant Hedge Ratio vs. Dynamic Hedge Ratios

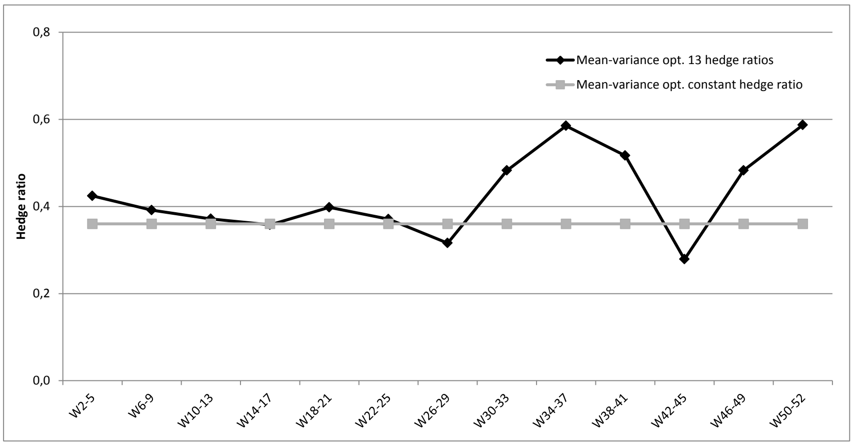


Figure A35: Constant hedge ratio vs. 13 seasonal hedge ratios based on mean-variance optimization in Norway from 01.03.2004 to 31.10.2013

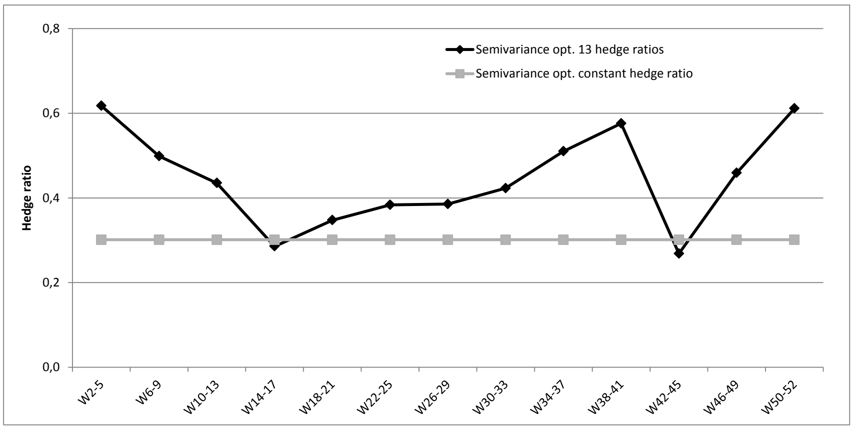


Figure A36: Constant hedge ratio vs. 13 seasonal hedge ratios based on semivariance optimization in Norway from 01.03.2004 to 31.10.2013

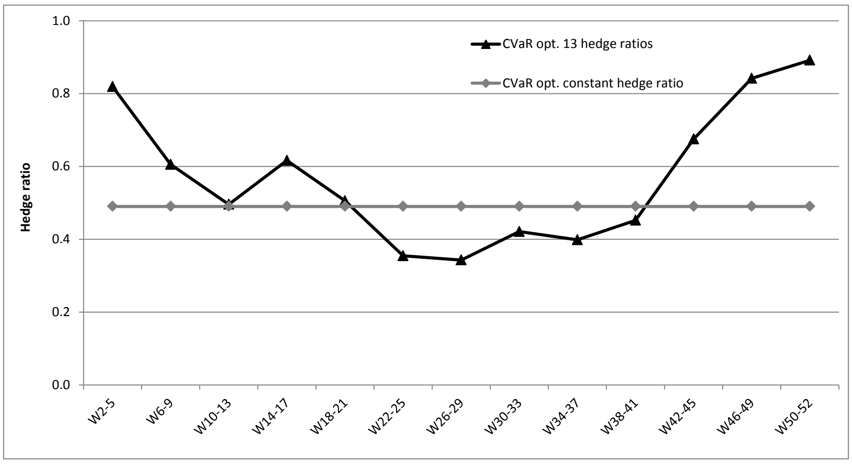


Figure A37: Constant hedge ratio vs. 13 seasonal hedge ratios based on CVaR optimization in Norway from 01.03.2004 to 31.10.2013

Table A16: Average weekly cash flow in Norway with 13 seasonal hedge ratios vs. one constant hedge ratio based on different risk metrics, from 01.03.2004 to 31.10.2013

Avg. weekly cash flow (Million EUR)	13 seasonal hedge ratios			Constant hedge ratio		
	Mean-variance	Semivariance	CVaR	Mean-variance	Semivariance	CVaR
W2-5	61,69	64,55	67,53	60,73	59,87	62,66
W6-9	62,58	63,36	65,79	62,11	61,86	64,06
W10-13	50,59	51,22	51,83	50,47	49,89	51,77
W14-17	40,97	40,56	42,43	40,98	40,65	41,71
W18-21	32,65	32,28	33,43	32,37	31,94	33,32
W22-25	28,61	28,64	28,57	28,58	28,45	28,89
W26-29	25,95	26,03	25,98	26,00	25,94	26,15
W30-33	25,54	25,38	25,37	25,20	25,03	25,57
W34-37	30,01	30,13	30,31	30,37	30,46	30,16
W38-41	35,01	35,35	34,65	34,12	33,79	34,86
W42-45	42,12	42,09	43,28	42,36	42,19	42,74
W46-49	52,58	52,38	55,56	51,56	51,07	52,64
W50-52	60,23	60,46	63,15	58,04	57,48	59,29

Table A17: Average weekly cash flow in Norway with optimized hedge ratios based on CVaR; constant hedge ratio, four seasonal hedge ratios and 13 seasonal hedge ratios from 01.03.2004 to 31.10.2013

Avg. weekly cash flow (Million EUR)	Constant hedge ratio	Four seasonal hedge ratios	13 seasonal hedge ratios
W2-5	62,66	64,66	67,53
W6-9	64,06	66,08	65,79
W10-13	51,77	51,64	51,83
W14-17	41,71	41,64	42,43
W18-21	33,32	33,22	33,43
W22-25	28,89	28,62	28,57
W26-29	26,15	26,02	25,98
W30-33	25,57	25,25	25,37
W34-37	30,16	30,26	30,31
W38-41	34,86	34,52	34,65
W42-45	42,74	42,56	43,28
W46-49	52,64	53,76	55,56
W50-52	59,29	60,59	63,15

Table A18: CVaR with optimized hedge ratios; constant hedge ratio, four seasonal hedge ratios and 13 seasonal hedge ratios from 01.03.2004 to 31.10.2013

CVaR (Million EUR)	Constant hedge ratio	Four seasonal hedge ratios	13 seasonal hedge ratios
W2-5	40,75	44,57	48,44
W6-9	43,63	46,43	46,95
W10-13	34,94	34,83	34,98
W14-17	29,83	29,81	30,00
W18-21	25,96	25,94	26,00
W22-25	20,47	21,14	21,27
W26-29	15,44	15,81	15,85
W30-33	14,98	15,39	15,56
W34-37	19,37	19,50	19,57
W38-41	23,98	23,95	24,00
W42-45	29,06	28,80	29,77
W46-49	35,60	37,01	38,92
W50-52	41,04	43,93	47,97