Electricity as a Risk Bearing Asset from a Portfolio Perspective, Studied Through the Concept of Value at Risk with a Time Varying Correlation Approach

LUNDS UNIVERSITET
Lunds Tekniska Högskola

Master Thesis in Industrial Engineering and Management
Department of Economics, Lund University
Lund Institute of Technology
Lund, Sweden

Jacqueline af Ugglas & Victor Guter
May 28, 2014

Supervised by:
Hossein Asgharian
Bujar Huskaj

Abstract

The purpose of this thesis is to examine if, from a portfolio perspective, the Value at Risk decreases when electricity is included as an asset to a portfolio of risk bearing assets and if this could have an impact on risk hedging strategies. The portfolio standard deviation used to calculate the Value at Risk is based on a Dynamic Conditional Correlation approach providing a time dependent correlation. Three Nordic industrial companies make up reference objects for the quantitative analysis. Findings show that electricity has a close to zero correlation, for all points in time, with all additionally examined assets. Therefore, it has a significant diversification effect on the portfolio variance and thereby reduces the Value at Risk. The portfolio weight allocated to electricity is however very limited, thereby reducing the possible overall effect to hedging strategies.

Keywords: Value at Risk, DCC, Electricity, Risk Bearing Assets, Variance, Correlation

Acknowledgment

This thesis has been a collaboration between SEB, Global Financial Solutions, and the Department of Economics in Lund. Fredrik Sundvall, SEB, was the initiator to the project and has also been our main supervisor. Coming into the project our previous experiences were limited, especially regarding the relevant assets. On that basis we would like to sincerely thank Mats Forsell, SEB, and Mats Hedberg, SEB, who both were of great assistance in explaining the fundamentals of the asset time series and providing us with the relevant data.

Contents

List of Figures

List of Tables

Acronyms

FX - Foreign Exchange

FI - Fixed Income

GFS - Global Financial Solutions

VaR - Value at Risk

OTC - Over The Counter

USD - United States Dollar

LSE - London School of Economics

EUR - Euro

Q - Quarter

TWh - Terawatt hour

GWh - Gigawatt hour

SEK - Swedish Krona

GBP - Great British Pound

ARMA - Autoregressive Moving Average

GARCH - Generalized Autoregressive Conditional Heteroskedacity

DCC - Dynamic Conditional Correlation

WN - White Noise

IID - Independent and Identically Distributed

CCC - Constant Conditional Correlation

AIC - Akaike Information Criterion

CDF - Cumulative Distribution Function

YR - Year

STIBOR - Stockholm Interbank Offered Rate

EBITDA - Earnings before Interest, Tax, Depreciation and Amortization

Chapter 1

Introduction

1.1 Background and Motivation

A company is generally exposed to a number of operational risks when performing its daily activities. If not encountered and hedged in best possible manner, these risks can have a large negative effect on the company's total profits. When specifically viewing a company within the production industry, common risks are noted such as prices of commodities needed in the production, exchange rates, when having production and distribution in foreign countries, and interest rates for loans financing their activities. These risks may not come as a surprise for the untrained eye, but another risk that argues for a discussion is the volatility of the electricity price, which can be studied on the spot market, both live and historically. The risk aspect of the electricity price is especially interesting and necessary for companies in the electricity-intense production industries. Many companies in these industries spend a considerable amount of money every year, when buying electricity needed for the production of their goods.

The general perception today is that each risk is encountered for and mitigated by each risk's associated division, e.g. the commodity price risk is handled within the purchasing department, the foreign exchange risk (FX-risk) is allocated to the treasury department, as is the interest rate risk (FI-risk). There is often no, or little, interaction between the different divisions risk handling, limiting the possibility of collaboration for risk management. A question is raised, and that is, whether or not it is possible to manage these different risks from a portfolio perspective. SEB, the leading corporate and investment bank in the Nordic region, has highlighted this cause for discussion with the curiosity of analyzing possible financial affects for a company to use a portfolio approach when managing their risk exposures instead of the 'traditional' approach being used today. The problem, however, is the behavior of electricity prices when electricity is added as a risk-bearing asset to a portfolio, being extremely volatile and having no correlation with other goods. The spot market for electricity shows 'spikes' in the prices, giving rise to an extreme

volatility. As a consequence the correlation between electricity and other assets could possibly be altered. This results in difficulties when accurately trying to calculate the variance of the portfolio and the correlation between the different risk bearing assets in the portfolio.
On the other hand, this particular behavior is one of the main reasons why it is interesting to add electricity as an asset to the risk portfolio and to study the risk from the portfolio point of view. With reference to Mats Forsell, Commodity Trader at SEB, the effects of adding electricity may be particularly evident, as 25% of the commodity price risk is assessed to electricity. The text below is written in the context of investing in different assets, but the principles are the same for this investigation - when analyzing how a company can decrease its total variance, hence the total risk, when adding the electricity price to a company's portfolio of risk bearing assets.

'The electricity market is volatile and offers therefore the opportunity to a high return- implying a high risk. At the same time, the correlation with other assets, such as fixed income, foreign exchange and other forms of raw material, is low. This makes the investment in electricity attractive seen as a complement to a well diversified portfolio or as a pure speculation product'[1].

The Global Financial Solutions department at SEB, GFS, is offering far-reaching risk financing advisory to corporations and institutions within SEB Merchant Banking, with the aim to improve a company's financial outcome. They advise within all risk-related areas, such as financial market risks, strategic risks and operational risks, as they are specialized in interest rate hedging, equity hedging, commodity hedging and long-term foreign exchange hedging. In order to deliver top services, GFS considers the stated approach, examining the risk of a portfolio when electricity is added as a risk bearing asset, an interesting topic worthy looking into. This since SEB always desires to provide the best possible solutions when it comes to a company's risk management.

When GFS raised this cause for discussion, we saw a great opportunity to mathematically investigate the effects of adding electricity as an asset to a company's portfolio of risk bearing assets. In this way we were given the ability to test our numerical abilities based on a topic that we truly found interesting with the hope of also providing value to GFS, SEB. With the help of electricity's rather special behavior, having low or none correlation with other risk bearing assets, it is interesting to investigate how the total portfolio's risk exposure for an energy intense company can be altered when adding electricity as a risk bearing asset. A dynamic conditional correlation model (DCC), taking time varying correlation into account, was chosen to get the best possible results. This enables a time varying portfolio variance, both regarding the variance of the individual assets as well as the covariance between assets, making it possible to study the effect for all points in time. It also makes it possible to study the effect during specific time periods, such as financial crises, to provide further noteworthy findings. With the motivation for SEB and for us, to provide top risk management to their clients, we provide a study where electricity is added as a risk-bearing asset to a portfolio of traditional risky assets. This is done to examine, for different points in time, how the Value at Risk is affected.

1.2 Choice of Measurement

Value at Risk (VaR) is the choice of comparable measurement for this thesis. VaR is a statistical technique to quantify the level of financial risk that a company or a portfolio is facing over a specific period of time. VaR has been called the 'new science of risk management'[2] and since the technique is focusing on potential losses, the approach is very suitable for this thesis. The VaR-statistic has three components; a potential loss amount, a confidence level and a specific period of time. It is a preferred market risk measurement according to the Basel II accord and a measure widely used in the banking industry. The VaR will be based on a time varying portfolio variance to get as realistic results as possible. Both the variance of individual risk bearing assets and the correlation between them are subject to differ for different points in time. This will be solved by using a Dynamic Conditional Correlation model (DCC). The DCC is a two-step estimation where the first step is a univariate GARCH approach to obtain the individual conditional time varying variances of each of the portfolios assets. The second step is the correlation estimation providing the time varying correlation between all portfolio assets. DCC has the advantage of being a complex model but following the two-step estimation approach greatly simplifying the computations by reducing the number of parameters to be estimated. It entails that large correlation matrices easily can be estimated hence allowing numerous assets. VaR, GARCH and DCC will be thoroughly explained further on in the thesis.

1.3 Research Questions

In order to examine to what extent electricity is value adding in a Value at Risk perspective and what is distinguishing for electricity as a risk bearing asset the following questions will be answered. It will be the ones the thesis will be centered on with the aim to provide a solid and fruitful conclusion.

- How are electricity prices behaving on the financial markets and with what other inputs of risk bearing assets is it showing correlation or no correlation?

- Can the special properties and volatile nature of electricity price movements be seen as a risk management complement?

- Using three different energy intense industrial companies as inspiration, regarding their current risk exposures, can electricity be added to the portfolio of risk bearing assets in order to have a significant effect on the companies VaR?

- If so- it is enough for the company to consider a different risk hedging approach?

1.4 Purpose

The purpose of the thesis is to test, throughout quantitative analysis, what benefits an energy-intense company gains by adding electricity to its' portfolio of risk bearing assets. The results and conclusion will be studied throughout the concept of Value at Risk (VaR) where the portfolio variance input is time varying, both regarding the assets individual variance as well as the correlation between assets. By comparing different portfolio compositions for which we calculate our VaR upon, we will then analyze the difference in the portfolios VaR to conclude the effect of having electricity as a risk bearing asset in the portfolio. The diversification possibilities for the portfolio are therefore tested, and a conclusion regarding how to construct the portfolio can be drawn, having the electricity as an input variable or not. The test will be carried out on portfolios with asset weights inspired by real companies, allowing us to stretch to a more flexible and allowing framework. See *Appendix A* for portfolio weights.

1.5 Limitations

The thesis is subject to a number of limitations, which must be considered when reviewing the both the mathematical outcome and the subsequent analysis and conclusion.

We have chosen to focus our investigation to the manufacturing industries due to their particular high demand of energy in their production. After comparing different industries, regarding the energy and electricity consumption, we have come to the conclusion that the focus should lie on the steel and metal industry and on the paper and pulp industry. They have, by far, the highest energy consumption within their production, and therefore we consider these industries as the most relevant ones to base the thesis upon[3]. SSAB, Sandvik and Stora Enso are the companies relevant to the investigation when these limitations have been accounted for.

To further restrict the scope of the thesis, we have chosen to target the industries present in Sweden and its surroundings. This limits the amount of data at hand and gives us the ability to maintain a consistency throughout the analysis, leading to a more reliable analysis and conclusion. If desired, the analysis is applicable to all of the Nordic region, since factors determining the electricity price, demand and access to alternative energy sources are similar throughout the whole of the Nordic region. The analysis and conclusion is however only applicable to this region since the factors are subject to significant geographical differences.

In order to model a credible portfolio variance the choice of risk bearing assets is of importance. To limit the number of assets we only include the prominent risk bearing assets mentioned by the investigated companies. After researching the chosen companies, there are a number of reoccurring risk bearing assets mentioned as being of great importance. These assets are linked to three main areas of risk, foreign exchange rate risk, interest rate risk and price risk of commodities. Electricity price risk is part of the total price risk of commodities but will be handled separately in this thesis since it is the differentiating asset.

To provide reliable results, we include as long a period of time as possible to account for seasonal variations and different economic business cycles. Also, since many of the mathematical models are of a conditional nature, dependent on previous values produced by the model, long time series are needed to get significant parameters. Ultimately deciding the period of time is the available length of the data used. For the mathematical modeling the length of the data is 500 historical weakly data points, approximately 10 years. This was less than desired but data points, further back in time, for prices of commodities were non existing.

As mentioned in the paragraph above there was an issue finding relevant commodities with sufficient price history lengths. The reason for this is that functional markets for commodities are fairly new. The only commodity series with sufficient amounts of data was Nickel. This is a major limitation which will have the biggest affect on the whole thesis. Nickel serves as a substitute for all commodities used by the relevant companies, even when the commodities are entirely different from Nickel.

The data used will, to some extent, already be of a 'hedged approach'. This means that some of the data series used will not be traded on a spot market, but rather on the derivatives market. This applies to the electricity price, which is the 1 yr forwards price, and nickel price which is the 3 month future. The reason for this is to avoid to have to model electricity spot prices extreme volatility, the same applies for nickel. The derivatives series used do have the spot prices as underlying assets meaning price movements will follow the same pattern as the spot prices.

1.6 Sources of Information

The thesis has been based on research such as interviews, annual reports, sustainability reports and historical price data for the different risk exposed assets. With the appropriate and selected data at hand, applicable mathematical models were chosen to model the time varying components needed for the VaR-calculations.

1.7 Outline

The theoretical background will be explained in *Chapter 2* where both the current risk management of the examined companies and the mathematical background for the quantitative analysis is explained. First an overall explanation of different risk management tools is outlined. Common financial instruments for risk management within commodities, FX, FI and electricity are presented. Secondly the chapter will deal with the different mathematical models and statistical instruments being used for the mathematical estimation.

Chapter 3 will provide an explanation and introduction to the electricity price market. It explains how the electricity price behaves on the market and answers questions, such as what factors determine the volatility. Also, trends and cyclicality are analyzed. It continues with an introduction to the companies examined in the thesis. The different companies will be presented and their relevant risk bearing assets will be examined. Their general electricity consumption will be sorted out and how they are mitigating the risk that is present throughout their activities.

In *Chapter 4*, the method adopted for this thesis is explained. The approach explains all different steps that guide us through the investigation. The data is then explained in detail, both the reasons for the selection, the description for it and the modeling of it.

In *Chapter 5* the results of the mathematical modeling is presented. Here it will be outlined in what way electricity as a risk bearing asset has affected the VaR and the dynamics of the time varying correlation presented.

Further on in *Chapter 6*, the results will be commented and analyzed. The portfolio approach to risk mitigation will be discussed. Through a portfolio VaR perspective it will be analyzed if electricity, as a risk bearing asset, is value adding or not.

The conclusion and findings are presented in *Chapter 7* where the main conclusions are outlined. Based on the conclusions, companies can choose to account for the findings or not.

Chapter 2

Theoretical Background

The aim of the sections below is to explain the underlying theoretical background for the investigation-both the current risk management of examined companies and the mathematical theory. The companies, being investigated, will however be presented in the subsequent chapter.

2.1 Risk Management

The sections below will aim to account for the different methods and strategies to mitigate the financial risks that arise from the daily activities within the investigated companies, as well as the background information for the implied risks. The risks, of interest and focus for the thesis, are the ones that arise from fluctuations and uncertainty of prices for commodities, including electricity, foreign exchange rates and interest rates. The financial hedging strategies are many, and therefore the focus of this thesis will be on the ones applicable for the selected companies and the assets of interest. For the same reason as there are two markets for the trade of electricity assets, there are derivative markets for the other assets as well, in order to manage risk and avoid gambling.

2.1.1 Commodity Risk management

Many companies engaged in manufacturing activities use one or several commodities in their refinement process. Electricity can be viewed as a commodity, but is handled separately in this thesis. The price of commodities often account for a large portion of a company's overall costs, especially when using expensive raw materials. According to Oliver Whymans's Energy practice, commodity price swings are now considered the second-largest driver of earnings uncertainty at publicly traded companies[5]. Managing this risk is becoming more important, and therefore moving up on many companies' agendas, increasing the roll of the procurement teams. The price for the commodities used in the production process has a great impact on the total production cost of the produced goods, and therefore have an impact on the profit made when selling the product. The selling price of goods is often decided upon before production and changing prices is often a struggle especially when producing consumer goods. Therefore, managing costs is a very important factor in order to avoid deteriorating margins. One issue, with commodity price risks, is the illiquidity of certain commodities, which causes problems when trying to manage the risk.

The uncertainty implied by the above can however be managed by the help of risk management of commodity price risks. The commodities in question, such as metals and fiber, and can be treated in the same manner- by so called financial contracts, or derivatives. The contracts that are most commonly reported in the annual reports of interest, are forward contracts and futures contracts.

Forward contracts are entered by two parties- the buying and the selling party- where the buying party is guaranteed a specified quantity and quality at a pre agreed price at a future decided date[6]. It is usually an over-the-counter traded product suitable for two parties having different point of views of what to expect of the future price of a certain commodity. The forward contracts are specifying quantity, quality and delivery periods and if any of these parameters are not met, the deviating party is usually obligated to compensate the counterpart and therefore it is difficult to extinguish the contract[6].

Another financial contract that is commonly used, and even further applicable for risk management, is futures contracts. They include the same properties as forward contracts, but also the ability of extinguishing the contract through an offsetting financial strategy. This is explained in the next paragraph. Futures are traded on regulated exchange market places where traders and brokers are meeting bids and offers, enabling them to establish the forecast prices before the commodities are traded[6]. The main difference between a forward and a futures contract is that the futures is marked-to-market daily, meaning that daily changes are settled for, day by day, whilst the forward contracts are, only settled once at the end on the contract[7]. Another major difference between the two contracts is that futures contracts are usually standardized and traded on exchange markets whilst forwards are traded over the counter, OTC, in order to customize it.

Offset hedging allows the executing company to extinguish or liquidate the future position by engaging in an opposite but equivalent position by which the net position for the company becomes zero. By that, no further gains or losses can be made from that position and further associated liabilities are removed[8] as well as any risk of price volatility[9]. This way of managing risk is actually more commonly used than realizing the actual futures contract[8].

2.1.2 FX Rate Risk Management

Companies have several components that are affected by a change exchange rates. The LSE- Risk & Stochastic Group defines exchange rate risk as the variability of a firm's value due to uncertain changes in the rate of exchange[10]. Forecasting exchange rates, in a correct way, is extremely difficult, so the focus for companies is often to correctly measure their exposure to fluctuations in the relevant exchange rates. There are three main areas of exchange rate risk- transaction risk, translation risk and economic risk[10]. In addition, to the above stated, there are also several indirect risks, such as overseas companies becoming more competitive due to movements in exchange rates.

Transaction risk is the cash flow risk having an impact on receivables, payables and possible dividends to be received. If a change in the exchange rate occurs between the fixing of the contract and the date of payment there is a possibility of receiving less, or paying more, than stated in the contract. This occurs if the local currency value of a foreign currency receivable falls or if the local value of a foreign currency payment rises.

Translation risk is the balance sheet risk having an impact on the value on assets and liabilities with foreign origin. At the end of every accounting period the value of overseas assets and liabilities must be translated into the accounting currency. This might have a negative effect on the value of the assets and an increasing effect on the liabilities. Depending on the accounting regulations, the translation exchange rate may be an average over the period or the end of the period value.

Economic risk is the market value risk having an impact on the core business compared to individual transactions as the previous explained risks. The present value of the firm's future cash flow is dependent on the exchange rate. A change in exchange rates will have an effect on revenues, sales and exports, and operating expenses, inputs and imports.

Risk management is especially occurring when it comes to the foreign exchange market. After investigating the different companies, the FX rate risk is of major importance as the companies have a high volume of cash flow in foreign currencies. If a foreign exchange pair is properly hedged, a trader with a long position is protected against downside risk and a trader with a short position is protected against upside risk. The first contract that appears on the FOREX market is the short-term spot contract, which by implication is traded on the spot market. Two days are given as the delivery period where the exchange rate is set to two days ahead. The short-term nature of this contract is in fact the main reason why a hedge is needed, which leads us to the most commonly traded contract- the currency forward.

By foreign exchange forwards a company can be protected against fluctuations in the currency rate, also, the exact future cash flow can be predicted and calculated in advance. The deal is made by the specific company and a trader, for instance a bank, where the company is guaranteed to buy or to sell a specific currency at today's rate but with delivery at a future date. So, for instance, if the company knows in advance that a large transaction in a foreign currency is going to occur in 6 months time, the FX currency on that future date, in 6 months time, is going to be of interest. The bank can then offer the company to trade on today's foreign exchange rate but to be delivered in 6 months. The contract is binding[11]. The forward contract can also be converted to a currency swap, whereby the currency market is making use of a 'two-legged' approach ,with two future dates, instead of the above 'one-legged' approach, where only one future date is of interest. The currency swap allows the company to 'roll out' the position to another future date, as the contract contains two different dates, which is beneficial if the company is having uncertainties of when the cash flow is needed. By swapping the currency it is also possible to roll just a part of the cash flow to another date. When using forward contracts and currency swaps, the foreign exchange rates are subject to interest rate fluctuations, taking the time perspective into account. The closer to the spot-date, the lower the change in basis points that the interest rate can come to vary.

Another form of contract that is commonly exercised on the foreign exchange market is foreign exchange options, which serve in two different ways. The fundamental function is still to protect the company against foreign exchange rate fluctuations, but as an add-on, the options also enable the company to increase its return by taking a speculative approach when the exchange rate varies[12]. So, at the same time as the company is protected against negative rate changes, it can benefit from positive rate changes since the option gives the party the right, without being obligated, to exercise the option[13].

2.1.3 FI Rate Risk Management

A company is subject to interest rate risk if it possesses any interest-bearing assets or liabilities, of which loans and bonds are two common examples. Depending on the assets and their attributes a change in the interest rate will have different effects on the company. The attribute having one of the largest effects is the length of the loan term, limiting the possibility to refinance or change the exposure to the interest rate. According to Cima and their investigation of interest rate risk management, the interest rate risk is probably one of the most important of all financial risks affecting a company[14]. If a company has a liability linked to the market's interest rate, a change in the interest rate will have an impact on the cost of borrowing. Interest income on monetary investments and the value of current bonds will also be affected by a change. Indirect effects might include a decrease in buying power from costumers, which has an impact on the operating income.

To encounter for the above, the companies are offered several methods that can mitigate the interest rate risk. By entering a deal to hedge potential future interest rate increases, the company can be guaranteed today's rate even if the loan is to be taken tomorrow. This can be done up to one year in advance[15]. Another option for the company is to engage in an interest swap, which is a widely used contract today. It enables the company to be flexible in their liability management with a possibility to adapt the interest rate risk for a loan to current market conditions. In practice every interest rate agreement is customized, where two parties agree to change payment flows with each other. For example an industrial company may prefer to have a pre-determined interest rate to pay to the bank every month, in order to control the costs. In turn the bank agrees to pay the difference between the real interest rate and the pre-determined interest rate back to the company. This strategy allows the company to control the interest rate costs without affecting the balance sheet nor the underlying liability[16].

Furthermore, the company can engage in a swaption, which elaborates the above mentioned interest swap by allowing the company to have the above wanted features but at a future date. The part taking the long position in the swaption therefore has the right, but not the obligation, to exercise the swaption at the date of interest[17].

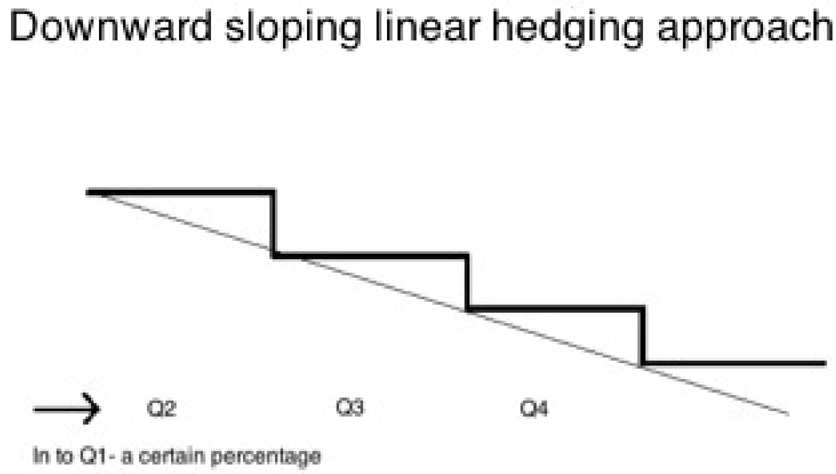
2.1.4 Electricity Risk Management

As mentioned below in *section 3.1* the electricity price possesses rather difficult features determining its price. The demand and supply factors implies the 'volume' risk, where participants have difficulties in predicting the correct volume and quantities of consumption or production. The supply/demand matching is further complicated since storage of electricity is costly on the supply side at the same time as the demand side shows low flexibility[18]. These aspects give rise for risk exposures when a company faces volatile electricity prices as they are buying electricity for their production.

The Nord Pool Spot is still the most common place for the Swedish electricity-labor[19], but looking more into companies that demand a high quantity of electricity and where actual price risks arise, companies today manage the risk more commonly via private bi-lateral power purchase agreements in order to protect the company from volatility. As short-term contracts are not enough to encounter for the volatility, long term contracts are increasingly popular, allowing buyers to hedge against price booms and sellers to hedge against price bursts[18]. To meet increasing demand for futures, Nord Pool developed the futures market into a financial market and today Nasdaq OMX Commodities is responsible for the trading with futures and forwards. These financial contracts are used for price hedging and risk management with contracts containing time horizons up to six years. The price for the future is based on the spot price setting a reference point[20]. The financial market for the contracts meets the increasing demand for information, availability, trading and settlement mechanisms, providing high liquidity on the market. In the same way as above, the futures and forward contracts differ as to how settlements are carried out, but both contracts give rise to the same profit and risk[21]. As well as the use of contracts, where a price is set to a quantity to be delivered at a certain point in time, many companies engage in generating electricity within the production processes. This enables them to totally control the consumption adapted to their particular production and demand. Since 1999 the financial market also offers trade in power options, which are standardized products with pre-determined contract specifications[21].

After further investigations, consisting of both telephone interviews as well as personal meetings with industry representatives, a more thorough explanation of how the companies protect themselves against volatility in electricity prices was carried out. The general strategy is to use a so-called 'layering hedging strategy', whereby companies are refining exposures and layering in hedges throughout the year instead of setting the hedging strategy for the entire year at the beginning of the year. By doing so, the companies experience more flexibility through varying the coverage and forming new forecasts as time goes by. Coverage mismatch due to uncertain exposure forecast can also be avoided[22]. The securing of electricity purchases is carried out so that the time horizon, and the predicted quantity needed, follows a downward sloping linear approach. This extends the traditional layering hedge approach. First the company predicts the total energy-demand for the specific year they want to hedge. The next step is to engage in financial contracts so that a rather high percentage of the total electricity purchases are secured to a pre-determined price coming into the first quarter of the fiscal year. Further into the year, the hedging quantity decreases, allowing the company to adapt to new market conditions. The downward sloping model is followed throughout the year and the goal is to keep to the plan, but still allowing the manager to alter the rate of the hedged quantity, given that he returns to the plan when his risk mandate is exercised. What should be mentioned is that layering hedging strategies are not just applicable to electricity- today it is widely used throughout numerous types of assets.

Figure 2.1: Electricity hedging approach



2.2 Theoretical Models

To obtain the comparable measure, Value at Risk, the data is subject to several mathematical models to deliver the desired output. The following sections will introduce the mathematical models used along with mathematical tests and theory to test and prove critical conditions. $ARMA$, $GARCH$, DCC and finally $ValueatRisk$ are the models used to first model the conditional time varying portfolio variance and then computing the weekly value at risk. A thorough explanation of all steps and explanations of input and output is explained in *section 4.3*, Estimation Method.

2.2.1 ARMA

Autoregressive moving average or $ARMA$ process is a linear model used for describing a time series over time. It is the sum of an autoregressive process of order p and a moving average process of order q.

According to Brockwell and Davis [28], if the process $\{X_t\}$ is stationary and if for every t,

$$X_t = \phi_1 X_{t-1} + ... + \phi_p X_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + ... + \theta_q \varepsilon_{t-q}$$

where $\varepsilon_t \sim WN(0, \sigma^2)$ it is said to be an $ARMA(p, q)$ process.

$\{X_t\}$ is an $ARMA(p, q)$ process with the mean μ if $(X_t - \mu)$ is an $ARMA(p, q)$ process.

2.2.2 GARCH

Generalized autoregressive conditionally heteroskedastic ($GARCH$) models are used for expressing conditional variance as a linear function depending of past variances and observations.

According to Jondeau [29], the $GARCH(p, q)$ model is defines as

$$\begin{aligned} &\varepsilon_t = \sigma_t z_t \qquad z_t \sim i.i.d\ N(0,1) \\ &\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \end{aligned}$$

with the constraints on the parameters: $\omega > 0$,$\alpha_i > 0$ for $i = 1, .., p$ and $\beta_j > 0$ for $j = 1, .., q$ ensuring strictly positive variance.

Adding the constraint $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1$ ensures that the model is strictly stationary and has finite variance.

In order to obtain the optimal parameters the $GARCH$ model uses maximum likelihood estimation.

Estimating a $GARCH(p,q)$ with $m = \max(p,q)$ focuses on the conditional likelihood function:

$$f(\varepsilon_1, ..., \varepsilon_T; \theta | \varepsilon_{-m+1}, ..., \varepsilon_0) = \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp(-\frac{\varepsilon_t^2}{2\sigma_t^2})$$

giving the log-likelihood function:

$$\log(L_T(\theta)) = \sum_{t=1}^{T} \log(\ell_t(\theta))$$
$$where \ \log(\ell_t(\theta)) = -\frac{1}{2}\left[\log(2\pi) + \log(\sigma_t^2) + \tfrac{\varepsilon_t^2}{\sigma_t^2}\right]$$

Solving for $\frac{\partial \log(L_T(\theta))}{\partial \theta} = 0$ maximizes the likelihood equation.

In practice the solution is gained by computing the log-likelihood function, $\log(L_T(\theta^{(0)}))$, for some theta, $\theta^{(0)}$, and iterating for different thetas, $\theta^{(1)}, ..., \theta^{(p)}$ until the log-likelihood converges to a maximum value. The thetas are vectors containing the unknown parameters of the model, in the $GARCH(1,1)$ case $\theta = [\omega, \alpha, \beta]$.

It can be shown that when using the $GARCH$ model ε_t^2 belongs to an $ARMA$ process which is a nice feature since, in this thesis, an $ARMA$ process is used to obtain the residuals.

For this thesis a $GARCH(1,1)$ model is sufficient. This implies that the variance at time t depends on the previous squared residual and variance giving the following model:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

In terms of calculation power needed this is a pretty simple model since there are only three parameters to calculate, ω, α and β.

2.2.3 Stationarity

To use the $GARCH$ estimation there exists a condition that the process being modeled, $\{X_t\}$, must be stationary. According to Francq and Zakoian [30] there are two types of stationarity, *Strict stationarity* and $Second-order\ stationarity$. The second definition being less demanding than the first and the one of interest to this thesis since it is sufficient for the models used.

The process $\{X_t\}$ is said to be second-order stationary if:

$$E[X_t^2] < \infty \qquad \forall t \in Z;$$
$$E[X_t] = m \qquad \forall t \in Z;$$
$$Cov(X_t, X_{t+h}) = \gamma_x(h) \qquad \forall t, h \in Z;$$

meaning it has finite variance, constant mean which is not dependent on t and the covariance function only depends on the time lag h.

A simpler example of the $second - order\ stationarity$ is called white noise. It is an important process since it allows for more complex processes to be modeled.

The process $\{\varepsilon_t\}$ is said to be a weak white noise if, for some positive constant σ^2:

$$E[\varepsilon_t] = 0 \qquad \forall t \in Z;$$
$$E[\varepsilon_t^2] = \sigma^2 \qquad \forall t \in Z;$$
$$Cov(\varepsilon_t, \varepsilon_{t+h}) = 0 \qquad \forall t, h \in Z, h \neq 0;$$

2.2.4 DCC

To model the dynamic correlation between assets a *Dynamic conditional corelation*, DCC, model is used. It is an alternative approach to the *Constant conditional corelation*, CCC model proposed by Bollerslev in 1990. The difference is that the conditional correlation matrix is time varying meaning that the conditional covariance matrix depends on the both the conditional variances and the conditional correlations.

According to Jondeau [31] the conditional covariance matrix is given by:

$$\sum\nolimits_t = D_t^{1/2} \Gamma_t D_t^{1/2}$$

where D_t is the (nxn) matrix with the time varying conditional variances

$$D_t = \begin{pmatrix} \sigma_{1,t}^2 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t}^2 \end{pmatrix}$$

and Γ_t, the conditional correlation matrix defined by:

$$\begin{aligned} \Gamma_t &= diag(Q_t)^{-1/2} \times Q_t \times diag(Q_t)^{-1/2} \\ Q_t &= (1 - \alpha - \beta)\bar{Q} + \alpha(u_{t-1}u'_{t-1}) + \beta Q_{t-1} \\ u_t &= D_t^{-1/2}\varepsilon_t = \{\varepsilon_{i,t}/\sigma_{i,t}\}_{i=1,\cdots,n} \end{aligned}$$

$\bar{Q}$ is the sample covariance matrix of u_t. If α and β satisfy $0 \leq \alpha,\ \beta \leq 1$ and $\alpha + \beta \leq 1$ the conditional correlation matrix, Γ_t, is sure to be positive definite.

2.2.5 Portfolio Variance

When calculating the variance of a portfolio consisting of more than one risk bearing asset the correlation between assets must be considered. The variance becomes a function of the variance of the individual assets, the weight of each asset as well as the correlation between the assets. Given that the correlation between assets is less than one the portfolio variance is lower than the weighted average of the variance of the individual assets, this due to the diversification effect.

According to Bode, Marcus and Kane [32] the general formula for the portfolio variance, σ_p^2, is given by:

$$\sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j Cov(r_i, r_j)$$

in the case of a portfolio consisting of two assets the variance is given by:

$$\begin{aligned} \sigma_p^2 &= w_i^2\sigma_i^2 + w_j^2\sigma_j^2 + 2w_i w_j \sigma_i \sigma_j \rho_{i,j} \\ \sigma_i \sigma_j \rho_{i,j} &= Cov(r_i, r_j) \end{aligned}$$

Where $Cov(r_i, r_j)$ is the covariance and $\rho_{i,j}$ is the correlation between the returns of asset i and asset j.
Constraints on the weights are; $\sum_{i=1}^{n} w_i = 1$ where w_i is the portfolio weight of asset i.

Diversification When considering a financial assets there are two types of risk, systematic risk, also known as market risk and nonsystematic risk, also known as security-specific risk. According to Bode, Marcus and Kane [32] the systematic risk will always be present but through diversification all nonsystematic risk can be eliminated. The power of diversification to decrease risk can be said to be limited by systematic risk. To gain advantage of the diversification effect one must consider a portfolio perspective where the correlation between assets is the factor responsible for decreasing the nonsystematic risk, hence reducing the overall portfolio risk.

Consider an equally weighed two asset example:

$$w_a = 0.5,\ w_b = .5,\ E[r_a] = 8\%,\ E[r_b] = 14\%,\ \sigma_a = 12\%,\ \sigma_b = 20\%,\ \rho_{a,b} = 0.3$$

viewing the assets by themselves would give:

$$E[r] = w_a E[r_a] + w_b E[r_b] = 11\%$$
$$\sigma = w_a \sigma_a + w_b \sigma_b = 16\%$$

Since the correlation is less than one putting the assets into a portfolio perspective would give:

$$E[r_p] = w_a E[r_a] + w_b E[r_b] = 11\%$$
$$\sigma_p^2 = w_a^2 \sigma_a^2 + w_b^2 \sigma_b^2 + 2 w_a w_b \sigma_a \sigma_b \rho_{a,b} = 1.72\%$$
$$\sigma_p = \sqrt{\sigma_p^2} = 13.1\%$$

Through the diversification effect the portfolio has the same expected return as in the case of individual assets but the standard deviation is approximately 3% less. If the correlation between the assets would equal 1, $\rho = 1$ then the standard deviation of the portfolio would be the same as in the case of the individual assets.

2.2.6 AIC Criterion

There are several ways of deciding what order of the autoregressive and moving average process to use in the $ARMA(p, q)$ model, see *section 2.2.1*. Choosing the best suited order of p and q is often a trade off between estimation error and complexity. Choosing a higher-order model will often result in a smaller estimation error but at the same time add complexity to the model, often resulting in several statistically non-significant model parameters.

As mentioned there are several approaches to deciding the optimal order of the model. This thesis will introduce a popular and widely used method called Akaike's information criterion (1974) or AIC. The model aims at minimizing the information loss by combining maximum likelihood and the Kullback-Leibler information (1951).

The AIC criterion, according to Mazrolle [33], can be written as:

$$AIC_k = 2k - 2\log(L)$$

k is the number of parameters estimated and L the value of the maximum likelihood of the model. Since the model used is the $ARMA$ model where the estimated errors, ε_i, are normally distributed the AIC criterion can be simplified to:

$$AIC_k = 2k + N\log(\sum_{i=1}^{N}\varepsilon_i^2/N)$$

One must however be careful when using $AIC's$ criterion. The information criterion is most reliable for small values on the order and large sample sizes. For larger values of p and q or sample sizes close to the chosen order the parameters become unstable.

2.2.7 Ljung-Box Q-test

Ljung-box Q-test is a test used for testing independence. It is based on a Portmanteau test and proposed by Box and Pierce in 1970. The modified test statistic was introduced in 1978 and provides better finite-sample properties. Jondeau [34] states that the null hypothesis being tested is $H_0 : \rho_1 = \rho_2 = ... = \rho_m = 0$ against $H_0 : \rho_i \neq 0$ for some $i \in 1, .., m$:

$$Q_m = T(T+2)\sum_{k=1}^{m}\frac{1}{T-k}\hat{\rho_k}^2$$

$$where \quad \hat{\rho_k} = \frac{\sum_{t=k+1}^{T}\varepsilon_t\varepsilon_{t-k}}{\sum_{t=1}^{T}\varepsilon_t^2} \quad \forall 0 \leq k \leq T-1$$

if ε_t is an iid sequence we have that $Q_m \sim^a \chi^2(m)$ and we receive and acceptance of the null hypothesis.

2.2.8 Q-Q Plot

A $Q-Q$ *plot*, or quantile plot, is a graphical measure used to determine if two probability distributions are the same by plotting their quantiles. If the quantiles of a known probability distribution, for example the quantiles from a simulated normal distribution, is plotted against the quantiles of a series with unknown probability one can determine if they belong to the same distribution or not. Essentially one compares the theoretical quantiles consistent with the desired distribution and the empirical quantiles of interest. In the case of the two distribution being the same the plot will be linear.

According to, Jondeau [35] , the $Q-Q$ *plot* is obtained by the following procedure:

Let $y_1, ..., y_\tau$ be the standardized maxima, $y_\tau = \frac{m_\tau - \mu_T}{\psi_T}$, over N histories and let $y_1 \leq ... \leq y_\tau$ be the ordered maxima, then the plot $\{y_t, H_\xi^{-1}(\frac{t}{\tau})\}$ is the quantile plot.

y_t is the empirical quntile and $H_\xi^{-1}(\frac{t}{\tau})$ the theoretical quantile. In the case where the theoretical quantiles come from a normal distribution $\xi = 0$, one obtains that under the null:

$$H_{\xi=0}(y_t) = exp(-exp(-y_t)) = \frac{t}{\tau}$$
$$equaling \quad y_t = H_{\xi=0}^{-1}(\frac{t}{\tau}) = -\log(-\log(\frac{t}{\tau}))$$

where $H_{\xi=0}^{-1}$ is the inverse to the normal CDF.

2.2.9 T-statistic

A $t-$ *statistic* is a way to test if an estimated regression variable is significant or not. It measures how many standard deviations the estimated parameter is from zero. The test statistic is a relatively simple measure only consisting of the estimated parameter, its standard deviation and sometimes also the true mean or the mean given given by not rejecting the null hypothesis. It is a similar measure to the z-score but relies on an estimated standard deviation instead of the known standard deviation of the parameter.
According to Ash [36], the test statistic is given by:

$$t_{\hat{\beta}} = \frac{\hat{\beta} - \beta_0}{\sigma_{\hat{\beta}}}$$

where $\hat{\beta}$ is the estimated parameter, β_0 is the true mean or mean according to the null hypothesis and $\sigma_{\hat{\beta}}$ the standard deviation of the estimated parameter.

If $\hat{\beta}$ is a consistent estimator and the sample size is larger then the distribution of the t will approach the normal distribution meaning that the $t - statistic$ will asymptotically belong to a standard normal distribution.

In the case of the t belonging to the normal distribution and assuming p-value is the significance level of rejection then it is possible to derive an absolute value for the $t - statistic$.

$$p - value = 2\phi(-|t|)$$

given a p-value of 0.05 and the null hypothesis being the rejection of the significance of the estimated parameter

$$Reject\ H_0\ if\ p < 0.05$$
$$equals$$
$$Reject\ H_0\ if\ |t| > 1.96$$

This gives us that a $t - value$ above 1.96 will give us, at a 95% level, that the parameter is significant given that the sample size is large enough.

2.2.10 Value at Risk

$Value\ at\ Risk$, VaR, is a measure of the maximum amount of expected loss given a specified time frame and level of confidence. To use the VaR calculation one must assume that the price of the assets follow a normal distribution. There are three different methods of calculating $Value\ at\ risk$, the variance/covariance model will be the model in this thesis. The other two are through historical simulation and monte carlo simulation.

According to Bissantz, Bissantz and Ziggel [37] the VaR is calculated by:

$$VaR_\alpha(P) = E[r_p] - \Phi^{-1}(\alpha)\sigma_p$$

where $E[r_p] = \sum_{i=1}^{n} w_i E[r_i]$ the expected return of the portfolio, σ_p the portfolio standard deviation and $\Phi^{-1}(\alpha)$ the quantile for the chosen confidence level.

Chapter 3

Introduction to the Electricity Market and Investigated Companies

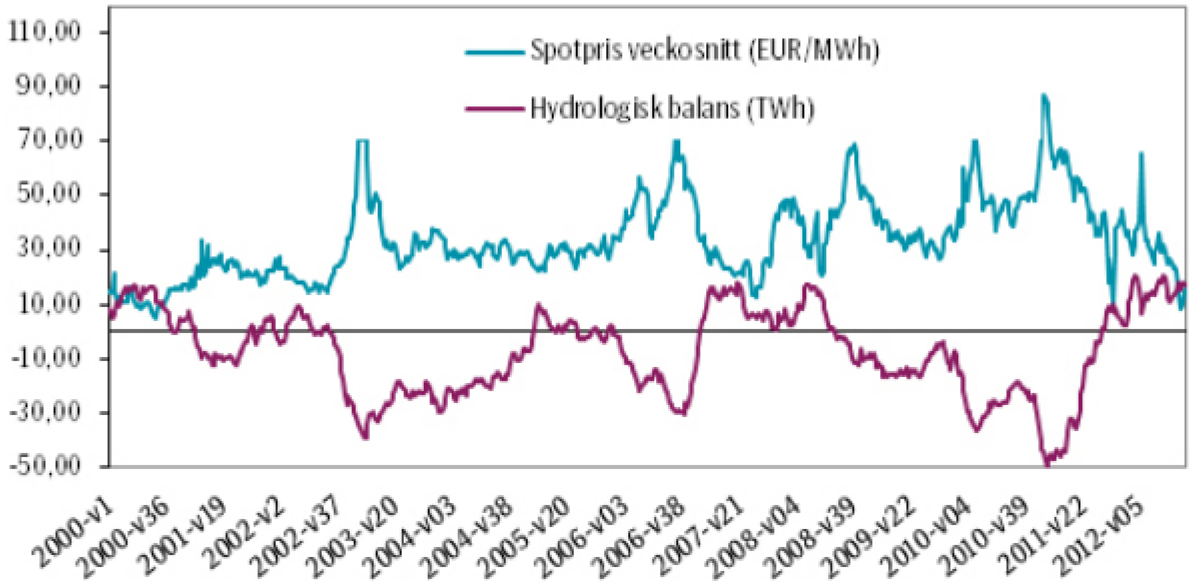
3.1 Electricity Price Movement on the Market

The market for electricity is a fairly new market. Up until 1992, all European electricity markets were regulated, meaning that the markets were state-owned. Norway was the first country to deregulate the market with Sweden, Denmark and Finland all having followed suit by 1999. A combined market called Nord Pool emerged consisting of all four countries electricity grids. Today Latvia, Estonia and Lithuania are also included in the cooperation[4].

Currently electricity is traded on two separate markets, the spot market and the derivatives market. The spot market is owned and operated by the grid companies and approximately 75%[4] of the consumed electricity is traded through Nord Pool. The spot price is determined by taking the average price of each of the 24 hourly prices. In 2011 the annual turn over on the spot market was approximately 130 billion SEK[4]. Due to the volatile nature of the spot price a derivatives market emerged. The derivatives market is owned and operated by Nasdaq OMX trading forwards, futures and options with a delivery period of up to 5 years. The underlying asset for these contracts is the price on the spot market. Annual turnover for the derivatives market is substantially larger than for the spot market, in 2011 the turn over was roughly 900 billion SEK[4].

Electricity has a big difference compared to other commodities, its limited ability of being stored. What ultimately has the most effect on the electricity price is however the weather. In the Nordic region close to 60%[4] of the electricity production comes from hydropower. The amount of precipitation therefore determines the water level in the reservoirs and has a great effect on the spot price. Below is a graph showing the spot price and water levels[4].

Figure 3.1: Spot price and water levels



Demand is a second factor affecting the price levels, with prices showing distinct seasonal variations. During cold and harsh winters demand rises whilst the summer season and weekends show a drop in demand. One explanatory factor being the decrease in use from the industry.

Weather is not the only factor influencing the price. Stoppages in nuclear power production and power grid failures give rise to price spikes. Also what happens on the continent has an impact on the price in the Nordic region. The interlinking between the Nordic power grids and the rest of Europe adjusts for over production and thereby affects the Nordic price levels. In a long-term perspective, there are several macro economic variables that have an impact. In recent years the ban on nuclear power in Germany is a prominent and highly important example.

Taking all the above into account, it follows that electricity price movements are hard to model and predict. This is one of the main reasons why electricity prices have a volatile behavior on the market, which was mentioned in *section 1.1.*

3.2 The Energy Intense Companies

In accordance with ekonomifakta.se, the electricity consumption in Sweden has had a steady growth since 1970. Different sectors, such as the industry, the housing market and the service sector all follow the same trend with an increase of 120% in the total electricity consumption[23]. The industry in Sweden has an intense consumption of electricity and the increase from 1970 to 2012 adds up to a total of 56%, from 33 TWh to $51,5$ TWh on a yearly basis[23]. The increase is greatly due to the fact the oil consumption has been declining within the Swedish industries.

Narrowing down the electricity consumption span, only investigating the industry sector, the most energy intense companies are found within the steel and metal industry and the paper and pulp industry[24].
For the thesis companies within these two industries will be analyzed, based on their significant electricity consumption. These selected companies will stand as inspiration when deciding what risk bearing assets to include in the portfolio and latter the portfolio weights assigned to each of the assets.

In the sections below the examined companies are presented. The information is mostly retrieved from the companies annual reports, where relevant information regarding their financial risk bearing assets is of priority. The aim of studying the companies is to gain an understanding of what risk bearing assets are the most prominent and how they are hedged today.

After reviewing the companies annual reports, the financial risks of greatest importance are foreign exchange risk, commodity risk and interest rate risk. The electricity price risk will also be included for previously stated reasons. This risk is not often subject to discussion in the annual reports, therefore interviews have been held with the companies Energy Managers. Through the interviews an understanding of how electricity is purchased and hedged has been obtained.

3.2.1 SSAB

SSAB is a world leading producer of high-tensile steel, with production both in Sweden and in the United States. SSAB's products are developed in close interaction with its clients, in order to create a stronger, better and a more sustainable world. Their sales are spread all over the world where their high-tensile steel is superior, as it contributes to a reduced weight, compared to ordinary steel. Additional advantages include increased strength and life span of the steel.

SSAB is working actively to identify and analyze the risks that the company is exposed to and how to mitigated these risks is an area of priority. The risk manager cooperates with the different divisions in order to identify the different risks derived from the industrial processes and financial activities.

In the sensitivity analysis, in the annual report, the risks SSAB are exposed to, and to what extent they can affect the results, are presented. The conclusion, that the commodity price risk is the one of largest importance, can be drawn. Secondly, after price changes in raw materials, foreign exchange rate differences has the largest possible affect on the results. A third aspect, highlighted in the sensitivity analysis, is a change of the interest rate level. As a comparison, SSAB considers the interest rate risk (FI-risk) to be a third of the foreign exchange rate risk (FX-risk)[25].

The prices of raw materials, such as steel and ore, are strongly affected by cyclicality in the economy. Since the steel industry is an industry associated with high fixed costs, due to the large investments needed, the cyclicality is a prominent risk factor for SSAB. This results in an increased, and difficult to hedge for, sensitivity to changes in the economy. SSAB's solution to this problem is investing in niche-products[25]. Regarding the prices of raw materials, the market has been leaning towards more short-term agreements. This has contributed to a more volatile market, adding risk to the cost of purchasing materials. This transition has forced SSAB to enter short-term agreements with the sell side[25], on order to limit the risk.

The foreign exchange risk in SSAB's activities is mainly derived from the translation risk and the currency conversion risk, when accounting for the net assets in foreign subsidiaries. This issue is handled by Equity Hedging, enabling SSAB to borrow in the specific currencies of interests to cover for the accounted net assets. Hedging the majority of the currency flows, which mostly consists of purchasing of coal and ore in USD and sales in EUR, mitigates the transaction risk. Smaller short-term transaction flows in foreign currencies, appearing in connection to sales and purchasing, are not hedged[25].

SSAB is fixating the interest rate level, on average, for around one year ahead. The duration is possible to alter with help of interest swaps, meaning the fixation can come to be up to 2.5 years ahead[25].

In reference to an interview with Thomas Hirsch, manager at SSAB's Energy Department, the company both buys electricity on the market and generates its own electricity. By generating its own electricity the risk exposure towards volatility in electricity price movements is limited. During 2013 SSAB consumed a total of 1.5 TWh electricity where 0.492 TWh electricity was generated within their production. SSAB's electricity purchases are managed completely by an external portfolio manager. The managers task is to hedge $95 - 100\%$ of the predicted electricity consumption, for the year, coming into Q1 and further in in Q1, the total hedge should stay at the same level. They hedge in advance for 3 years predicted electricity consumption by a layered hedging strategy. The strategy follows a downward sloping linear approach throughout the three years. According to Thomas Hirsch the plan is to be followed, but the manager is allowed to deviate from it to a certain extent, given that he returns to the plan when his risk mandate is exercised.

3.2.2 Sandvik

Sandvik is a world-leading high-technology engineering group, offering advanced products in more than 130 countries. Their unique expertise is within materials technology and the competence that Sandvik possesses regarding processing systems. Within their five business areas, Sandvik Mining and Sandvik Construction are two examples, each area have the responsibility for research and development, production and sales of their products.

Sandviks financial risk management organization has the objective to create value by managing the financial risk exposures that Sandvik face throughout their business and through their financial strategies. According to the annual report, and a separate financial risk management report, Sandvik are exposed to the same risks as SSAB. Theses risks are however slightly differently ranked sorted by possible affect on the results. According to Lars S Andersson, Category Manager at Sandvik, foreign exchange rate risk is considered the most crucial risk to hedge. Unpredictable currency fluctuations have the, by far, largest possible affect on the total operating profit for the company.

The foreign exchange rate risks refers to the possible exchange rate movements that may affect the result for the year. Sandvik are offering their customers to pay in their local currencies through their global sales organization. Therefore the transaction exposure is related to global sales and purchasing in a wide range of foreign currencies. Production is concentrated to a number of countries making it possible, to some extent, to cancel out sales and production flows in foreign currencies. Sandvik has the mandate to hedge transaction exposures and the average duration for the hedged volume in 2012 was around 1.4 years[26].
Regarding the translation exposure, Sandvik's subsidiaries' receivables and liabilities are currency hedged. This reduces the translation risk but the profits and losses, of the subsidiaries, are still bearing a translation risk. This risk arises when the results are translated into SEK, by using the average exchange rate for the period. The same applies to the net assets, which refers to the subsidiaries' shareholder equity. Additional currency risks, that arises internally, are managed by using various derivatives[26]. A combination of the transaction risk and translation risk make up for the combined exchange rate risk Sandvik are facing.

If changes occur in market interest rates, the company's net interest items may be affected. The impact is determined by the terms of the agreements. Both the investments and liabilities are affected, the net effect is dependent on the size of the positions. For the investment items the interest rate risk is considered to be low. This since surplus liquidity is placed in bank deposits and in money-market instruments with a duration of less than 90 days. For the borrowings, liabilities, the interest rate risk is of higher concern. To mitigate the risk interest rate swap agreements are entered. The financial risk manager is allowed to alter the debt portfolio and its average fixed-interest terms, assuring that the duration does not exceed 48 months[26].

Sandvik is also experiencing risk exposure towards prices of raw materials, as they tend to vary over time. Sandvik's largest commodity price risks are primarily concentrated to nickel and electricity. Sandvik is one of few examined companies that illustrate the importance of electricity price movements and how it is a major risk for the company. The price risk of raw materials is partially hedged by the use of financial contracts. The metal price risk is for instance managed by an offset hedging strategy[26].

In reference to Sandvik's annual report and an interview with Lars S Andersson, the electricity price is continuously hedged via derivatives. The total consumption of electricity is bought on the market and during 2012 the company used 900 GWh electricity. The hedging and the management of the financial derivatives are coped by the external managers Statkraft, Vattenfall and Skelleftekraft. All have a hedging horizon of 4 years. Layer hedging is used, with a downward sloping linear curve, where the goal is to have 85% of the yearly predicted consumption hedged coming in into Q1. Further into the year, the hedging level should have risen to 95% of the remaining yearly predicted electricity consumption. The managers have a mandate to deviate from the plan to a certain extent.

3.2.3 Stora Enso

Stora Enso is a Swedish-Finnish world-leading company within sustainable forest industry. They serve in 35 different countries spread out all over the world. Its main products are paper, biomaterials, wooden products and packaging products. By focusing on renewable material, the company meets the rising global challenges in terms of material and material handling. Their products have therefore significant advantages for the planet and for the companies on it.

The risk management is of great importance for Stora Enso. The risky assets of importance for this thesis are noted in the annual report, which Kaarlo Höysniemi the Vice President of Stora Enso especially referred to. They are stated as the interest risk, currency risk and commodity price risk, in particular for fiber and energy. By using different financial instruments to hedge for these risks, they aim to decrease earnings volatility and to have a cost-effective funding in the company[27]. According to their sensitivity analysis, the risk exposures are ranked as the foreign exchange risk to be the highest, followed by the prices for raw materials including electricity, and then the interest rate risk.

The company is facing currency transaction risks when exchange rates fluctuate. This is extra evident for Euro as Euro is the company's reporting currency. Stora Enso production facilities, the sourcing of raw material and sales are spread out over the world and the major currency flows occurs in SEK, USD and GBP. The group desires to hedge 50% of the predicted currency cash flows up to 12 months in advance[27] via foreign exchange forward contracts and foreign exchange options[27].

The risk exposures that appear in relation to commodity and energy price risk volatility can come to affect the financial outcome to a great deal. The commodity risk is hedged to the extent that is economically possible. In addition to traditional commodity contracts, Stora Enso has major joint venture interests in forest companies in countries where the production occurs, such as in Finland, Sweden, Brazil and Uruguay[27].

Energy risk management is of great importance and financial energy hedges and long-term derivatives are a part of the energy price risk management. In addition to having physically fixed price purchase agreements, the company also have a 14.8% holding in a privately owned group of companies in the energy sector[27]. 35% of the electricity used is also generated internally, in order to control the costs and supply[27]. Half the consumption is however relied on outside suppliers, which makes the company exposed to market fluctuations in energy prices. This allows for hedging strategies to be applicable[27].

If the interest rates were to fluctuate the interest expense of the company would be affected. By the use of interest swaps the company is enabled to synchronize the interest costs with earnings over the business cycle and by that mitigate the financial effects of interest rate fluctuations. Stora Enso is aiming to hedge with the duration of 12 months but is allowed to deviate between 3 and 24 months[27].

Chapter 4

Method

4.1 Approach

The thesis aims to evaluate how a company's VaR is affected if electricity is added as a risk bearing asset to the portfolio of risky assets, and if the difference is significant enough to suggest a change in possible hedging strategies. Companies within the energy-intense sector have been examined, where three different companies ended up serving as inspiration for the thesis. External data has been provided, enabling testing and evaluation of different portfolio compositions and examining which will benefit the VaR statistics the most. The exact mathematical procedure is explained in *section 4.3* but to understand the methodology used, the process in outlined below.

- Different risk exposed assets will be identified as suitable for portfolio modeling. The three selected companies will be the base for which assets to examine and how the different input variables are weighted

- Appropriate data is chosen, showing price history of commodities, foreign exchange rates as well as historical interest rate levels

- The conditional time varying variance will be modeled separately for each asset and then subject to a dynamic conditional correlation model to attain a time varying covariance matrix for the assets. Combining the different chosen asset weights with the covariance matrix will result in comparable time varying portfolio variances.

- The VaR will then be calculated with the weights obtained from studying the chosen companies. Two portfolios for each company is examined, one containing electricity as an asset and one without electricity.

Hopefully conclusions can be drawn from the findings derived from the Value at Risk regarding electricity as an input and a given auxiliary recommendation.

4.2 Data

4.2.1 Data Selection

Investigating energy-intense industries is an extensive topic. Their business and production is a material-intense industry, where many factors can contribute to risk exposures. To narrow the investigation down to an approachable and solid thesis several limitations are to be made. Inspiration was to be found in the annual reports where it was easy to spot the assets that contribute to the largest proportion of risk. The following assets were selected; for the FX rates Dollar, Pound and Euro were selected. Theses are the currencies having the largest total cash flow for the studied companies, thus bearing the foreign exchange rate risk. The spot price data for the FX series is used, since the exchange spot market is one of the most liquid and well functioning markets in the world. The recurring commodities mentioned are nickel, iron and ore, all input materials for the production of goods. Iron and ore do however have to short of a price history to provide sufficient results for the mathematical modeling and are therefore omitted. As a consequence the commodity risk is represented solely by nickel. With reference to Mats Forsell, Commodity Trader at SEB, Nickel and other base metals follow the same standard. The most liquid contract is the 3 months future. The future contract is updated everyday meaning that the future of tomorrow is another than the one of today. This is unique for the commodity exchange market.

The electricity price data in this thesis is based on forward prices, meaning that it does not settle everyday. This thesis is using the one-year forwards that is rolled throughout the year, meaning that today the forward being used is the forward of YR15. This same forward is used until the 31^{st} of December when it matures. The price will therefore settle as the mean of the spot prices for all the days of 2015. Due to this special settling process the one-year forwards was selected in order to get a series dependent on the whole year and not just a single, arbitrary, quarter. For the interest rate data the Stibor 3-month series is used. SEB recommended a focus on this particular interest rate, as it is the most common reference rate reflecting the actual interest rate the companies is facing. Since the calculations are based on returns, the same result will be implied using a reference rate as an actual rate.

All time-series selected are in compliance with SEB. The data is on a weekly basis, all extracted on the same dates. Weekly data points are more than enough to spot trends without ending up with to much data. Weekly data is also the most applicable in investigations of this nature and this thesis has data points up to 10 years back in time. All the assets that were measured in other currencies than SEK were converted to SEK, as SEK is the base currency for this investigation.

4.2.2 Data Description

All data series used are, as mentioned, provided by SEB and extracted from Bloomberg. The lengths of the series are dependent on the quality of the data series and the interval of the data points is one week for all series. When the joint modeling begins, 500 values are extracted from each series and denoted as week 0 - week 500. Week 0 is the date $2004-07-30$ and week 500 is the date $2014-02-28$.

Foreign Exchange Rates

The currency series used for this thesis are US dollar, Pound sterling as well as Euro. These three currencies are three of the most well known in the world and often used when trading and exporting in the northern European region. The currency market is considered to be the most efficient market, at least regarding the main currencies, and is highly liquid. Traits present on highly liquid markets are immediacy, small transaction costs and a great order depth. The immediacy implies that a transaction is instantly carried out, small transaction costs means there is a small bid/ask spread and great depth states that a change in supply and demand will not change the price. The currencies are traded on a decentralized market where the main participants are large international banks. There are two main markets for currencies, the spot market and the futures market.

US Dollar is the official currency in the United States and its territories. It is the number one for international transactions and foreign exchange reserve. The series used in the thesis is the spot price extracted on a weekly basis. Prices are extracted every Friday, when possible, and the range of the series is from $2000-01-01$ until $2014-02-28$ giving a total of 739 observations. The values are given as the price of one Dollar in terms of Swedish kronor. This means that an increase in the spot price will make the Dollar appreciate against the Swedish krona, and a decrease in the spot price will make the Dollar depreciate against the Swedish Krona.

Pound Sterling or simply Pound is the official currency of Great Britain and some of its territories. It is the fourth most traded currency, only surpassed by the Dollar, Euro and Yen. It is also an important reserve currency, just like the US dollar. The series used in the thesis is the spot price extracted on a weekly basis. Prices are extracted every Friday, when possible, and the range of the series is from $2000-01-01$ until $2014-02-28$ giving a total of 739 observations. The values are given as the price of one Pound in terms of Swedish kronor. This means that an increase in the spot price will make the Pound appreciate against the Swedish krona and a decrease in the spot price will make the Pound depreciate against the Swedish Krona.

Euro is the official currency in 18 of the European Unions membership states. It was introduced as late as 2002 and is today the currency with the highest combined value of banknotes and coins in the world. It holds the number two spot, after the US dollar, both in its position as reserve currency as well as most traded currency. The series used in the thesis is the spot price extracted on a weekly basis. Prices are extracted every Friday, when possible, and the range of the series is from $2000-01-01$ until $2014-02-28$ giving a total of 739 observations. The values are given as the price of one Euro in terms of Swedish kronor. This means that an increase in the spot price will make the Euro appreciate against the Swedish krona and a decrease in the spot price will make the Euro depreciate against the Swedish Krona.

Electricity

Section 3.1 describes the dynamics of the electricity price market. The series used in this thesis is the 1 year forward price. Due to the relatively short existence of the current electricity market, the series will not be as extensive as the currency series. The series used in the thesis is the one year Nordic forwards closing price, extracted on a weekly basis. The price is quoted in Euro but will be transformed into SEK using the concurring spot rate. The range of the series is from $2003-01-12$ until $2014-03-02$ giving a total of 582 observations.

Nickel

Nickel is a metal with atomic number 28, abbreviated as Ni. The primary use of Nickel is in production of stainless steel, where Nickel is a main component. The series used in the thesis is a 3 month future traded on the London Metal Exchange. The price is quoted in Dollar but will be transformed into SEK, using the concurring spot rate. The range of the series is from $2000-01-14$ until $2014-02-28$ giving a total of 738 observations.

Interest Rate

The Stibor 3 month rate is used for the deposit interest rate series. Stibor is the Stockholm Interbank Offered Rate, which is the average of the interest rates at which a number of Swedish banks, all active on the Swedish money market, are willing to lend to one another without collateral[38]. The banks responsible for determining Stibor are Danske Bank, Handelsbanken, Länsförsäkringar Bank, Nordea, Swedbank and SEB. The series used in this thesis is the 3 month Stibor rate. Rates are extracted every Friday and the range of the series is from $2000-01-01$ until $2014-02-28$ giving a total of 739 observations.

4.3 Estimation Method

All series are subject to the same procedure up until the joint modeling, beginning with the DCC model. All significance tests are at a $\alpha = 5\%$ level.

If series are to be comparable, one must look at a comparable measure. It would be of no interest comparing prices of commodities to interest rates, where the first one is stated in the price of an amount of the commodity whilst the latter is presented as a percentage. Even comparing price levels of different commodities could provide deviating results as the amounts have to conform. To eliminate this problem of deviating measures it is suitable to look at returns of series and thereby getting a comparable measure. This thesis uses the simple return as the measure of return. It is the percentage difference from one point in time to another, giving a positive value if the price or rate of an asset has increased and a negative value for a decrease.
The formula can be written as:

$$X_t = \frac{P_t - P_{t-1}}{P_t}$$

where X_t is the return at time t, P_t is the price or return level at time t and P_{t-1} is the price or return level at the previous observation.

To get a comparable measure it is also very important that the observations are from the same points in time. If $t_{x_1} \neq t_{x_2}$ then all comparison will be in vain. This also implies that no extremes may be smoothened or removed. However, for the first part of this thesis, the series are not required to be of the same length. A series containing more observations will often provide more realistic and better models as the degrees of freedom have increased. The reason being that many statistical models use an iterative scheme when modeling parameters. When proceeding with the parts where several series will be interlinked they must be of the same length and then the most historic value of the longer series will be removed. This will be the case when modeling the $GARCH$ parameters.

Removing trends from series is often a good way to get a better fit when using econometric models. The hope is to remove all correlation between the values at different points in time, meaning the series are all, by themselves, independent . This is a sought after feature since many models are to provide output which is independent. Since the models used often are linear models, trends present in the input will often be present in the output. Removing trends does have its drawbacks, when a trend is removed the data series is altered. An altered series might as stated above provide a better fit for the model but at the same time the model will not depict the original data series but the altered one. Combining several altered series into a single model will then provide results which could be quite far from reality. In order not to alter the series too much this thesis will only detrend the series by removing their mean. A zero mean is a nice feature since the output from the next step is supposed to be of a zero mean character and the most apparent seasonal variations will be eliminated.

Detrending is done by:

$$X_t = X_t - \bar{X} \quad \forall t = 1, ..., n$$
$$where \quad \bar{X} = \frac{\sum_{t=1}^{n} X_t}{n}$$

An $ARMA(p,q)$, see *section 2.2.1*, process is used for reducing the input, $\{X_t\}$, to an iid noise by using a parsimonious and linear model. An ideal model would reduce the input to a weak white noise process, see *section 2.2.3*, meaning it has a zero mean, finite variance and no correlation. This is done by combining a moving average process of order q and an auto regressive process of order p. A moving average process models each of the series observations as a linear combination of the observations current and previous white noise errors going back q lags. An autoregressive process models each of the series observations as a linear combination of its own previous values going back p lags. When combining these two models to the $ARMA(p,q)$ process one receives a model describing each observation of the time series as a mixture of the current and previous error terms and previous observations.

Since the output of the $ARMA(p,q)$ process is dependent on the order of lags, p and q, for the moving average and autoregressive process it is of importance to choose appropriate values. One popular way to decide the order is by using the Akaike's information criterion, see *section 2.2.6*, or AIC for short. The AIC test aims at minimizing the information loss by combining maximum likelihood and the Kullback-Leibler information. This is done by calculating the AIC-value:

$$AIC_k = 2k + N \log(\sum_{i=1}^{N} \varepsilon_i^2 / N)$$

for different values on p and q where the ε_i $i = 1, ..., N$ is extracted from the tested order $ARMA(p,q)$ process. The order of p and q providing the best fit according to the AIC criterion is the test providing the smallest value. As previously mentioned choosing the smallest AIC value is not always the best solution to deciding the order p, q. It is often a trade-off between the best fit according to the AIC criterion and the complexity of the model and thus the significance of the estimated parameters. The AIC test will give a hint of satisfactory values of p, q but it will still be a matter of trial and error to obtain significant parameters.

When the order of p and q have been decided the $ARMA(p,q)$ process can be modeled in order to extract the residuals, ε's, necessary for the next step. The residuals are then obtained by taking:

$$\varepsilon_t = X_t - \phi_1 X_{t-1} - ... - \phi_p X_{t-p} - \theta_1 \varepsilon_{t-1} - ... - \theta_q \varepsilon_{t-q}$$

To validate that the parameters acquired from the $ARMA(p, q)$ model are significant a $t - test$, see *section 2.2.9*, is used. It is an individual test, done for each parameter by itself. A confidence level of 5% implies a $t - stat$ over 1.96 for the parameter tested to be significant. The test statistic for ϕ_1 would be:

$$t_{\hat{\phi}_1} = \frac{\hat{\phi}_1}{\sigma_{\hat{\phi}_1}}$$

If a parameter is significant it is, with the probability of 1 minus the set confidence level, not equal to zero and therefore helpful in describing the obtained value. A significance of all parameters would be a nice feature since all estimated parameters are most likely not equal to 0 and therefore provide a good model for explaining the values.

To achieve the goal of obtaining the time dependent correlation the next step of the procedure is to estimate the time varying variance. Here a generalized autoregressive conditionally heterocedastic, $GARCH(1, 1)$, model is used, see *section 2.2.2*. The main concept is conditional variance meaning the variance is conditioned on the past. Similar to the $ARMA$ process it is a linear model where the output at time t is dependent on the squared past conditional variance, σ^2_{t-1}, and residual, ε^2_{t-1}. The $GARCH(1, 1)$ model is simple yet competent in capturing many of the main characteristics of financial series. A few of these characteristics are fat-tailed distributions, volatility clustering seasonality and autocorrelation of squared price returns. Using the $GARCH(1, 1)$ model with one lag on the squared residual and one lag on the conditional variance is not the best model but the most common and sufficient for this thesis. The conditional variance at time t can then be written as:

$$\sigma^2_t = \omega + \alpha \varepsilon^2_{t-1} + \beta \sigma^2_{t-1}$$

As with the $ARMA$ process it is important to check the $t - stat$ for the parameters, in this case there are only three ω, α and β. Once again this is done to determine the significance of the parameters. One must also check the added constraints, $\alpha, \beta > 0$ to ensure positive variance and $\alpha + \beta < 1$ to ensure stationarity and finite variance.

Part of the definition of the $GARCH$ model states that:

$$\varepsilon_t = \sigma_t z_t \qquad z_t \sim i.i.d\ N(0, 1)$$

rearranging the terms gives:

$$z_t = \frac{\varepsilon_t}{\sigma_t} \qquad z_t \sim i.i.d\ N(0,1)$$

which is the same as saying that the standardized residuals, $\frac{\varepsilon_t}{\sigma_t} \sim i.i.d\ N(0,1)$, are independent and belong to a normal distribution. This is a two folded problem, one checking for independence of the series and one checking the belonging to a normal distribution. An additional test to perform is to check that the squared standardized residuals also are uncorrelated, this to make sure the model properly explains the volatility clustering.

The best way of testing a time series for independence is by applying a hypothesis test, testing the null of no correlation against the opposite, that correlation is present. Ljung-Box Q-test, see *section 2.2.7*, is the method used in this thesis which tests the null, $H_0 : \rho_1 = ... = \rho_m = 0$ against $H_0 : \rho_i \neq 0$ for some $i \in 1, ..., m$. If the null is not rejected one can say that with the chosen confidence level the time series is not correlated. Testing for normality could also be done by hypothesis testing but a second approach is doing it graphically. For this purpose a $Q - Q$ *plot*, see *section 2.2.8*, is used to determine possible deviation from the normal distribution. Since no extremes have been removed it is expected that some tail values will deviate from the normal distribution.

Often when calculating the correlation between time series one uses the Pearson product-moment correlation coefficient. It is a linear measure providing a value between 1 and -1 to be the correlation between two time series X and Y. 1 indicating that the two series are fully correlated, 0 indicating no correlation and -1 indicating total negative correlation. The correlation is attained by calculating:

$$\rho_{X,Y} = \frac{Cov(X,Y)}{\sigma_X \sigma_Y}$$

simply taking the covariance between the two time series and dividing by the product of the standard deviation of the separate series. One major drawback with this approach of calculating the correlation is the lack of time dependence. The $Pearson's\ rho$ will give a single value for the correlation valid for all points in time which is not a realistic feature. The solution to this issue is to use a $Multivariate\ GARCH$ model. This approach gives a wide array or models to use and the chosen model for this thesis, *Dynamic conditional correlation*, has the advantage of focusing on the dynamics of the correlation opposed to the dynamics of the covariance.

The DCC model, see *section 2.2.4*, requires the conditional variances from the $GARCH$ model as well as the residuals obtained in the $ARMA$ model to derive the time varying correlation matrix:

$$\Gamma_t = \begin{pmatrix} 1 & \rho_{t,12} & \cdots & \rho_{t,1n} \\ \rho_{t,12} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \rho_{t,n-1,n} \\ \rho_{t,1n} & \cdots & \rho_{t,n-1,n} & 1 \end{pmatrix}$$

combining this with the diagonal matrix of the obtained conditional variances:

$$D_t = \begin{pmatrix} \sigma^2_{1,t} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma^2_{n,t} \end{pmatrix}$$

gives the time varying conditional covariance matrix:

$$\sum\nolimits_t = D_t^{1/2}\Gamma_t D_t^{1/2}$$

The DCC model is a two step approach making for easier computation than the *multivariate* $GARCH$ models. The log-likelihood function[31] for the DCC can be written:

$$\log(L_T(\theta)) = \sum_{t=1}^{T} \log(\ell_t(\theta)) = -\frac{1}{2}\sum_{t=1}^{T}\Big[n\log(2\pi) + \log|\textstyle\sum_t| + (r_t - \mu_t)' \textstyle\sum_t^{-1}(r_t - \mu_t)\Big]$$

since $\sum_t = D_t^{1/2}\Gamma_t D_t^{1/2}$ and D_t is diagonal it can be split into a sum of a correlation part and a volatility part:

$$\log|\sum\nolimits_t| = \log|D_t| + \log|\Gamma_t|$$

$$\begin{aligned}(r_t - \mu_t)' \sum\nolimits_t^{-1}(r_t - \mu_t) &= (r_t - \mu_t)'(D_t^{1/2}\Gamma_t D_t^{1/2})(r_t - \mu_t) \\ &= u_t'\Gamma_t^{-1}u_t + (r_t - \mu_t)' D_t^{-1}(r_t - \mu_t) - u_t' u_t\end{aligned}$$

This rewriting allows for rewriting of the log-likelihood function:

$$\log(L_T(\theta_v, \theta_c)) = \log(L_T^v(\theta_v)) + \log(L_T^c(\theta_v, \theta_c))$$

where

$$\log(L_T^v(\theta_v)) = -\frac{1}{2}\sum_{t=1}^{T}\Big[n\log(2\pi) + \log|D_t| + (r_t-\mu_t)'D_t^{-1}(r_t-\mu_t)\Big]$$
$$\log(L_T^c(\theta_v,\theta_c) = -\frac{1}{2}\sum_{t=1}^{T}\Big[\log|\Gamma_t| + u_t'\Gamma_t^{-1}u_t - u_t'u_t\Big]$$

As one can see, the second equation is dependent on the θ_v parameters obtained through the first log-likelihood equation where $\log(L_T^v(\theta_v))$ is the sum of log-likelihoods obtained in the $GARCH$ estimation described in the step prior to the DCC model.

The two-step model is a maximization estimation where the first step is the estimation of the volatility, $GARCH$, parameters and the second step the estimation of the correlation parameters.

Firstly the volatility parameters were estimated, better described in the prior step:

$$\hat{\theta}_v \in \arg\max_{\{\theta_v\}} \log(L_T^v(\theta_v))$$

Step two is the one of interest in gaining the correlations. Similar to the $GARCH$ estimation is is a log-likelihood maximization problem:

$$\hat{\theta}_c \in \arg\max_{\{\theta_c\}} \log(L_T^c(\hat{\theta}_v,\theta_c))$$

When all parameters, $\hat{\theta}_v$, $\hat{\theta}_c$ have been estimated one can easily obtain the time varying conditional covariance matrix, $\sum_t$.

Since the portfolio weights are set, there is a specified amount of each asset that will be needed or received, Value at Risk, see *section 2.2.10*, is the comparable measure used in this thesis. Value at Risk measures the maximum potential loss a portfolio of risk bearing assets can loose under the determined time frame with a chosen confidence level:

$$\Phi^{-1}(\alpha)$$

for a 95% confidence level:

$$\Phi^{-1}(\alpha) = 1.645$$

for a single sided interval, applicable here since the upside is of no interest.

From the steps above the input to gain the time dependent standard deviation of the portfolio, see *section 2.2.5*, have been obtained, what remains is to do the calculations:

$$\sigma_{p,t} = \sqrt{w' \sum_t w}$$

$$E[r_p] = \begin{pmatrix} w_1 \cdots w_n \end{pmatrix} \begin{pmatrix} E[r_1] \\ \vdots \\ E[r_n] \end{pmatrix}$$

where $w = \begin{pmatrix} w_1 \cdots w_n \end{pmatrix}$, w_i the weight of asset i and $E[r_i]$ the expected return of asset i.

The Value at Risk for each point in time is then simply:

$$VaR_{95\%} = E[r_p] - 1.645 \times \sigma_p$$

Chapter 5

Results

5.1 USD

Calculating the AIC value for different orders $ARMA(p, q)$ gives

Table 5.1: AIC values USD

p/q	1	2	3	4	5	6
1	-8.1250	-8.1227	-8.1200	-8.1176	-8.1155	-8.1133
2	-8.1208	-8.1203	-8.1202	-8.1175	-8.1132	-8.1129
3	-8.1297	-8.1287	-8.1261	-8.1238	-8.1244	-8.1221
4	-8.1284	-8.1260	-8.1233	-8.1256	-8.1225	-8.1296
5	-8.1279	-8.1271	-8.1244	-8.1268	-8.1249	-8.1532
6	-8.1258	-8.1294	-8.1267	-8.1250	-8.1223	-8.1546

The smallest value is -8.1546 from the $ARMA(6, 6)$ model and gives a significantly smaller AIC value than most other orders of p, q. Since the difference is so noticeable the $ARMA(6, 6)$ model will be chosen even though it will add complexity to the model by incorporating more parameters.

With the chosen optimal order for the $ARMA(p, q)$ model the received parameters are

Table 5.2: ARMA(6,6) parameters USD

Parameter	Value	T-statistic
ϕ_1	-0.8380	-507.6158
ϕ_2	-0.3023	-9.9860
ϕ_3	0.6590	4.4626
ϕ_4	0.6090	12.3653
ϕ_5	0.6369	18.5411
ϕ_6	0.2943	10.2326
θ_1	0.8249	6.2100
θ_2	0.2627	32.9791
θ_3	-0.7171	-1.4497
θ_4	-0.6371	-1.6247
θ_5	-0.6146	-9.7395
θ_6	-0.3075	-24.9925

For the parameters to be significant the t-statistic for the parameter should have an absolute value of above 2. Due to the complexity of the model,the high order of p, q, the two parameters θ_3 and θ_4 are not significant according to the t-statistic. However since 10 of the 12 parameters are significant this will be a sufficient model for such a high order model.

With the received residuals from the $ARMA(6, 6)$ model the $GARCH(1, 1)$ model is estimate providing the following parameters

Table 5.3: GARCH(1,1) parameters USD

Parameter	Value	T-statistic
ω	0.0000	1.6208
α	0.0644	2.8757
β	0.9146	31.1214

Both the α and β have t-statistics above two meaning they are significant. The parameter value for ω is estimated to 0 meaning the t-statistic is of no importance since a parameter with the value 0 will not contribute to the output value. Checking the additional constraints one can see that both α and β are greater than 0 and their sum less than 1 ensuring stationarity and finite variance.

Testing the standardized residuals for uncorrelation and normality and the squared standardized residuals for uncorrelation

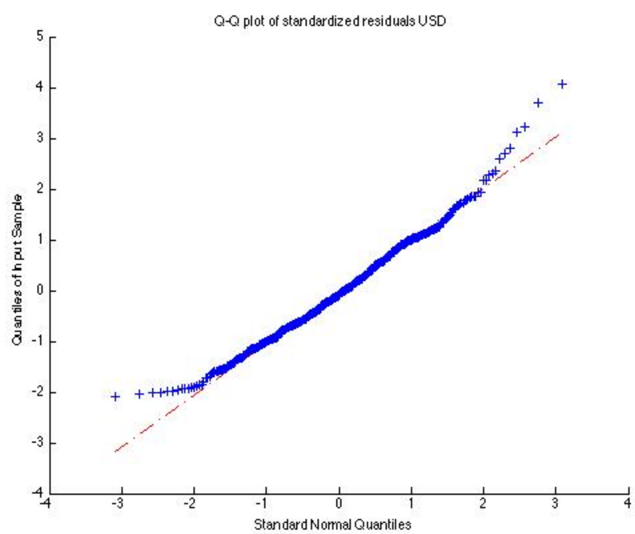
Table 5.4: Ljung-box test residuals USD

Type	H	P-value	Test statistic	Critical value
$\frac{\varepsilon}{\sigma}$	0	0.9763	9.5047	31.4104
$\{\frac{\varepsilon}{\sigma}\}^2$	0	0.9529	10.7325	31.4104

The null of no correlation is not rejected implying that both the standardized residuals as well as the squared standardized residuals are not correlated.

Examining the standardized residuals belonging to a normal distribution with the help of a *q−q plot*

Figure 5.1: Q-Q plot of the USD standardized residuals



As expected the tails will not consist with the assumption of normality, this since no extremes were removed or smoothened to get a better fit.

5.2 EUR

Calculating the AIC value for different orders $ARMA(p, q)$ gives

Table 5.5: AIC values EUR

p/q	1	2	3	4	5	6
1	-9.2856	-9.2830	-9.2832	-9.2827	-9.2805	-9.2784
2	-9.2836	-9.3000	-9.2898	-9.2954	-9.2980	-9.2898
3	-9.2832	-9.3020	-9.2998	-9.2971	-9.3114	-9.2954
4	-9.2894	-9.2876	-9.2929	-9.2962	-9.2935	-9.2912
5	-9.2884	-9.2887	-9.2985	-9.2970	-9.3139	-9.2994
6	-9.2865	-9.3137	-9.3118	-9.3092	-9.3118	-9.3116

The smallest value is -9.3139 attained from the $ARMA(5, 5)$ model. This AIC value is not that much smaller than the value of the $ARMA(2, 2)$ which is -9.3. Due to the small difference in values and the great amount of complexity added by picking a much higher order of the $ARMA$ process a $ARMA(2, 2)$ model will be picked to estimate the Euro residuals.

With the chosen optimal order for the $ARMA(p, q)$ model the received parameters are

Table 5.6: ARMA(2,2) parameters EUR

Parameter	Value	T-statistic
ϕ_1	-1.4819	-13.8472
ϕ_2	-0.8668	-10.5130
θ_1	1.3970	10.9713
θ_2	0.7849	9.7380

All parameters have a t-statistic with an absolute value larger than 2 meaning they are all significant and the model is a good fit for the purpose of this thesis.

With the received residuals from the $ARMA(2, 2)$ model the $GARCH(1, 1)$ model is estimate providing the following parameters

Table 5.7: GARCH(1,1) parameters EUR

Parameter	Value	T-statistic
ω	0.0000	1.7748
α	0.0904	2.6029
β	0.8952	28.2506

Once again the ω parameter is equal to 0 and therefore adding no impact to the model. The α and β parameters are both significant and also satisfies the additional constrains of α and β being greater than 0 and their sum less than 1 ensuring stationarity and finite variance.

Testing the standardized residuals for uncorrelation and normality and the squared standardized residuals for uncorrelation

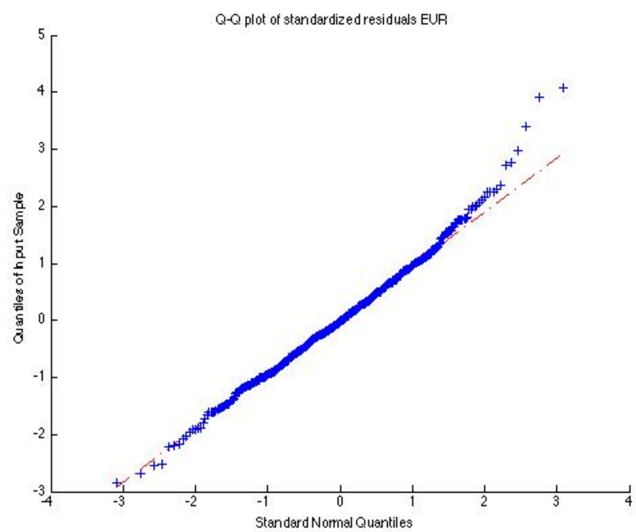
Table 5.8: Ljung-box test residuals EUR

Type	H	P-value	Test statistic	Critical value
$\frac{\varepsilon}{\sigma}$	0	0.3509	21.8099	31.4104
$\{\frac{\varepsilon}{\sigma}\}^2$	0	0.4808	19.6383	31.4104

The null of no correlation is not rejected implying that both the standardized residuals as well as the squared standardized residuals are not correlated.

Examining the standardized residuals belonging to a normal distribution with the help of a $q-q$ *plot*:

Figure 5.2: Q-Q plot of the EUR standardized residuals



Once again the extremes cause deviation from the normal distribution but the deviation can be considered relatively small, especially for the negative values.

5.3 GBP

Calculating the AIC value for different orders $ARMA(p, q)$ gives

Table 5.9: AIC values GBP

p/q	1	2	3	4	5	6
1	-8.5088	-8.5065	-8.5040	-8.5013	-8.4988	-8.4975
2	-8.5032	-8.5015	-8.4997	-8.5044	-8.5177	-8.5184
3	-8.5025	-8.5088	-8.5142	-8.5123	-8.5096	-8.5170
4	-8.5140	-8.5113	-8.5154	-8.5141	-8.5114	-8.5233
5	-8.5135	-8.5435	-8.5157	-8.5145	-8.5140	-8.5204
6	-8.5145	-8.5204	-8.5188	-8.5217	-8.5196	-8.5176

The smallest value is -8.5435 from the $ARMA(5, 2)$ model and gives, once again, a significantly smaller AIC value than most other orders of p, q. Since the difference is so noticeable the $ARMA(5, 2)$ model will be chosen even though it will add complexity to the model by incorporating more parameters.

With the chosen optimal order for the $ARMA(p, q)$ model the received parameters are

Table 5.10: ARMA(5,2) parameters GBP

Parameter	Value	T-statistic
ϕ_1	-0.9817	-7512611
ϕ_2	-0.0219	-2220
ϕ_3	-0.0962	-83312
ϕ_4	-0.1136	-2682
ϕ_5	-0.0621	-18488
θ_1	0.9026	3512000
θ_2	-0.1242	-227045

All parameters have a t-statistic with an absolute value greatly larger than 2 meaning they are all significant and the model is a good fit for the purpose of this thesis.

With the received residuals from the $ARMA(5, 2)$ model the $GARCH(1, 1)$ model is estimate providing the following parameters

Table 5.11: GARCH(1,1) parameters GBP

Parameter	Value	T-statistic
ω	0.0000	1.8733
α	0.1020	2.5269
β	0.8665	18.7686

Once again the ω parameter is equal to 0 and therefore adding no impact to the model. The α and β parameters are both significant and also satisfies the additional constrains of α and β being greater than 0 and their sum less than 1 ensuring stationarity and finite variance.

Testing the standardized residuals for uncorrelation and normality and the squared standardized residuals for uncorrelation

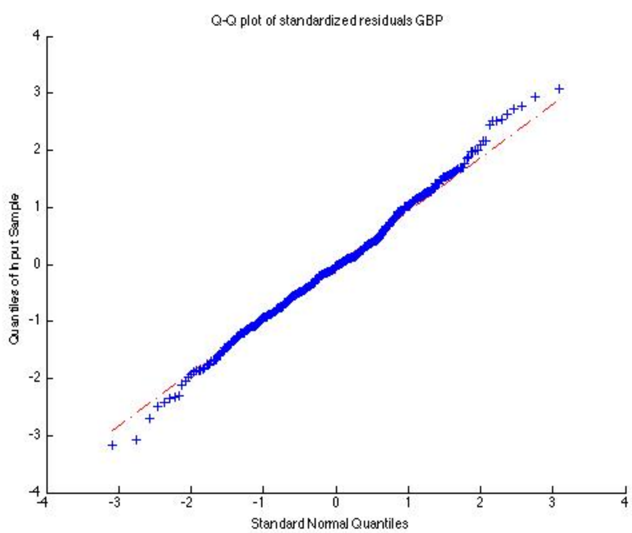
Table 5.12: Ljung-box test residuals GBP

Type	H	P-value	Test statistic	Critical value
$\frac{\varepsilon}{\sigma}$	0	0.3362	22.0790	31.4104
$\{\frac{\varepsilon}{\sigma}\}^2$	0	0.8901	12.6943	31.4104

The null of no correlation is not rejected implying that both the standardized residuals as well as the squared standardized residuals are not correlated.

Examining the standardized residuals belonging to a normal distribution with the help of a $q-q$ *plot*

Figure 5.3: Q-Q plot of the GBP standardized residuals



Here the standardized residuals are very close to belonging to a normal distribution even though no extremes have been removed or smoothened.

5.4 Electricity

Calculating the AIC value for different orders $ARMA(p, q)$ gives

Table 5.13: AIC values electricity

p/q	1	2	3	4	5	6
1	-6.8634	-6.8608	-6.8572	-6.8550	-6.8568	-6.8552
2	-6.8608	-6.8647	-6.8620	-6.8586	-6.8601	-6.8574
3	-6.8575	-6.9114	-6.8615	-6.8763	-6.8578	-6.8649
4	-6.8548	-6.8592	-6.8902	-6.8750	-6.8631	-6.9215
5	-6.8591	-6.8615	-6.8599	-6.8557	-6.9012	-6.9998
6	-6.8570	-6.8589	-6.9852	-6.8626	-6.8606	-6.9849

The smallest value is -6.9998 received from the $ARMA(5, 6)$ model. For the same reason as for the Euro series, the difference in AIC values are not that large, a lower order is chosen not to add complexity. An $ARMA(2, 2)$ model is chosen to represent the electricity return series.

With the chosen optimal order for the $ARMA(p, q)$ model the received parameters are

Table 5.14: ARMA(2,2) parameters electricity

Parameter	Value	T-statistic
ϕ_1	-1.2214	-10.6171
ϕ_2	-0.7895	-13.1842
θ_1	1.2186	14.4634
θ_2	0.8353	11.5579

All parameters have a t-statistic with an absolute value greatly larger than 2 meaning they are all significant and the model is a good fit for the purpose of this thesis.

With the received residuals from the $ARMA(2, 2)$ model the $GARCH(1, 1)$ model is estimate providing the following parameters

Table 5.15: GARCH(1,1) parameters electricity

Parameter	Value	T-statistic
ω	0.0001	1.8672
α	0.1100	3.0729
β	0.8494	18.2307

The ω parameter is not zero and but has a t-statistic less than $|2|$ meaning that for the electricity $GARCH(1, 1)$ model there are once again only two parameters describing the time series. α and β are significant and satisfy the additional constrains of α and β being greater than 0 and their sum less than 1 ensuring stationarity and finite variance.

Testing the standardized residuals for uncorrelation and normality and the squared standardized residuals for uncorrelation

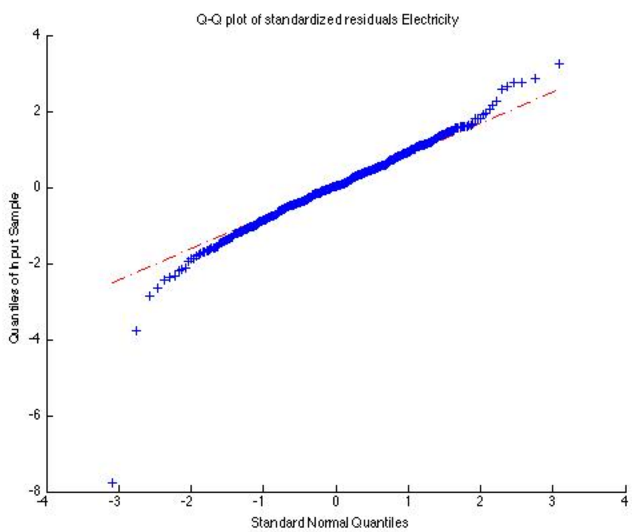
Table 5.16: Ljung-box test residuals electricity

Type	H	P-value	Test statistic	Critical value
$\frac{\varepsilon}{\sigma}$	0	0.9914	8.0757	31.4104
$\{\frac{\varepsilon}{\sigma}\}^2$	0	0.9999	4.0787	31.4104

The null of no correlation is not rejected implying that both the standardized residuals as well as the squared standardized residuals are not correlated.

Examining the standardized residuals belonging to a normal distribution with the help of a $q-q$ *plot*

Figure 5.4: Q-Q plot of the electricity standardized residuals



Once again the tails are deviating from the assumption of normality with the negative values having a tendency to deviate rather far for some values.

5.5 Interest Rate

Calculating the AIC value for different orders $ARMA(p,q)$ gives

Table 5.17: AIC values Interest rate

p/q	1	2	3	4	5	6
1	-7.2437	-7.2475	-7.2448	-7.2430	-7.2403	-7.2415
2	-7.2466	-7.2479	-7.2473	-7.2462	-7.2435	-7.2450
3	-7.2498	-7.2515	-7.2489	-7.2432	-7.2437	-7.2559
4	-7.2469	-7.2497	-7.2538	-7.2500	-7.2486	-7.2635
5	-7.2431	-7.2452	-7.2425	-7.2420	-7.2613	-7.3654
6	-7.2496	-7.2498	-7.3590	-7.2680	-7.3740	-7.3723

The smallest value is -7.3740 received from the $ARMA(6,5)$ model. The large difference in AIC values result in the picking of the $ARMA(6,5)$ model.

With the chosen optimal order for the $ARMA(p,q)$ model the received parameters are

Table 5.18: ARMA(6,5) parameters IR

Parameter	Value	T-statistic
ϕ_1	0.5726	107490103
ϕ_2	0.1587	3229127
ϕ_3	0.2986	30660069
ϕ_4	0.5068	49845201
ϕ_5	-0.7839	-8098127
ϕ_6	0.1836	4251549
θ_1	-0.3555	-8789877
θ_2	-0.0868	-22190207
θ_3	-0.4051	-63454162
θ_4	-0.6197	-3955034
θ_5	0.7276	78850995

All parameters have a t-statistic with an absolute value greatly larger than 2 meaning they are all significant and the model is a good fit for the purpose of this thesis.

With the received residuals from the $ARMA(6,5)$ model the $GARCH(1,1)$ model is estimate providing the following parameters

Table 5.19: GARCH(1,1) parameters IR

Parameter	Value	T-statistic
ω	0.0000	0.7690
α	0.1273	3.6683
β	0.8725	21.1434

Once again the ω parameter is equal to 0 and therefore adding no impact to the model. The α and β parameters are both significant and also satisfies the additional constrains of α and β being greater than 0 and their sum less than 1 ensuring stationarity and finite variance.

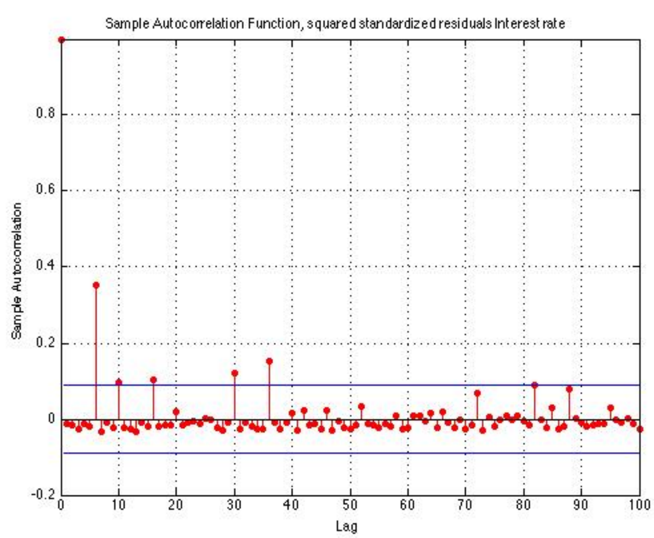
Testing the standardized residuals for uncorrelation and normality and the squared standardized residuals for uncorrelation

Table 5.20: Ljung-box test residuals IR

Type	H	P-value	Test statistic	Critical value
$\frac{\varepsilon}{\sigma}$	0	0.1966	25.1285	31.4104
$\{\frac{\varepsilon}{\sigma}\}^2$	1	0	77.8352	31.4104

The null of no correlation is not rejected for the standardized residuals but is rejected for the squared standardized residuals. To better get a view of the correlation between the standardized residuals a sample autocorrelation function with 100 lags is examined

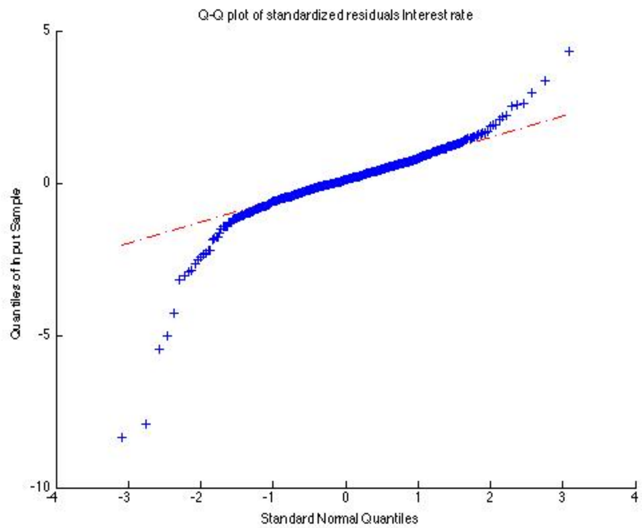
Figure 5.5: Sample autocorrelation function, squared standardized residuals Interest rate



As can be seen for some lags the autocorrelation function has values outside the 95% confidence

interval. There is no set lag interval for this, there is a tendency in the beginning towards a five and ten lag correlation but the tendency weakens.
Examining the standardized residuals belonging to a normal distribution with the help of a $q-q$ *plot*

Figure 5.6: Q-Q plot of the Interest rates standardized residuals



The q-q plot can here be seen to deviate quite far from the assumed normal. For large amount of the series there is a deviation from the normal distribution with a large discrepancy for the tails.

5.6 Nickel

Calculating the AIC value for different orders $ARMA(p, q)$ gives

Table 5.21: AIC values Nickel

p/q	1	2	3	4	5	6
1	-5.9934	-5.9907	-5.9881	-5.9872	-5.9850	-5.9846
2	-5.9908	-5.9882	-5.9855	-5.9894	-5.9867	-5.9841
3	-5.9882	-5.9878	-5.9872	-5.9869	-5.9846	-5.9818
4	-5.9876	-5.9883	-5.9858	-5.9925	-5.9847	-6.0863
5	-5.9854	-5.9862	-5.9836	-5.9843	-5.9821	-5.9794
6	-5.9843	-5.9833	-5.9813	-5.9852	-5.9790	-6.0534

The smallest value is -6.0863 received from the $ARMA(4, 6)$ model, the difference in AIC values are not that significant which leads to picking of a lower order not to add complexity. An $ARMA(2, 1)$ model is chosen to represent the Nickel return series.

With the chosen optimal order for the $ARMA(p, q)$ model the received parameters are

Table 5.22: ARMA(2,1) parameters Nickel

Parameter	Value	T-statistic
ϕ_1	0.6540	5.9054
ϕ_2	-0.0037	-0.2396
θ_1	-0.6783	-6.4911

Two parameters are significant, having a t-statistic larger than $|2|$, and one parameter, ϕ_2 is not significant since the t-statistic is less than $|2|$.

With the received residuals from the $ARMA(2, 1)$ model the $GARCH(1, 1)$ model is estimate providing the following parameters

Table 5.23: GARCH(1,1) parameters Nickel

Parameter	Value	T-statistic
ω	0.0000	0.9089
α	0.0774	3.3091
β	0.9140	32.4251

The ω parameter is equal to 0 and therefore adding no impact to the model. The α and β parameters are both significant and also satisfies the additional constrains of α and β being greater than 0 and their sum less than 1 ensuring stationarity and finite variance.

Testing the standardized residuals for uncorrelation and normality and the squared standardized residuals for uncorrelation

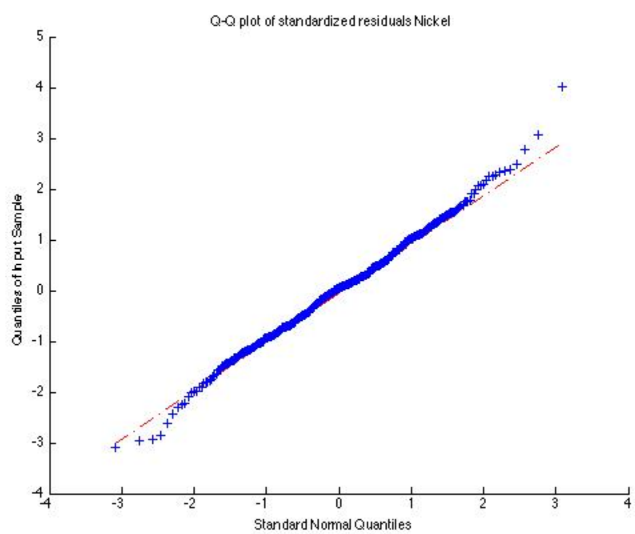
Table 5.24: Ljung-box test residuals Nickel

Type	H	P-value	Test statistic	Critical value
$\frac{\varepsilon}{\sigma}$	0	0.8252	14.1029	31.4104
$\{\frac{\varepsilon}{\sigma}\}^2$	0	0.4630	19.9185	31.4104

The null of no correlation is not rejected implying that both the standardized residuals as well as the squared standardized residuals are not correlated.

Examining the standardized residuals belonging to a normal distribution with the help of a *q−q plot*

Figure 5.7: Q-Q plot of Nickels standardized residuals



Here the standardized residuals are quite close to belonging to a normal distribution, with some discrepancy for the tails, even though no extremes have been removed or smoothened.

5.7 DCC

From the joint modeling of the *DCC* model the parameters obtained are

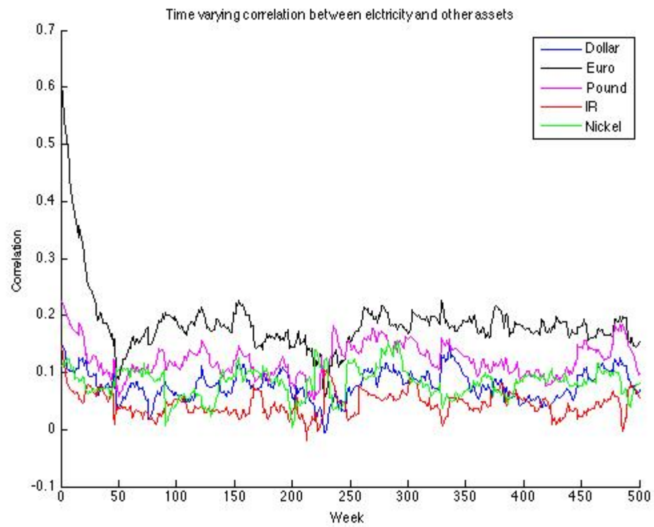
Table 5.25: DCC Parameters

Parameter	Value	T-statistic
α	-0.0068	-2.0972
β	0.9279	34.3200

Both α and β have a t-statistic above $|2|$ implying significance of the parameters. The additional constraints $\alpha \leq 0$ and $\beta \leq 1$ as well as $\alpha + \beta \leq 1$ are satisfied ensuring that the conditional correlation matrix is positive definite.

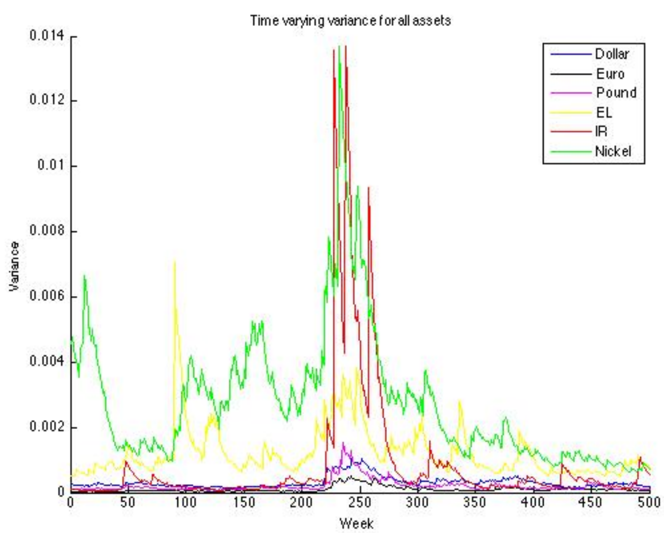
With the parameters received in the prior step the conditional correlation matrix, Γ_t, is obtained and used to plot the time varying correlation between the electricity return series and all other return series

Figure 5.8: Time varying correlation between electricity and other assets



and the time varying conditional variance for all return series

Figure 5.9: Time varying variance for all assets



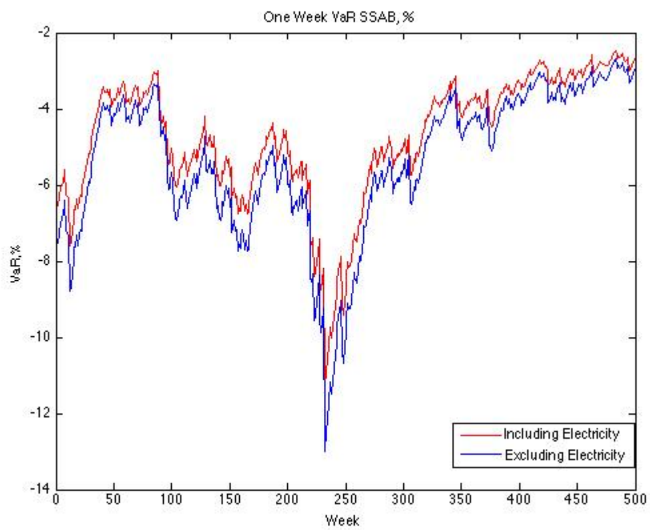
The results of the time varying correlations are to be especially highlighted as they contribute a great deal to the analysis further below. The correlation-graph is revealing a lot of useful and valuable information, enabling an interesting discussion to take form. As one can see, electricity is having a rather continuously low correlation with all the other assets, for all points in time. This behavior is of specific interest, as it will have an equal diversification effect on the VaR for all points in time even during a financial crisis. The power of the effects is however discussed in the analysis.

5.8 Value at Risk

5.8.1 SSAB

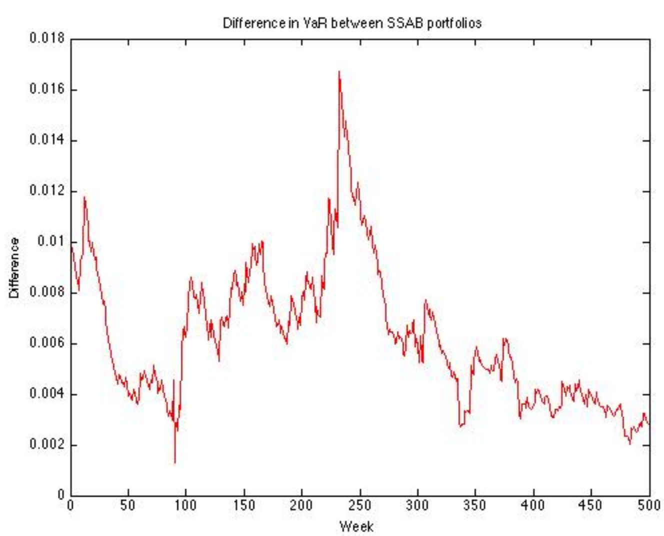
Plot of one week Value at Risk showing one portfolio including electricity and one portfolio excluding electricity. VaR is shown as a percentage. For portfolio weights see *Appendix A*.

Figure 5.10: One Week VaR for SSAB (%)



Difference in Value at Risk between the two portfolios. The portfolio containing electricity as an asset is subject do deduction of the value of the portfolio not including the electricity asset. A positive number means there is a lower Value at Risk in the electricity portfolio.

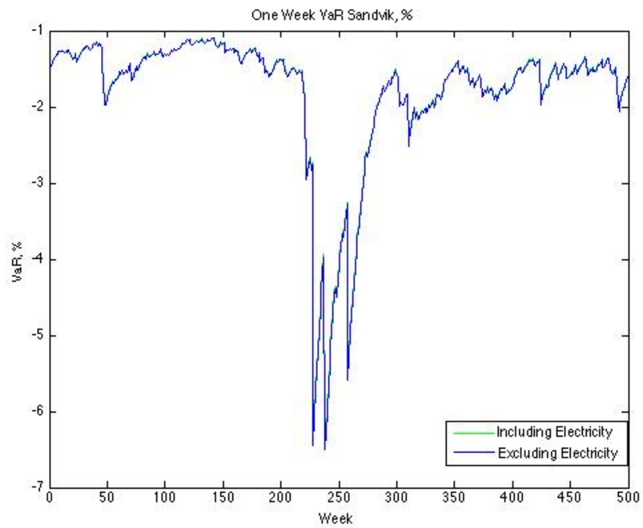
Figure 5.11: Difference VaR for SSAB portfolios



5.8.2 Sandvik

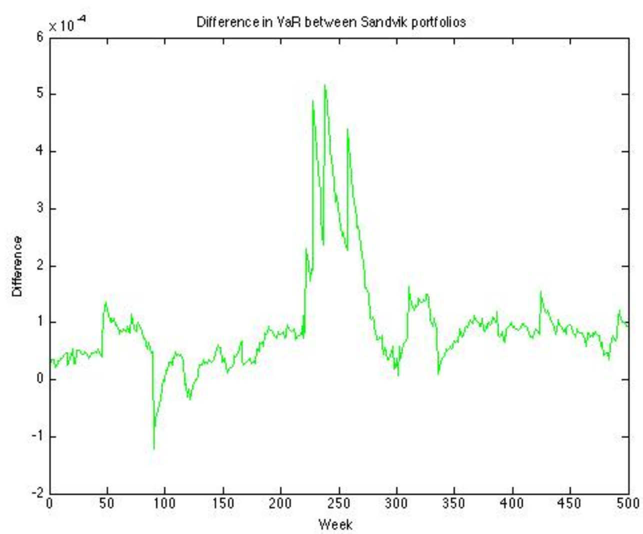
Plot of one week Value at Risk showing one portfolio including electricity and one portfolio excluding electricity. VaR is shown as a percentage. For portfolio weights see *Appendix A*.

Figure 5.12: One Week VaR for Sandvik (%)



Difference in Value at Risk between the two portfolios. The portfolio containing electricity as an asset is subject do deduction of the value of the portfolio not including the electricity asset. A positive number means there is a lower Value at Risk in the electricity portfolio.

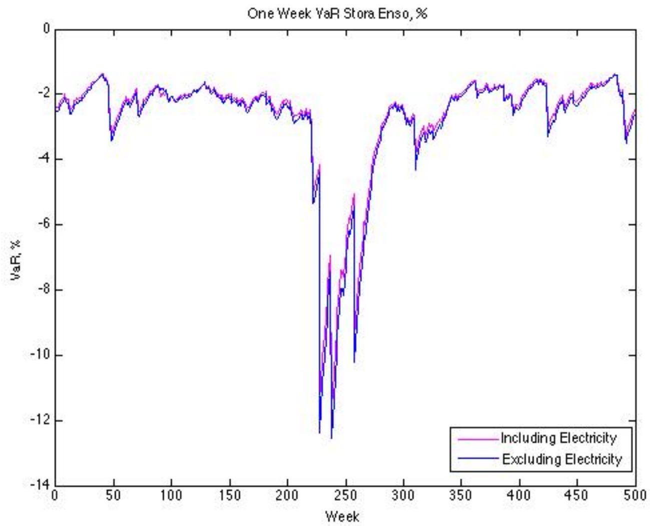
Figure 5.13: Difference VaR for Sandvik portfolios



5.8.3 Stora Enso

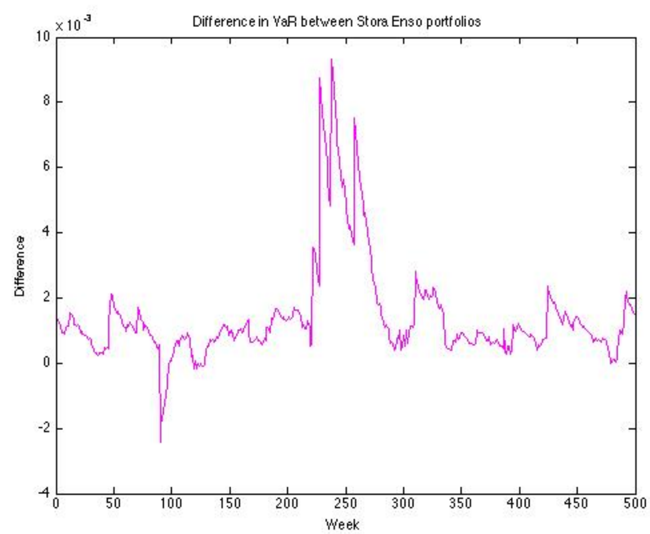
Plot of one week Value at Risk showing one portfolio including electricity and one portfolio excluding electricity. VaR is shown as a percentage. For portfolio weights see *Appendix A*.

Figure 5.14: One Week VaR for Stora Enso (%)



Difference in Value at Risk between the two portfolios. The portfolio containing electricity as an asset is subject do deduction of the value of the portfolio not including the electricity asset. A positive number means there is a lower Value at Risk in the electricity portfolio.

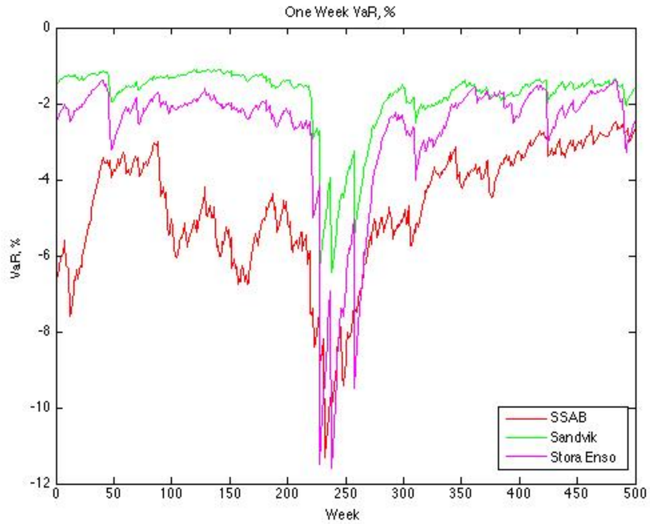
Figure 5.15: Difference VaR for Stora Enso portfolios



5.8.4 All Companies

Value at Risk for all companies, portfolio including electricity, to measure difference in size.

Figure 5.16: One Week VaR for all companies, portfolio including electricity



Chapter 6

Analysis

The investigation is subject to many and quite extensive limitations, which cause a great need for further analysis and discussion. The main goal for this thesis has been to evaluate whether or not it is favorable for an energy intense company to add electricity as an asset to their portfolio of risk bearing assets. The results have been measured by the concept of VaR, examining if a decreased VaR can be obtained if electricity is added to the portfolio. Firstly the analysis will account for discussions regarding general assumptions and drawbacks. Secondly the mathematical drawbacks will be accounted for and thirdly the correlation findings and results for the three companies will be commented and further explained.

Due to the limitations and the assumptions that have been made, the results may differ if the test was to be carried out again under different assumptions. An interesting aspect is the different view people are having regarding how large of a risk factor the electricity prices really is. The first thought was that it was considered to be relatively small, especially after dialogue with Lars S Andersson at Sandvik, who specifically supported that thought. After reviewing with Mats Forsell, Commodity Trader at SEB, this thought was revised. He stated for instance that the electricity risk is more likely to be $\frac{1}{4}$ of the total materials price risk that a company within the steel industry is subject to. Based on his perception, the electricity asset has been assigned quite a large portfolio weight for the companies. Since this is a debatable matter, and an approach assigning a larger weight to the electricity risk has been selected, the results presented in this thesis may show to good of an VaR improvement. This thesis is therefore extra sensitive towards assumptions of this nature.
The results are approving the reason for discussion and are actually showing a decreased VaR for portfolios with increasing electricity asset weight. What should be noted is that even though electricity can be seen as a good risk managing complement, it is important to evaluate the behavior that electricity show in relation to other, not investigated, assets. Electricity may show a totally different correlation outcome combined with other assets, under different assumptions.

Another simplification that is quite determining, if the test is to be carried out again, is that the commodity input for all the companies is represented by nickel. This can be considered a major error source, since nickel and fiber, for instance, have no similar features at all. The reason for this is that no satisfactory data was to be found for other commodities than nickel, due to the fact that there was no functioning exchange market for other commodities up until recently. The price data for nickel was also given in the currency of USD. Since this thesis is having SEK as its base currency, the nickel prices were converted with the corresponding FX-rate for every point in time. What should be mentioned is therefore that the currency conversion may contribute to an extra currency risk.
A third major generalization is that all the companies are assigned the same currencies of interests for the investigation- USD, EUR and GBP. However, other currencies are being used and frankly, even used to a greater extent. To take all the used currencies into account would greatly extend the numerical analysis, and therefore the thesis was narrowed down to these three common currencies.

From the mathematical results one can see that the series do not fit equally well in the used framework. For the USD and Nickel time series some parameters for the ARMA model are not significant. This is not a major deal but might have had an impact on latter parameter estimations. For the rest of the models, the GARCH and DCC, most parameters are significant at a 5% confidence level excluding the constants, which often are estimated to zero. What is more worrying is the correlation of the squared standardized residuals for the IR series. This implies that there is volatility clustering present meaning that large changes are likely followed by large changes and vice versa for small changes. Examining *figure 5.9* it can be seen that this is the case. During most of the points in time the variance for IR is small with small or no changes but during the weeks 200-300 the changes are suddenly very large. This will greatly increase the portfolio variance, during specific points in time, for a portfolio that assigns a large weight to the IR asset. Having the largest affect on the VaR measure is the deviation from normality of the standardized residuals. For the VaR to show a true value, risk assets are assumed to follow conditional normal distributions. This is equal to assuming that the standardized residuals, of individual assets, belong to a normal distribution. As can be seen in the Q-Q plots this is often not the case. Whilst the GBP standardized residuals are quite close to belonging to the normal distribution the interest rates standardized residuals deviate far from the normal. A deviation implies that fat tails are present implying more weight is present in the tails. For the VaR this will cause problems, in this case the calculated VaR will be less than in reality, since more than 5% of the values will lie on the tail side of the boundary.
The time varying correlations are estimated using the DCC model but there are several, perhaps better, models to estimate the correlations. As mentioned in the first chapter DCC has several advantages but also some disadvantages. Other multivariate GARCH models can be used to gain the time varying correlation but to examine this would extend the thesis too much.

Two main areas from the presented results are of greatest interests for the analysis. Firstly the results of the different VaR calculations are, as expected, subject for discussion. Those are discussed below with reference to the corresponding company. The second area of interest is the time varying correlation between electricity and the other risk bearing assets.

Figure 5.8 shows the time varying correlation between Electricity and the other assets. The finding of interest is not that Electricity is showing a low, or close to no, correlation with the other assets rather that the correlations are relatively constant during the whole period of time.

This could imply that electricity is worth having as a component in the risk portfolio due to the constant diversification effect it may contribute to. Even during times of financial crises, data points 230-270, the correlation remains low and constant. This is particularly notable since it is commonly known that the correlation between financial assets is generally increased during periods of crises. If electricity is one of few asset that does not follow that pattern, it is potentially a good hedging complement during financial crises. To get the best possible diversification effect a negative correlation is a sought after feature. Electricity's constant correlation does however posses another advantage, there are no surprises in the correlation between assets. As risk management is about eliminating uncertainties, a constant correlation vouches for consistency, which is a positive feature. What should be mentioned in the context of financial crises and the drawn conclusions is the limited period of time. This investigation only covers one financial crises, the one during 2008-2009. If a solid conclusion is to be drawn, a much greater amount of data points need to be analyzed, covering more than only one period of financial crises.

One might wonder what it is that differentiates electricity, and why it shows low correlation with other assets, during times of financial crises when one might expect an upturn. One possible explanation, looking beyond variables of macroeconomics, can be that the underlying factors determining the price is driven by factors that has no connection to economic cycles. For instance, the price is largely driven by weather and wind, which is always independent of macroeconomic variables.

SSAB is the company that supports the thesis to greatest extent, showing a considerably smaller VaR for the risk portfolio including electricity. The difference in VaR between the portfolio with, and without, electricity is constantly positive during the examined period of time. Electricity is, at every point in time, value adding to the portfolio from a risk perspective. SSAB is also the company assigning the highest weight to the electricity input, making it is easier to spot the difference in VaR examining *figure 5.11*. What should be mentioned is the reason for why SSAB assigns such a large weight to the electricity factor. It is not because SSAB values this particular risk asset to a greater extent than the other companies, rather because SSAB is showing a greater number in their sensitivity analysis towards changes in material prices. The electricity asset weight is higher since the electricity weight is a fixed percentage of the total materials weight.

For Sandvik however, it is much more difficult to spot graphically if the one week VaR is decreased if the electricity asset is added or not. It is due to the relatively small weight that is assigned to the materials asset and hence the smaller weight for the electricity asset. *Figure 5.13* is therefore of more use, where the trend is more easily spotted. The adding of electricity is both showing a positive and a negative impact on the one week VaR of the portfolio. No absolute finding can therefore be concluded, but one aspect of importance still remains. The difference is showing strong positive numbers around the weekly points of 230 and 270, in other words during the financial crises. This supports the fact that in times of financial crises it may be beneficial for Sandvik to add the electricity risk asset into the portfolio allowing the diversification effect to cancel out some risk.

Stora Enso shows a small but still mention worthy improvement for its VaR when the electricity asset is added. *Figure 5.15* also goes in line with the analysis for Sandvik, it can be beneficial for the company to add electricity as a risk-bearing asset into the portfolio in times of financial crises.

Figure 5.16 aims to conclude a comparable finding between the three companies. The one-week VaR for all companies is plotted in a comparing graph where one can conclude that the company that is subject to the highest VaR is SSAB. This is due to the fact that SSAB assigns larger weights to the assets possessing the highest variance over time period. The high VaR is therefore not a result of just the adding of the electricity asset, which one might believe when examining the graph. The comparing *figure 5.10* is still supporting the fact that electricity is value adding from a portfolio perspective. The companies who assigns the largest weights on high-volatile assets are therefore always going to be the companies with the highest VaR. Both Sandvik and Stora Enso are assigning larger weights on the FX-variables, which are not as volatile as commodities and electricity in general. This is concluded in *figure 5.9*, were one also can conclude that FI generally is a low-volatile asset. Exceptions for this is evident, a large increase in variance, during the financial crises. If one examines the time varying correlation graph in (*figure 5.8*), one can spot that electricity actually has the lowest correlation with FI, meaning that electricity may be extra useful when interest rates are particularly volatile. The electricity is generally showing the highest correlation to the FX-variables, especially to the Euro. This is however, partially, explained by the fact that electricity prices are given in EUR and converted to SEK. This eliminates the currency risk between the two assets but adds dependence, and therefore increases correlation. It must be mentioned that VaR is not a hedge instrument, it is only a good measure to compare the size of the risk for different portfolios. In *figure 5.16* the Value at Risk is shown to be as large as 12% which is a very high number considering the large monetary value assigned to the portfolios. In the sensitivity analyses of the companies the possible percentage change is often smaller than 5% implying that an overall decrease of 12% would be devastating for a company.

The values received for the VaR calculations must not be misinterpreted as the actual risks the companies are exposed to. All calculations are based on data and weights that are not subject to any hedging strategies. To calculate the actual portfolio risk for the companies one must take into account all the hedging strategies in place, altering both asset weights and risk bearing assets. Especially the assets weights will be altered since an asset which is completely hedged has no risk and therefore no asset weight in the risk portfolio. This fact will further limit electricity's possibility to lower the portfolio VaR, since up to 90% of the yearly predicted electricity usage is hedged in advance. With this said the electricity forward could still be used, if desired, for its diversification benefits. Since this is a derivative, without any actual delivery of electricity, it could be bought as a financial asset with no connection to the usage of electricity.

Chapter 7

Conclusion

This thesis has investigated how a company's VaR is affected if the electricity asset is added to a portfolio of risk bearing assets. The numerical analysis show that the VaR is decreased, if electricity is included, particularly for the companies that assign the largest weight to the electricity asset. One can conclude that electricity is an interesting asset, from a portfolio perspective, due to the low and constant correlation with the other risk bearing assets. Due to the constantly low correlation with the other assets the investigation show that electricity is, particularly, value adding during times of financial crises. It is commonly known that correlations between financial assets tend to increase during times of crises but this is not the case with the electricity asset. The positive outcome in this thesis can be questioned since the actual asset weight assigned to electricity is too small to have a significant effect. The used measure, Value at Risk, is also subject to discussion. VaR is a measure showing a possible maximum amount that can be lost. It does not explain if the given results are significant enough for a company to truly value and examine the effect that electricity might have on the company's risk management.

Bibliography

[1] Redaktionen at RÅVARUMARKNADEN.SE (2012), *SEB lanserar certifikat på elpriset*, viewed 8 May 2014, <http://ravarumarknaden.se/seb-lanserar-bull-bear-certifikat-pa-elpriset-investera/>.

[2] Harper, D (2010), *An Introduction to Value at Risk (VAR)*, viewed 8 May 2014, <http://www.investopedia.com/articles/04/092904.asp>.

[3] Henning, D., (2005), Energimyndigheten, *El till vad och hur mycket i svensk industry*, pp.7, viewed 8 May 2014, <http://www.energimyndigheten.se/Global/Forskning/Energisystemstudier/El%20till%20vad%20och%20hur%20mycket%20i%20svensk%20industri.pdf>.

[4] Guider at RÅVARUMARKNADEN.SE (2012), *Den nordiska elmarkanden och elpriset*, viewed 8 May 2014, <http://ravarumarknaden.se/den-nordiska-elmarknaden-och-elpriset/>.

[5] Ernst, F., Galonske. B., Schmitz, J., *Commodity Price Risk Management- The new front line for margin management*, viewed 12 May 2014, <http://www.oliverwyman.com/insights/publications/2013/oct/commodity-price-risk-management.html#.U3CSfeZ_txo>.

[6] OMAFRA Staff (2008), *Managing Commodity Price Risk Using Hedging and Options*, viewed 8 May 2014, <http://www.omafra.gov.on.ca/english/busdev/facts/08-053.htm#conclusion>.

[7] Phung, A (2009), *What is the difference between forward and futures contracts?*, viewed 8 May 2014, <http://www.investopedia.com/ask/answers/06/forwardsandfutures.asp>.

[8] Investopedia, viewed 8 May 2014, <http://www.investopedia.com/terms/o/offset.asp>.

[9] London Metal Exchange's home page, viewed 8 May 2014, <https://www.lme.com/trading/risk-management/what-is-hedging/?language=en-GB>.

[10] Habibnia. A (2013), *Exchange Rate Risk Measurement and Management*, viewed 12 May 2014, <http://personal.lse.ac.uk/habibnia/Exchange%20Rate%20Risk%20Measurement%20and%20Management%20-%20Ali%20Habibnia.pdf>.

[11] Swedbank's home page, *Valutatermin*, viewed 8 May 2014, <http://www.swedbank.se/foretag/affarer-med-utlandet/produkter-och-tjanster/valutatermin/index.htm>.

[12] Swedbank's home page, *Valutaoption*, viewed 8 May 2014, <http://www.swedbank.se/foretag/affarer-med-utlandet/produkter-och-tjanster/valutaoption/index.htm>.

[13] Danske Bank's home page, *Hantering av valutarisken- Valutaoption*, viewed 8 May 2014, <https://www.danskebank.fi/sv-fi/Foretag/Medelstora-foretag/Riskhantering-och-penningmarknader/Pages/Hantering-av-valutarisken.aspx?tab=2#tabanchor>.

[14] Dhanani. A. et al (2005), *Interest Rate Risk Management- an investigation into the management of interest rate risk in UK companies*, viewed 12 May 2014 <http://www.cimaglobal.com/Documents/Thought_leadership_docs/Interest%20rate%20risk%20management%20-%20an%20investigation%20into%20the%20management%20of%20interest%20rate%20risk%20in%20UK%20companies.pdf>.

[15] Swedbank's home page, *Räntesäkring i Swedbank Hypotek*, viewed 8 May 2014, <http://www.swedbank.se/foretag/finansiering/ranteriskhantering/rantesakring/index.htm>.

[16] Swedbank's home page, *Ränteswap*, viewed 8 May 2014, <http://www.swedbank.se/foretag/finansiering/ranteriskhantering/ranteswap/index.htm>.

[17] Swedbank's home page, *Swaption*, viewed 8 May 2014, <http://www.swedbank.se/foretag/finansiering/ranteriskhantering/swaption/index.htm>.

[18] Borenstein, S (2001), *POWER- The Trouble With Electricity Markets (and some solutions)*, viewed 12 May 2014, <http://www.ucei.berkeley.edu/PDF/pwp081.pdf>, pp 2.

[19] SvenskEnergi's home page, *Elbörsen Nord Pool Spot*, viewed 14 May 2014, <http://www.svenskenergi.se/Elfakta/Elmarknaden/Elborsen-Nord-Pool-Spot/>.

[20] Nordpoolspot's home page, *Financial market*, viewed 12 May 2014, <http://www.nordpoolspot.com/How-does-it-work/Financial-market>.

[21] Nordpoolspot's home page, *Eltermin*, viewed 12 May 2014, <http://wwwdynamic.nordpoolspot.com/marketinfo/content/content.cgi?theme=eltermin>.

[22] Bird. J, *Layering Hedges and Extending the Hedge Horizon Trough Rolling Hedge Programs*, viewed 12 May 2014, <http://www.treasury-management.com/article/4/265/2222/layering-hedges-and-extending-the-hedge-horizon-through-rolling-hedge-programs.html>.

[23] Ekonomifakta.se,(2013), *Elanvändning per sektor- utveckling*, viewed 12 May 2014, <http://www.ekonomifakta.se/sv/Fakta/Energi/Energibalans-i-Sverige/Elanvandning-utveckling/>.

[24] Henning. D, (2005), *El till vad och hur mycket i svensk industri*, viewed 12 May 2014, <http://www.energimyndigheten.se/Global/Forskning/Energisystemstudier/El%20till%20vad%20och%20hur%20mycket%20i%20svensk%20industri.pdf>, pp.7.

[25] SSAB, (2013). *Annual Report 2012*, <http://www.ssab.com/en/Investor--Media/Investors1/Financial-reports--presentations1/Financial-reports--presentations/Report-page/?itemid=1280870>, s 45.

[26] Sandvik, (2013), *Annual Report 2012*, <http://www.sandvik.com/Global/Investors/Annual%20reports/Annual%20Report%202012.pdf>, pp.35-39.

[27] Stora Enso Oyj, (2013), *Annual Report 2012*, <http://assets.storaenso.com/se/com/DownloadCenterDocuments/Stora_Enso_E_Financial_Report_2012.pdf>, pp. 30-106.

[28] Brockwell, P., Davis, R., (1991), Stationary ARMA Processes, *Time Series: Theory and Methods*, 2nd ed, pp.78.

[29] Jondeau, E., (2012-2013), *Modelling Volatility: GARCH models*, lecture notes distributed in Financial Econometrics at Ecole Polytechnique Fédérale de Lausanne March 2014.

[30] Francq, C., Zakoian, J., (2010), Classical Time Series Models and Financial Series, *GARCH Models*, pp.2

[31] Jondeau, E., (2012-2013), *Modeling Correlation*, lecture notes distributed in Financial Econometrics at Ecole Polytechnique Fédérale de Lausanne March 2014.

[32] Bodie, Z., Marcus, A., Kane, A., (2010), Optimal risky portfolios, *Investments*, 9th ed, pp. 197-217.

[33] Mazerolle, M.,(2007), *Making sense of Akaike's Information Criterion (AIC)*, viewed 7 May 2014, <http://theses.ulaval.ca/archimede/fichiers/21842/apa.html>.

[34] Jondeau, E., (2012-2013), *Characteristics of Financial Time Series*, lecture notes distributed in Financial Econometrics at Ecole Polytechnique Fédérale de Lausanne March 2014.

[35] Jondeau, E., (2012-2013), *Extreme Value Theory*, lecture notes distributed in Financial Econometrics at Ecole Polytechnique Fédérale de Lausanne March 2014.

[36] Ash, M., *Statistics and Hypothesis Testing*, viewed 7 May 2014, <http://courses.umass.edu/pubp608/lectures/l5.pdf>.

[37] Bissantz, K., Bissantz, N., Ziggel, D., *Diversification effects between stock indices*, viewed 7 May 2014, <http://www.ruhr-uni-bochum.de/imperia/md/content/mathematik3/publications/bissantz__ziggel_aktien_engl_100926.pdf>.

[38] Svenska Bankföreningen, (2014), *Stibor*, viewed 15 May 2014, <http://www.swedishbankers.se/web/bf.nsf/all/E54E88F19057DCFDC1257AD400323DB9?OpenDocument>.

Appendix A

Portfolio weight calculations

To be able to model a realistic portfolio, the different weights of the input variables need to be calculated so that the modeling of the VaR will be as truthful as possible. In accordance with Mats Forsell at SEB (mail correspondence), industries within the steel-production value the risk of electricity as $20-30\%$ of the total commodity price risk. Based on that we will assign 25% of the other commodity-goods to as electricity price risk. He also stated that industries within the paper and pulp-industry are showing a larger risk exposure to energy consumption and he estimate that 50% of the other commodity- goods make up for how the company value the electricity- risk exposure. This estimation was of great importance since neither company in this examination were showing all digits needed to analyze the exact weights for our portfolio. So therefore we have, for those companies revealing the amount for electricity price risk, calculated our way back to find out the amount for their commodity goods. In the same way we have used the information to calculate the electricity price risk based on their other commodity price risk exposure. Therefore the results may come out as arbitrary and what must be mentioned is that the weights are only possible estimates for a potential portfolio. Other companies may disagree on these numbers, but this course of action was the only one that would give us a potential answer. What also should me mentioned and considered as interesting is that all the three companies under investigation are all valuing the risk exposures in different ways. SSAB emphasizes the weight of commodity price risk, Sandvik is more keen to highlight the FX-risk exposure, whilst Stora Enso values the FI-risk to a greater deal.

SSAB's sensitivity analysis presented different raw materials for which a 10% change in price would affect the EBITDA. We choose only to focus on their steel-exposure since nickel is the commodity that is representing our modeling and is the commodity that resembles nickel to greatest extent. How an interest rate shift of 100 basis points (1%) affects the EBITDA is also presented as well as how a foreign exchange rate- change of 5%. The percentages are added up to 100% to show a comparable result. The numbers are in millions of SEK.

Total risk bearing amount excluding electricity: 47200

Table A.1: Sensitivity analysis SSAB

Asset	% Change	Value Change	Total Value
Metal	10%	3100	31000
FI	1%	100	10000
FX	5%	310	6200
		Total	47200

Electricity price risk amount: 25% of 31000 = 7750

Total risk bearing amount including electricity: 54950

The weights are then calculated by dividing the value change by the grand total giving

Table A.2: Portfolio weights SSAB

Asset	Weight	Weight no electricity
Metal	0.5641	0.6568
Electricity	0.1410	0
FI	0.1819	0.2119
FX	0.1128	0.1313

Sandvik are more eager to highlight the risk exposure of FX. In the sensitivity analysis they are expressing the same percentages of interest that could differ the input variables as SSAB. The annual report also provides us with this info:

'A change in the electricity price of SEK 0.10 per kWh is estimated to impact Sandvik's operating profit and other comprehensive income by plus or minus 90 million SEK on an annual basis, based on the prevailing conditions at year-end 2012'.

We therefore converted the change of SEK 0.1 to SEK 1, as the other amounts are showed in integers. Therefore the amount at risk is 900 millions SEK. Based on Mats Forsell's opinion we then divided 900 with 0.25 and ended up with the amount for the commodity-risk exposure (3600 million SEK).

Table A.3: Sensitivity analysis Sandvik

Asset	% Change	Value Change	Total Value
Metal			3600
FI	1%	335	33500
FX	5%	3000	60000
		Total	97100

Total risk bearing amount excluding electricity: 97100
Electricity price risk amount: 25% of 3600 = 900
Total risk bearing amount including electricity: 98000

Giving the weights

Table A.4: Portfolio weights Sandvik

Asset	Weight	Weight no electricity
Metal	0.0367	.0371
Electricity	0.0092	0
FI	0.3418	0.3450
FX	0.6122	0.6179

Stora Enso is considering their greatest risk exposure to be the FI-risk. They are also showing the same percentage- changes in their sensitivity analysis as the companies above. We use their number for commodity price risk and multiply it with 50% to get the number for the electricity price risk (in accordance with Mats Forsell). What should be mentioned is that the main commodity within Stora Enso's production is fiber, but unfortunately there is no data of fiber that is showing same quality as the data of nickel. The series is too short, since trading with fiber has not a history that is sufficiently long for our modeling. Therefore the numbers below are subject to reservation and should be interpreted with caution.

Table A.5: Sensitivity analysis Stora Enso

Asset	% Change	Value Change	Total Value
Metal	10%	260	2600
FI	1%	950	9500
FX	5%	142	2840
		Total	14940

Total risk bearing amount excluding electricity: 14940
Electricity price risk amount: 50% of 2600 = 1300
Total risk bearing amount including electricity: 16240

Giving the weights

Table A.6: Portfolio weights Stora Enso

Asset	Weight	Weight no electricity
Metal	0.1601	0.1740
Electricity	0.0800	0
FI	0.5850	0.6359
FX	0.1749	0.1901

The FX weight is in turn weighted differently since we are modeling with three different currencies; USD- with highest ratio (60%) followed by EUR (30%) and then GBP (10%) with the smallest ratio. These numbers are based on annual reports where the currency flows are shown for the investigated companies.