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Mat-2.4177 – Seminar on Case Studies in Operations Research

Modeling Long-Term Electricity Prices

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Final Report

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ABSTRACT OF THE FINAL REPORT

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Electricity has special characteristics which make it different from other commodities. Since it cannot be stored, standard procedures for modelling the forward price fails to give accurate estimates for its behaviour.

The objective of the study is to consider the dynamics and characteristics of electricity forward contracts. In order to capture some of this dynamical structure, we develop a CVAR (Cointegrated Vector Autoregressive) model for the generic electricity forward prices with time to maturity from two to five years and a delivery period of one year. The parameters of the CVAR model structure are estimated for all contracts separately.

In this study, we suggest that the contracts with longer time to maturity adapt market changes more slowly even though the changes follow the same general pattern. No seasonal components were identified, but the volatility of contract prices was dependent on the changes in the previous weeks. Our results suggest that there was a structural break in the price dynamics in mid-2008 that restricts the use of CVAR models. Additionally, the risk premium of the forward contracts is discussed. The preliminary results suggest that the risk premium is not constant over different times to maturity. This conclusion is heavily affected by the amount of studied data.

The impact of the evolving CO_2 market and possible long-term structural changes are also discussed.

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Preface

This work was carried out as a course project in Aalto University School of Science and in collaboration with Danske Markets Finland (a part of Danske Bank).

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Otaniemi, 2011
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Contents

Symbols and Abbreviations

Matrices are capitalized and vectors are in bold type.

Notation

t	Observation time (mostly in weeks)
N	Number of observations
$\mathbf{y}_t$	Vector of endogenous variables
$\mathbf{x}_t$	Vector of exogenous variables

Abbreviations

AR	Autoregressive (model)
VAR	Vector Autoregressive
CVAR	Cointegrated Vector Autoregressive
SARFIMA	Seasonal Autoregressive Fractionally Integrated Moving Average
RS-SARFIMA	Regime Switching SARFIMA
EU-ETS	European Union Emission Trading System
NELxY	The generic xth nearest annual electricity forward contract
NELFxY	Electricity forward price for year 201x
ENWSSPAV	Electricity spot prices
ELGBY1x	German electricity forward price for year 201x
ELGBYRx	The generic xth nearest annual German
API2YR1	Price for API2 coal for xth year
CLx	Crude oil price with x months to maturity
MOZx	EU emission allowance prices for xth contract
GDP	Gross domestic product

1 Introduction

The purpose of this project is both quantitative and qualitative modelling of long-term electricity forward prices. We limit our interest to long-term electricity forwards with a delivery period of one year and a time to maturity of two years or more. The essential part of our approach is to interpret our model and discuss its limitations considering the market structure of electricity derivatives and changing market conditions.

The long-term dynamics of the electricity contracts differ from each other. Based on the findings of the general features of price dynamics we also briefly discuss contracts with longer time-spans that are not traded at present due to their low liquidity. The prices for the annual forward contracts are not changing linearly so we are also interested in their relative prices across the forward curve.

Based on the market data the seasonal factors are also discussed in brief in this study. Some remarks related to the stability of the risk premium are also presented.

In addition, changes in market conditions and the technological and economic environment affect the model largely. These phenomena will be discussed with respect to general features of the electricity market. We have also paid attention to the long-term perspective of the production and consumption of electricity in the time horizon of decades rather than only a couple of years.

This report is structured as follows: In the introductory part background factors and essential concepts will be presented as well as a brief review of the research previously done in the field. The Materials and Methods section presents the datasets we are using and the tools that we use for modelling. The actual results are presented in the third section and the findings are discussed in more detail in the Discussions section. The report ends with concluding remarks in the last section.

Later on in this report the following concepts will be referred to frequently. For the reader's convenience they are defined at this stage:

The spot prices tell the current balance between the demand and supply of the electricity. They are usually updated hourly, whereas *the closing price* is the latest price of the day which thus is the most up-to-date price until trading continues. The spot prices are determined at the spot market where the delivery of the electricity is based on hourly quoted chunks. The market is a day-ahead market where the need for electricity is settled the day before the delivery.

The electricity forward contracts are financial derivatives whose payoff values are tied to the value of electricity. The buyer of the electricity is said to hold the *long position* whereas the seller has a *short position* (see, *e.g.*, Luenberger, 1998). The forward contracts are purely financial, so there is no physical delivery of energy at the time of buying and selling.

During the *trading period* the forward contracts are sold in the energy market as can be seen in Figure 1. For instance in the end of year 2011 one can buy a one year forward

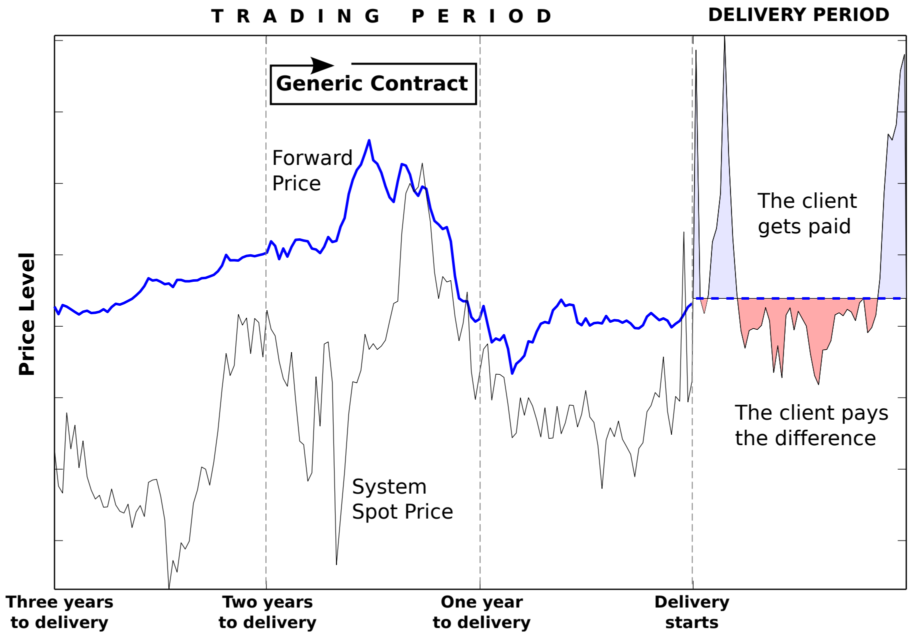

Figure 1: Illustrative figure explaining the electricity forward contract life span. The thin black line represents the spot price and the blue thick line the forward contract price.

contract whose physical delivery of electricity starts at the beginning of year 2013. This means that the *delivery period* of the contract is one year from the beginning 2013 to its end. The *maturity date* of the contract is in the end of the year 2012 when the financial payments related to the contract will begin. As there are transactions along the delivery, one interpretation of the maturity date would be in the middle of the delivery period. The financial payments of forward contracts are settled only during the delivery period, thus the profit and losses are realized only when the delivery of energy starts (Botterud *et al.*, 2002).

In general, the *risk premium* means how much the expected return of a financial instrument must exceed the value of a risk-free option. In the case of the electricity derivatives there is systematic price difference when considering contracts with different times to maturity. For example, it is logical that the contract for year 2015 is more expensive than a contract for a year 2014 even though we do not have any reason to expect the spot prices of 2014 and 2015 to be significantly different from each other.

Generic contracts are combinations of consecutive contracts as implied in Figure 1. For example if we have a generic time series for the second nearest contract, then we have in the year 2011 the forward contract for a year 2013, in the year 2012 the forward contract which maturity date is 2014 and so on. This means that the contract captures always characteristics of the certain time-to-maturity lag.

1.1 Background

Electricity is a commodity with special characteristics. As there exist no convenient and economic way of storing electricity, the prices of short- and long-term electricity contracts exhibit very different dynamics compared to other commodities. The consumption and production of electricity have to match at any time and the seasonal effects cause high volatility in price and eventually high peaks. Thus, participants in the electricity market need to reduce price-related risk with forward trading.

The Nordic energy market has a history of two decades and is exceptionally integrated. Nord Pool was established 1996 to attain a common electricity market for Norway and Sweden. In the year 2010 NASDAQ OMX acquired all shares of Nord Pool and the name of the company changed to NASDAQ OMX Oslo ASA and its trade name to NASDAQ OMX Commodities Europe (Nord Pool, 2011). Nord Pool is nowadays the largest power exchange in Europe.

The organization offers clearing services and access to markets of different kinds of energy derivatives and carbon contracts to its members. The members are energy producers, consumers and financial institutions. Altogether there are over 360 members in 18 countries (Nord Pool, 2011). Botterud *et al.* (2002) list four main responsibilities of the power exchange: to operate as a physical and a financial market for e.g. forward contracts, to provide a market reference price, to act as a neutral and reliable power-contract counterpart to market participants, and to help to alleviate grid congestion.

The durations of the financial contracts are up to six years. Trading at Nord Pool is not compulsory, but the Nord Pool Spot price must be used in all day-ahead cross-border trading (Nordic Energy Regulator, 2010). The spot price is calculated from an aggregated demand and supply of the electricity. The market is a day-ahead market where the purchase and sale of hourly contracts cover the 24 hours of the next day. Transmission grids in the Nordic countries were originally built to meet needs of each country, but they are nowadays closely connected. In principle, there is only one price for the whole market, but due to some congestions in the transmission grids, there might be different prices over the grid (Botterud *et al.*, 2002).

Predicting the long-term prices of electricity is especially important to the electricity retailers; as the long-term investments including considerable risks and accurate forecasts of future prices help companies to adjust their production. The suppliers of the electricity as well as consumers can hedge themselves against highly volatile spot price in the NASDAQ OMX financial derivatives market. These contracts are purely financial contracts thus the profit and losses are realized only when the delivery of energy starts. In our project, we focus on longer period forward contracts where the payments are settled only during the delivery period between the keepers of long and short positions.

The Scandinavian electricity market has its own distinctive characteristics — there are for example the peaks in the demand of electricity due to cold winter season and the dominant position of hydro power on the supply side. Approximately 51 % of the electricity is produced by hydropower. The other most important sources are combined heat and power (21 %), nuclear power (12 %) and wind power (6 %). In year 2009 the total Nordic generation capacity was 96 043 MW (Denmark 13 %, Finland 17 %, Norway 32 % and Sweden 37 %) (Nordic Energy Regulator, 2010).

Another distinctive feature is the Nordic weather conditions, which generate seasonal fluctuation to consumption. The winters in Denmark are not as cold as in the other Nordic countries and it has little energy intensive industry, so the consumption of electricity is lower than in Finland, Sweden or Norway. The influence of the climate is clear, because the electricity consumption is considerably smaller in the warmer years because there is no need for intensive heating. Peaks loads in the spot prices happen usually during cold periods. Peak load is defined as the maximum instantaneous electricity consumption or the maximum average (Nordic Energy Regulator, 2010). The total electricity consumption has grown steadily during the last decade.

As the correlation between short-term and long-term electricity contracts is low, the short-term contracts are not suited for hedging long-term exposures in electricity markets such as long-term procurement costs and production revenues (Povh, 2009). Consequently, investors seek long-term forward contracts to hedge long-term price related risks properly. The long-term price information can also be important with regard to strategic decision making and policy adoption. For instance, in recent years, there has been a shift in electricity production technology from coal and nuclear to natural gas and renewable sources. As Povh *et al.* (2010) state, this ongoing shift requires investors to have relevant information about the electricity market in the future in order to support investment decisions today.

Long-term electricity price modelling faces many challenges, such as availability of relevant market data. Furthermore, being able to detect and include seasonal components in long-term pricing modelling can be problematic. For example, although a seasonal component is present in spot dynamics, at times of high stress from demand or supply side it may not be very visible. In addition, there is a limited number of monthly and quarterly forwards quoted in the market. Furthermore, electricity markets still struggle with low liquidity, which creates more challenges for efficient hedging. Reliable long-term forward contract could enhance this liquidity.

1.2 Literature Review

We present a brief literature survey on modelling and forecasting long-term electricity prices. The problem of forecasting long-term electricity prices is far from simple and, as discussed, the normal approach of using only spot prices is not relevant. Other independent variables must be included in the model, e.g. demand estimates, factor prices and seasonality. Also the choice of the best model is not unambiguous. This field of science has been under adequate interest. For example, Cabero *et al.* (2003) assumed that the probability distribution of the electricity spot price resembles the Beta distribution and used linear regression for fitting its parameters. Szkuta *et al.*

(2002) have used an artificial neural networks approach in short-term electricity price forecasting.

Haldrup and Nielsen (2006) and Haldrup *et al.* (2010) used a vector autoregressive model (VAR). In their model they explained the long memory of electricity prices with a SARFIMA (Seasonal Autoregressive Fractionally Integrated Moving Average) model to simulate the congestions in the transfer system including the seasonal effects. They also presented a 3-state regime switching model (RS-SARFIMA – Regime Switching SARFIMA) for electricity prices which takes into account switches in congestion states.

However, long-term modelling of commodity forward prices is relatively new, as the availability of the long-term forward data remains low. In contrast to the studies where long-term forward prices are modelled as an extension of short-term forward-price modelling, Povh and Fleten (2009) model long-term electricity forward prices with a vector autoregressive model (VAR). The model combines information on forward prices of commodities from financial markets which influence electricity price and information data on demand and supply of electricity capacity adjusted with a risk premium which depends on the time to maturity. They argued that the variables influencing the supply side of electricity markets are fuel prices, water-reservoir level in hydro-rich systems, emission allowance prices, supply capacity and electricity prices in neighbouring markets. The electricity prices experience a few substantial shocks during the study period. Cointegration analysis reveals two stationary long-run relationships between all variables except the gas price, indicating that these variables move together over time. They find some influence of the risk premium, however not on the long-term electricity forwards at Nord Pool.

Finally, Botterud *et al.* (2002) focus on future and spot electricity prices. They find that the future prices on average exceeded the actual spot price at delivery, concluding that there is a negative risk premium in the electricity futures market. This result contradicts the findings in most other commodities markets, where the risk premium from holding a futures contract tend to be zero or positive. They identify the difference in flexibility between the supply and demand sides of the electricity market, leaving the demand side with higher incentive to hedge their positions in the futures market, as a possible explanation for the negative risk premium. In general the importance of risk premium and its behaviour has been discussed extensively in recent research. For example Kettunen *et al.* (2010) discuss the impact of the risk attitude of the retailers and how this affects the prices.

In modelling, our approach will mostly be based on the work by Martin Povh and Stein-Erik Fleten (Povh and Fleten, 2009; Povh, 2009; Povh *et al.*, 2010). We will build a CVAR (Cointegrated Vector Autoregressive) model structure for the long-term electricity contracts with different times to maturity. The modelling will however only provide an insight into the market data, as statistically significant modelling of this problem is hard.

2 Materials and Methods

2.1 Actual Market Data

Our analysis is based on actual market data from the Nordic electricity market. In this section, we try to identify factors that are influencing the dynamics of long-term electricity forwards. In the approach by Povh (2009) care is taken regarding the use of data sources and we try to follow the same guidelines. Real financial markets are complicated and not all investors share the same information. To model and analyse long-term electricity prices we use only information that is available to everyone (i.e. common knowledge).

The datasets that are used in this study can be divided into two types of information: *High-resolution common-knowledge information* is data that is completely public and usually the result of trading and market forces in general. Quantitative measures as time to maturity or the time of year can also be put under this label. Data that cannot be measured with this kind of precision is called *low-resolution common-knowledge information*. Examples of such information are political decisions, political interventions, aggregated data and estimated information, for example quarterly estimates of the gross domestic product and energy consumption. In making reliable forecasts over long time periods this kind of information is essential but causes the forecasts to depend on qualitative estimates. On the other hand, short time forecasts are troublesome because predicting low-resolution variables over short time-spans can be ambiguous. (Povh, 2009)

To model the long-term forward prices we therefore try to restrict our interest mostly on high-resolution common-knowledge information. However, forecasting prices over long time horizons also require qualified guessing of future market conditions and forthcoming changes. This information is hard to include as exact data in the scope of our approach, but some variables will be discussed further on.

Following the path led by Povh (2009) and Povh and Fleten (2009) most of the following data was used to model the forward price of electricity. We present these drivers with some comments on their properties. Table 1 presents our datasets, of which not all are used in the modelling (the particular choice of variables will be done in the data analysis section). The same data is also used for the market structure analysis. The data was primarily supplied by Danske Markets and the names follow the naming convention used by Bloomberg. The data time series are included in Appendix A.

Typically in our case the same prices are present in the data twice. In the first set of prices we have the actual contract price time series. In the second set the different contracts of the same product have been combined into *generic datasets*. In these datasets the time to maturity is fixed within each set. For instance the third year generic data for the electricity forwards (NEL3Y) consists of the consecutive contracts and data for each year is always the third nearest annual contracts for that specific year. To achieve as long datasets as possible we decided to use generic data when possible.

Table 1: The datasets that were available for the model building. All observations have been interpolated to week level and each number of observations N corresponds to the number of weekly observations of the data. The time series are included in Appendix A.

Description	**Name**	**Start Date**	**End Date**	N **(weeks)**
Electricity spot prices	ENWSSPAV	05-Jan-2000	23-Feb-2011	582
The generic nth nearest annual electricity forward contract	NEL2Y	12-Jan-2005	23-Feb-2011	320
	NEL3Y	08-Feb-2006	23-Feb-2011	264
	NEL4Y	21-Jun-2006	23-Feb-2011	245
	NEL5Y	21-Jun-2006	23-Feb-2011	245
Electricity forward price for year 201X	NELF2Y	03-Jan-2007	23-Feb-2011	217
	NELF3Y	09-Jan-2008	23-Feb-2011	164
	NELF4Y	07-Jan-2009	23-Feb-2011	112
	NELF5Y	06-Jan-2010	23-Feb-2011	60
German electricity forward price	ELGBY12	12-Dec-2007	23-Feb-2011	168
	ELGBY13	21-May-2008	23-Feb-2011	145
The generic nth nearest annual German contract	ELGBYR1	12-Sep-2007	23-Feb-2011	181
	ELGBYR2	12-Sep-2007	23-Feb-2011	181
	ELGBYR3	12-Sep-2007	23-Feb-2011	181
Price for API2 coal for the nth year	API2YR1	16-Mar-2005	23-Feb-2011	311
	API2YR2	12-Sep-2007	23-Feb-2011	181
	API2YR3	05-Sep-2007	23-Feb-2011	182
	API2YR4	05-Jan-2005	23-Feb-2011	321
Crude oil prices	CL1	05-Jan-2000	23-Feb-2011	582
	CL21	05-Jan-2000	23-Feb-2011	582
EU emission allowance prices for yearly contracts	MOZ1	27-Apr-2005	23-Feb-2011	305
	MOZ2	27-Apr-2005	23-Feb-2011	305
	MOZ3	09-Apr-2008	23-Feb-2011	151
Finnish GDP	GDP	05-Jan-2005	23-Feb-2011	325

The Electricity Spot Prices tell the daily price level of electricity. We use the daily closing price of the Nordic electricity market (dataset name ‘ENWSSPAV’). The long-term electricity forward price should reflect assumptions regarding long-term spot price level. However, the spot price is mostly influenced by fundamental short-term drivers such as daily and yearly behavioural and temperature cycles and daylight hours. Economic drivers such as industrial and household consumption of electricity, which can be modelled to some extent with low-resolution GDP estimates, have a great impact on the spot price. Demographic drivers such as population growth and migration also cause changes in spot price dynamics.

The Electricity Forward Prices are the forward contract prices of electricity. The electricity forward price also serves as a proxy for expected long-term spot price, which has an influence on long-term electricity demand, assuming long-term price elasticity of demand (Povh, 2009). As the spot price tends to be highly volatile, hedging against this is common. The datasets starting with ‘NEL’ are forward price data.

Prices of Electricity in Neighbouring Markets have an influence on the electricity forward prices due to the effect of similar dynamics over different markets. A part of the electricity supply is also imported from neighbouring markets. This causes the prices to follow each other over the national borders. In Finland electricity is imported from Russia, but we use forward price data from the German market since no Russian data is available. The name of these datasets begins with 'ELGBY' and they represent the yearly futures traded up to five years ahead.

Coal Prices are linked to electricity, as coal is an important source in electricity production and it is typically used during peaks in demand. Therefore its price has an impact on the electricity price. Despite the fact that coal-fired power plants typically use local coal resources, the value of this coal is measured by benchmarking it with global coal prices usually valid for major nearby ports (Povh, 2009). The 'API2YRx' data is the most recently available official monthly price per tone of steam coal, x being the number of years to maturity.

Crude Oil Forward Prices have similar relations to the electricity production process as coal. To reflect the dynamics of oil price we use global crude oil data. 'CLx' is the official settlement price for one barrel, x being the number of moths to maturity. The long-term crude oil price is influenced by the global long-term supply and demand.

European Union Emission Allowance Prices that are available under the European emission trading scheme (EU-ETS) which was implemented in 2005 for carbon dioxide (CO_2) emissions. Electricity producers received a limited amount of free carbon allowances, whereas additional allowances can be purchased in the market. (Povh, 2009) We include the emission allowance prices (dataset name 'MOZ') available at Nord Pool to present the influence of the CO_2 market.

The Gross Domestic Product in Finland presents dynamics that would often be replaced by peak dummy variables. However, we chose to include quarterly estimates of the Finnish national economy to be able to account for drivers over the whole economy. The quarterly estimates were interpolated using linear interpolation to week level. The data is publicly available at Statistics Finland and it has been normalised to the reference year 2000.

Time to maturity, also addressed to as time-to-delivery, is the time to date at which the forward contract expires. Because we are using the generic data, the datasets are not fully continuous. Thus we decided to introduce an external variable (time to maturity) to depict the change of the contract to the model. This sawtooth-like variable gets a value one when a contract changes in the dataset and the value of the external variable goes linearly to zero until a new contract emerges and the time to maturity dummy resets to one.

The datasets vary in terms of observation time and delivery period resolution. As we wish to minimize the influence of short-term variations in price due to different short-term factors and, at the same time, produce an adequate data sample to obtain significant results, we use a weekly resolution. The data is downsampled to week level so that the week mean prices are taken from the Wednesday closing price — or the nearest price available (nearest neighbour interpolation). In Table 1 all the data has been sampled to matching time steps.

Instead of plain price level information, we use the conventional econometric *log-level* approach, which means transforming price level information into logarithmic prices by taking the natural logarithm of the levels. (see, *e.g.*, Heij, 2004)

2.2 Model Structure

Vector autoregression (VAR) is an econometric method used to capture the evolution and the interdependencies between multiple time series, generalizing the univariate AR models. All the variables in a VAR model are treated symmetrically by including for each variable an equation explaining its evolution based on its own lags and the lags of all the other variables in the model. (Pindyck and Rubinfeld, 1997) In this sense a VAR model can be interpreted in standard state–space equation form.

In the autoregressive process of order k the current observation $\mathbf{y}_t$ is generated by past observations going back k periods, together with a random disturbance in the current period. We denote this process as VAR(k) and write its equation as

$$\mathbf{y}_t = \mathbf{a}_0 + \sum_{i=1}^{k} \mathbf{A}_i \mathbf{y}_{t-i} + \sum_{j=1}^{m} \mathbf{B}_j \mathbf{x}_{t-j} + \varepsilon_t, \tag{1}$$

where $\mathbf{y}_t \in \mathbb{R}^n$ is a vector of *endogenous variables* at time step t and $\mathbf{x}_t \in \mathbb{R}^s$ is a vector of *exogenous variables*. $\mathbf{A} \in \mathbb{R}^{n\times n}$ and $\mathbf{B} \in \mathbb{R}^{n\times s}$ are coefficient matrices and $\varepsilon_t \in \mathbb{R}^n$ is the error term. Here $\mathbf{a}_0$ is a constant term which relates to the mean of the stochastic process.

The cointegrated vector autoregressive (CVAR) model which can alternatively be interpreted as a vector error correction model (VECM) is a extension to handle cointegrated variables. The model can be formulated as

$$\Delta\mathbf{y}_t = \mathbf{a}_0 + \mathbf{\Pi}\mathbf{y}_{t-1} + \sum_{i=1}^{k-1} \mathbf{A}_i \Delta\mathbf{y}_{t-i} + \sum_{j=1}^{m} \mathbf{B}_j \Delta\mathbf{x}_{t-j} + \varepsilon_t, \tag{2}$$

where $\Delta\mathbf{y}_t = \mathbf{y}_t - \mathbf{y}_{t-1}$ corresponds to the differentiated endogenous variables, $\mathbf{x}_t \in \mathbb{R}^s$ is a vector of exogenous variables, $\mathbf{A}_i$, $\mathbf{\Pi} \in \mathbb{R}^{n\times n}$ and $\mathbf{B}_j \in \mathbb{R}^{n\times s}$ define the system dynamics and $\varepsilon_t \in \mathbb{R}^n$ are the error terms (Pindyck and Rubinfeld, 1997).

The model building is automated in a sense that we use the *Johansen cointegration test* procedure for determining the cointegrated relationships between the endogenous variables. The cointegrated terms in the CVAR models are chosen by this test while composing the model structure.

Furthermore the lag order k of the models is determined by the *likelihood ratio test* of various model specifications by comparing the log-likelihood. The model that is assigned with the highest likelihood is automatically chosen.

Model validation is based on primarly diagnostic checking. The autocorrelation functions for both original data and in-sample estimated forecasts of data points. The residuals are analyzed by comparing them to the hypothesis that they should be both normally distributed and independent. We use the Lilliefors' composite goodness-of-fit test for testing against normality. The Ljung–Box Q-test, which is a Portmanteau test, is used for testing against residual autocorrelation.

As estimation tools we use the ready-made *Econometrics Toolbox* by LeSage and the *Matlab Econometrics Toolbox* (for details, see LeSage, 1999). All relevant tests and estimation can be done with the help of these two toolboxes in Matlab. All data is handled by Matlab and all tests were run with the aforementioned toolboxes or built-in Matlab tools. In this project MathWorks Matlab 2010a was primarily used.

3 Results

3.1 Statistical Analysis of Market Data

As presented in Section 2.1, we are using generic datasets for Nordic and German electricity prices, the electricity spot price, Finnish quarterly GDP estimates, and price of coal, crude oil and emission allowances. The time series are presented in Appendix A.

Before the financial crisis of 2008 all datasets behaved very similarly but after it the dynamics have differed from each other. In general the price is higher the further away time to maturity of a contract is. There should be a small shift in generic datasets when one contract ends and a new one begins in January but this characteristic is so small compared to other changes that it cannot be distinguished easily.

Figure 2 shows the cross-correlations between the different generic electricity prices with lags from minus ten to ten. All datasets have high correlation at zero lag. The maximum correlation lag value is -1 between NEL2Y and NEL4Y, -3 between NEL2Y and NEL5Y and -2 between NEL3Y and NEL5Y. The longer the difference in time to maturity, the farther away the correlation lag. One explanation to this is that the contracts with longer times to maturity are traded less frequently and their prices are less volatile. In other words, NEL5Y reacts more slowly to same phenomena than NEL2Y.

The same kind of behaviour can be seen in figures presenting the generic datasets for German electricity prices as well as in the non-generic datasets in Appendix A. We decided to use generic German forward prices in our model to depict the influence of imported electricity. Because we only have datasets for generic contracts for the first, second and third nearest contract, we use the second nearest in the model for the corresponding Nordic electricity price and the third nearest for the three other models.

Nordic electricity spot price is very volatile and does not include any kind of trend. The price level is higher during winters than summers because heating play a big part in electricity demand in Nordic countries. Big peaks in prices are usually encountered during extremely cold periods.

Coal prices exhibit same kind of dynamics as the electricity prices. Differences between contracts were small prior to the recession and there was a growing trend in prices in general. The drop in prices in the autumn 2008 was very deep and after that differences between contracts have been larger than before. Datasets for API2YR1 and API2YR4 are the longest and capture same price dynamics so we decided to use the price of API2YR1 for all our models.

We have two datasets for the crude oil price. The general features of CL1 and CL21 are quite similar but CL1 is more volatile. Because we are interested in long-term contracts, dataset CL21 is used in all our models. Both sets depict also the general trends in economy.

Emission allowance prices have not been traded for very long. Contracts with longer time to maturity tends be more expensive than ones with shorter time to maturity. Prices

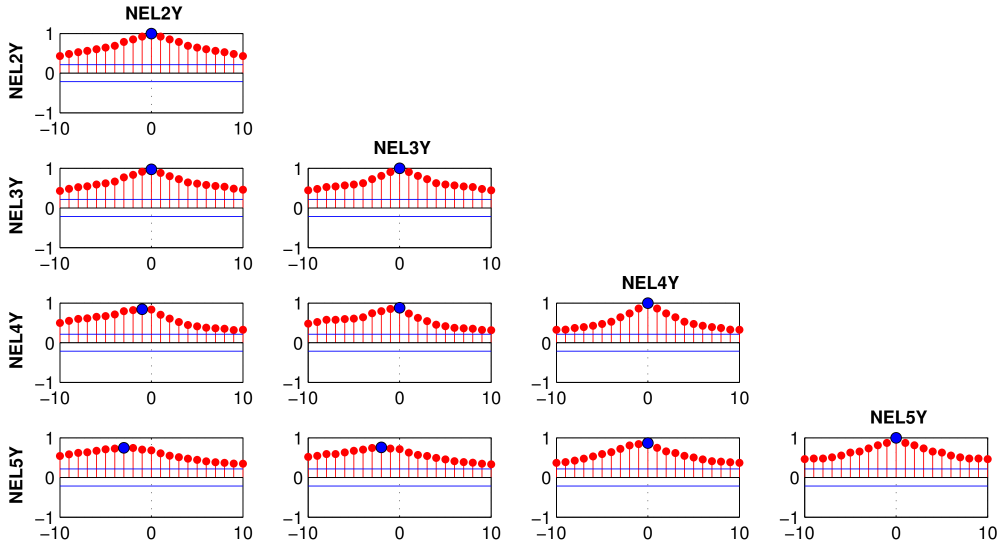

Figure 2: Cross-correlation between the electricity forward prices with lags $-10, \ldots, 0, \ldots, 10$. The figure is interpreted as a cross-correlation matrix; the correlation between the row data and the column data is shown in each plot. The maximum correlation value is emphasised.

were quite volatile prior to the financial crisis. Because the dataset for MOZ3 begins only as recently as 2008 and differences between MOZ1 and MOZ2 are not large, we decided to use MOZ1 in all our models.

We use the Finnish gross domestic product adjusted with a trend in our model. The dataset captures general features of economy including fast recovery from recession. Last data points were extrapolated linearly for early 2011. This is quite an optimistic forecast but consistent with most current estimates as of spring 2011.

Appendix B presents statistical plots for logarithmic datasets (*log-levels*) used in the model building. The trend is in a sense removed and the figures represent relative changes in price levels. From the histograms with normal fits can be seen that most of our datasets cannot be considered normally distributed. This was expected because datasets are time series reacting to various exogenous aspects of e.g. weather, changes in the economy and market. In some cases (e.g. NELF2Y, CL21 and MOZ1) there are two peaks in the histogram. This is probably consequence of the dynamic change due to the financial crisis. The data does not follow same distribution before and after mid-2008.

Most of the datasets are also non-stationary. As discussed, the dynamics of some datasets change quite dramatically after year 2008. These kinds of shocks or structural changes are not so uncommon and it would be sensible to assume that the statistical characteristics of time series would remain unchanged.

In studying the autocorrelations of the log-level and differentiated log-level datasets, we notice that the one week lag is quite high for all contracts but absolutely value of two and three week lags are much smaller. The dependence between consecutive values does not stretch over many lags. This means that if price has changed considerably during the couple of previous week it will presumably change a lot in this week also.

There is no quarterly or yearly correlation between observations as seen in the sample autocorrelation plots in Appendix B. Some yearly correlation could have been expected because change of the contract for generic datasets. To some extent this is caused by the aliasing effect of the week-level downsampling. In addition, some yearly correlation could have been assumed because the price seems to be higher during cold periods. On the other hand there are also other aspects creating higher prices for some periods that do not follow yearly fluctuation so clearly. For instance the amount of electricity produced with hydropower depends heavily on the weather.

The autocorrelation and partial autocorrelation plots of two and three year Nordic non-generic electricity prices are clearly different. This cannot be spotted in the plots of the generic contracts. The reason is that the datasets for 2014 and 2015 prices are quite short starting 2009 and 2010. This is why there has been no big shocks influencing the price dynamics.

All datasets have a high peak at lag one in the partial autocorrelation plot that determines the degree of the matching AR-part. This means that it should be one in each model. For the shortest time series (NELF4Y and NEF5Y) also some bigger lags show high peaks but these results are inaccurate because of the short time series.

3.2 Estimation of CVAR Models with Different Times to Maturity

We estimated four separate models corresponding to the different generic datasets of the electricity forward prices (NEL2Y, NEL3Y, NEL4Y, NEL5Y). We used seven endogenous candidate variables for each. These included generic German electricity forward contracts, coal price, crude oil price, emission allowance prices and linearly interpolated quarterly observations of the Finnish GDP. We also have a variable representing the sawtooth-like time to maturity cycles.

We used a multiply lagged CVAR model to model the weekly price levels. All variables were considered endogenous in CVAR sense, and the price levels were converted to *log-levels*. The estimation was done by using *brute-force* comparison of the different models. We estimated models corresponding to all combinations of our variables. This was no computational burden as it only meant estimating

$$\binom{7}{1} + \binom{7}{2} + \cdots + \binom{7}{7} = 127$$

different models. The number of available data points was restricted by the shortest available data series, but due to a clear change in dynamics prior to mid-2008 we

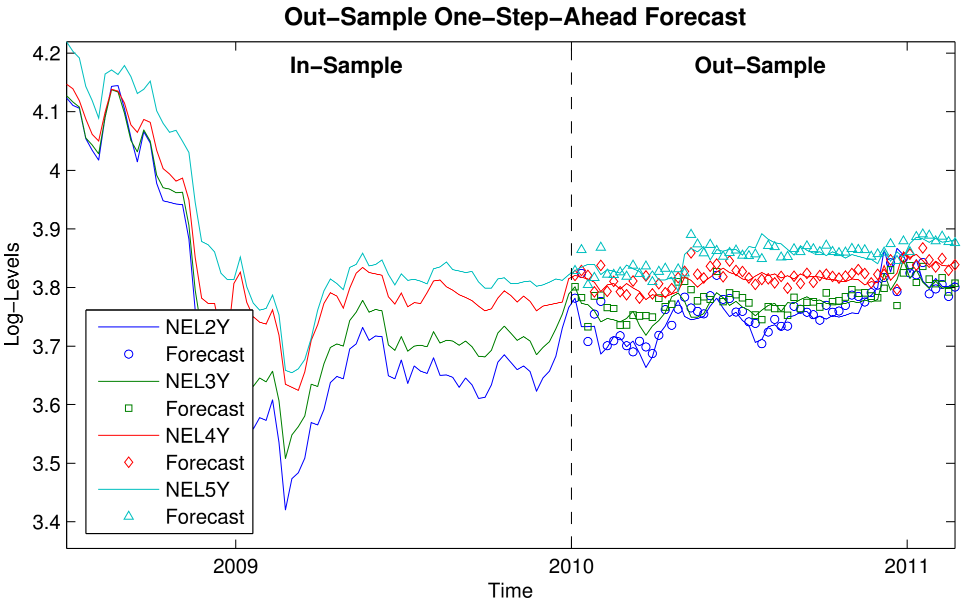

Figure 3: Out-sample one-step-ahead forecast for electricity forward prices. Only the electricity forward component is visualized. A number of 81–137 datapoints have been used to predict the closing price the following Wednesday.

also excluded some half a year of data before this point. The *Johansen test* was used for determining the optimal cointegration relationship, and the likelihood ratio test provided the optimal lag length.

After we estimated 127 different models for each four datasets, we used the adjusted R^2 and residual analysis for the model selection. The model combinations were ranked individually and then the intersection of sets corresponding to the best models were calculated. This resulted in proposing two different models that were performing equally well in estimating results for different times to maturity. Finally, inspecting the statistical properties of the coefficient matrices left us with one model.

The chosen model is a CVAR model of degree 7 and lag count 3. The models are far from well-behaved, and they can be described as the least bad choices. The lack of data forced us to do some compromisses in composing the datasets for each model. The final models were estimated using these four dataset combinations: the generic contaracts with time to maturity of two years (NEL2Y, ELGBYR2, ENWSSPAV, MOZ1, CL21, API2YR1, GDP), the generic contracts with three years to maturity (NEL3Y, ELGBYR3, ENWSSPAV, MOZ1, CL21, API2YR1, GDP), the generic contracts with four years to maturity (NEL4Y, ELGBYR3, ENWSSPAV, MOZ1, CL21, API2YR1, GDP), and the generic contracts with five years to maturity (NEL5Y, ELGBYR3, ENWSSPAV, MOZ1, CL21, API2YR1, GDP). Notably the time to maturity dummy variable was rejected.

The adjusted coefficient of determination R^2 (the non-adjusted R^2 in parentheses) for

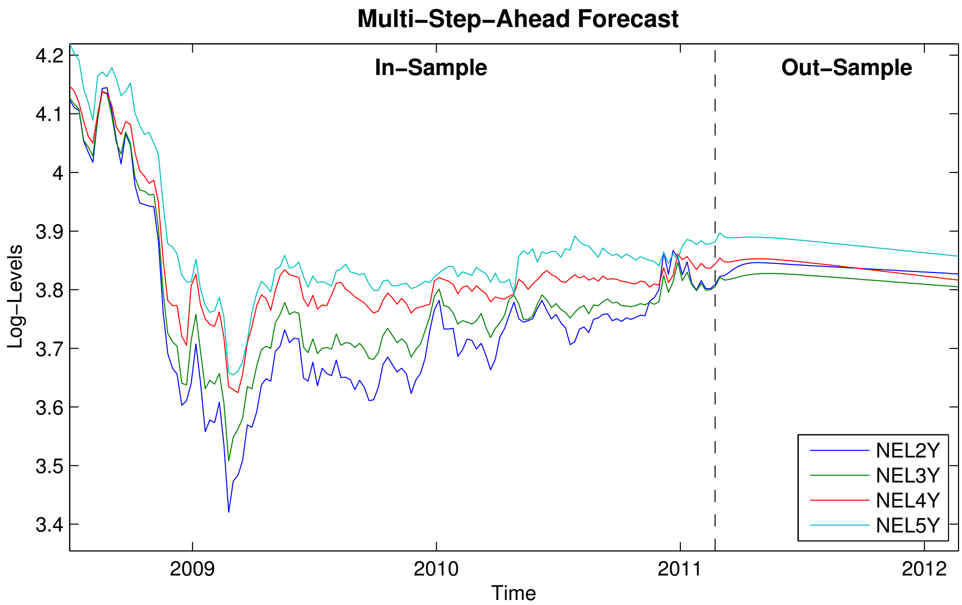

Figure 4: Out-sample multi-step-ahead forecast for electricity forward prices. Only the electricity forward component is visualized. Each curve corresponds to different generic contracts.

the electricity forward price were $R^2 = 0.36$ (0.48), 0.38 (0.49), 0.48 (0.58), and 0.37 (0.48). The residual normality tests (the Lilliefors' composite goodness-of-fit test) implies that normality cannot be rejected at a $5\,\%$ significance level for all except the GDP and CL series. The spot price also caused non-normal residuals for some models. The independence of the residuals was tested using the Ljung–Box Q-test for autocorrelation. For a tolerance level of 0.01 the null hypothesis of no autocorrelation can be accepted for all except the CL series. Residual cross-correlation was clear between the residuals of the Nordic and German time series and the German series and coal.

The error correction term consist in all models of three cointegrated factors. The Johansen test chose the generic forward price (NELxY), the generic German forward price (ELGBYR) and the GDP dataset to present the long-term dynamics in the model.

The models try to capture the dynamics of the different generic electricity forward contracts. The vector models simultaneously also model the dynamics of all the included endogenous variables. We however restrict our interest purely to the electricity price component.

We test the forecasting power of the models by using out-sample one-step-ahead forecasting. This means that we have used only data from the in-sample for estimating the model and then tried to forecast data points in the out-sample with the help of this model. In other words, we use available data up to the current week to predict the next week's Wednesday closing price of the electricity forward contract. Figure 3 shows one-step-ahead forecasts accomplished with models estimated with only the prior in-sample data. As can be seen in the figure, there are clear differences between the four generic datasets.

Forecasts regarding longer time-spans are problematic. We present a simple out-sample multi-step-ahead forecast for the electricity forward components in each model. Figure 4 shows a one-year forecast for each model. The short memory (three steps) and the cointegrated variables of the model turns the forecast into a linear trend. Nevertheless, the different long-term equilibria of the different generic contracts differ quite a bit.

4 Discussion

4.1 Interpreting the Modelling

In this study we estimated a 7-dimensional CVAR model structure that was tested by fitting the parameters to match generic electricity forward contracts with different times to maturity — in this case 2–5 years. The outcome was that this resulted in unreliable models, but still, the models were able to capture some useful information about the forward price process. In the models, the value of the adjusted coefficient of determination R^2 spanned from 38 % to 48 % (unadjusted 50–60 %).

The Johansen test chose three cointegrated variables to account for the long-term dynamics of the model. These were the generic forward price, the neighbouring market price and the interpolated quarterly gross domestic product.

Model validation proved that the models suffered primarily from the lack of information. The datasets incorporated strong cross-correlation, which resulted in non-significant parameter estimates and gap between the adjusted and unadjusted coefficient of determination R^2.

We chose to include the gross domestic product (GDP) in the model as a low-resolution common knowledge factor of the current state of the economy. The quarterly anounced GDP captures factors that the other datasets clearly fail to cover. In forecasting however, the model is depending on capturing the dynamics of the GDP estimate as well which is troublesome. In practice including more variables presenting low-resolution factors can make the model prone to mistakes by putting weight on subjective factors.

We also presented both a one-step-ahead and a multi-step-ahead forecast for one year. These were visualized in Figures 3 and 4. The out-sample one-step-ahead forecast performed acceptably in estimating the general direction of the market over a one-week time-span. The short memory of our models with only three lags had difficulties in adopting dynamics over longer time-spans. The multi-step-ahead forecast present the model's view of the general direction of the electricity forward market price.

During the estimation we noticed that there is a clear change in dynamics starting summer 2008. This change is most probably due to the financial crisis and changes in market conditions caused by it. This is why special care should be taken when using data prior to this point for forecasting future prices. The forecasts in Figure 4 are based on data after July 2008. The forecasts resemble linear extrapolation of the data, but notably the forecast remains very much the same even if only data from January 2009 onward is used.

One interesting factor is how these results could be generalized to even longer forward contracts. We note that even if the models fail to capture many aspects of the market, the hypothesis, that the drivers of the market could be brought into a common formulation, cannot be rejected. The performance of the models is similar for each time-to-maturity.

The CVAR family of models is useful in modelling and forecasting many kinds of econometric conditions, preferably over short time-spans. However, care must be taken when using this type of structural models for building models over long time periods. Most notably, if there is no permanent price process to model or the market is undergoing constant changes CVAR estimates probably result in unreliable forecasts.

4.2 Long-Term Versus Short-Term Dynamics in Electricity Contracts

The electricity market forecasting is a trade-off between identifying short and long drivers in the dynamics. In the Nordic electricity exchange Nord Pool, electricity is traded on the day-ahead spot market and derivatives market. We have restricted our interest to the very short and very long-term dynamics regarding spot and forward prices, leaving out the future contracts with time-to-maturity under one year.

Empirical research has shown that commodity prices have higher volatility in short-term forward prices and lower volatility of long-term forward prices (Bessembinder and Lemmon, 2002). Furthermore, short-term forward prices can be more sensitive than long-term forward prices. This will be discussed in more detail in Section 4.4, *Stability of Risk Premium*, since the time-to-maturity also affects the adjustment to risk.

In this study we have been able to confirm that the time to maturity affects the behaviour of the forward price. The nearer the maturity, the more actual information is linked to the forward price. This results in the forward price following the tightly the spot market price as the delivery starts draws nearer. In Section 3.1, *Statistical Analysis of Market Data*, we were able to identify that the 2-years-ahead and 3-years-ahead forward price follow the spot price dynamics within the same week, whereas the 4-years-ahead forward price and 5-years-ahead forward price adopt slower with about one and four weeks of lagging.

We can speculate that the short-term and mid-term contracts are mainly used for hedging uncertain future consumption and electricity price spikes. On the other hand we can assume that the very long contracts are often used for hedging long-term production of producers. This affects both the risk premium and the market dynamics, which might explain the deviant behaviour of the 4- and 5-years-ahead forward contracts.

As stated in many studies before, we agree that the models designed for capturing short-term dynamics cannot be generalized in the case of electricity to cover the dynamics in the longer end of the curve.

4.3 Seasonal Factors

In all non-generic electricity prices (NELFxY and ENWSSPAV) the couple of first lags are significant in the autocorrelation plots of differentiated datasets. As discussed in Section 3.1 this means that the volatility of the electricity price depends on the volatility over the previous weeks. For example, if the spot price of the electricity has increased quickly it is likely that it will drop in the following week (the correlation at lag one is negative). This means that there is no clear trend in the behaviour of the spot price. On the other hand in the case of NELF2Y the first lag is positive which means that the price has a tendency to continue in the same direction, but this phenomenon is not as clear as in the case of the spot price.

Electricity spot price is very volatile and reacts strongly on changes in the weather. In general price is higher during winter than during summer and peak loads happen during the coldest periods. It can be observed that the electricity spot price increases in the beginning and the end of the years (except for the years 2004–2006) that is during winter time in — this can be confirmed in Appendix A.

However, in Appendix B the lags around 52 weeks in the autocorrelation plot of neither the differentiated nor non-differentiated dataset are distinctive. The cold periods are not each year matching the same weeks and there are also other factors creating fluctuation. Each explaining variable might have its own seasonal pattern and therefore the electricity prices follow a trajectory for which is difficult to define the existence and the pattern of seasonality.

There is no clear seasonality in the non-generic electricity forward prices either. In the autocorrelation plots the lags around 52 weeks are not unusually high and do not indicate a yearly seasonal factor. The current weather should not have influence on the forward price because the contract is done for whole year in future. Nevertheless we assumed that the price of forward contract is higher in the end of year despite how long time it is until the maturity of the contract.

In autocorrelation plots of NELF2Y and NELF3Y there are some significant lags around 26 weeks that equals half a year. In addition, lags around one year are very distinctive in the partial autocorrelation plots of NELF4Y and NELF5Y. This gives reason to expect that some kind of seasonal pattern exists.

4.4 Stability of Risk Premium

Because there is a risk of losses related to financial contracts their expected profit must exceed one of the risk-free assets. The difference in expected returns, or the price of the risk, is called as a risk premium. Usually the price of a forward contract can be estimated based on the spot prices and then the contracts can be compared with risk-free assets to calculate risk premium when arbitrage condition holds (see, *e.g.*, Luenberger, 1998).

However, in the case of electricity the normal approach is not possible because it is not economically efficient to store electricity. Povh and Fleten (2009) argued that the risk premium is influenced mainly on time to maturity. In their empirical study Diko *et al.* (2006) found that the risk premium of a contract decreases as the time to maturity increases. In their model the risk premium of the forward contract is determined by the skewness and variability of the spot price.

There are also some other factors that may have an influence on the spot prices. The effect of the price spikes due to seasonality and price level decreases when considering

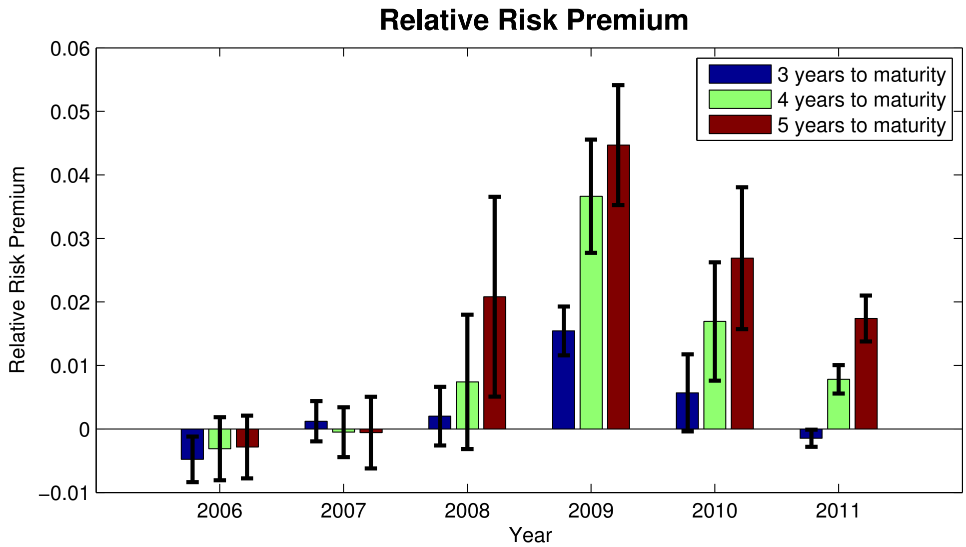

Figure 5: The evolution of the risk premium for three different times to maturity. The premium is illustrated as the relative difference to the 2-years-to-maturity contract. The error bars show the standard deviation of the estimates.

forward contracts with long maturities. As we assumed in our approach, the effect of possible speculators is probably negligible because electricity markets are not very tied with other asset markets (Bessembinder and Lemmon, 2002).

Analysis of market data suggests that the risk premium is clearly affected by time to maturity. In our study we were able to find alternating behaviour in the risk premium over the past six years. Figure 5 shows the relative risk premium obtained by assuming that the nearest available generic contract incorporate our best knowledge of the true price process of the electricity forward price (see Section 4.2). Our interpretation of the bar plot suggests that negative risk premium values can be explained by two-way hedging.

The contracts are used for hedging both uncertain future consumption and electricity price spikes, and on the other hand, production of producers. The one of these being more dominant decides the positivity or negativity of the premium.

4.5 The Impact of the Evolving CO_2 Market

To reduce CO_2 emissions the European Union has implemented a trading scheme (EU-ETS, The European Union Emissions Trading System) where emission allowances can be bought. This market is young; its first pilot phase ran from 2005 to 2007. The reduction targets are stricter in phase two which runs till 2012 (Fell, 2010). The new trading system phase starts 2013 with a tighter emission cap and stricter rules. As this market evolves its influence on electricity prices will presumable rise.

In general the determinant elements of electricity prices are more expensive and easily adjustable coal and oil prices instead of hydropower despite its large share. As we discussed both the coal and crude oil prices have high correlation with electricity forward prices. Fell has found that coal and natural gas prices influence electricity prices. In addition, Fell discusses that the causality goes also in a reverse direction.

The trading of emission allowances will thus affect a marginal price of electricity and decrease its demand. Fell (2010) argued that because of the elasticity of electricity prices the burden due to allowances goes primarily to the consumers. This is especially interesting in Finland, Denmark and Sweden where nonrenewable sources of energy are used extensively compared with Norway (Nordic Energy Regulator, 2010). The structure of Nordic market is somewhat different from other markets; not only the dominant position of the hydropower, but also well-functioning energy markets are likely to soften the impact of emission allowances.

The time series of the emission allowance prices are presented in Appendix A. The prices of 'MOZx' are volatile before the structural change in mid-2008. After that the price has fluctuated inside of only five level units. This dramatic change can be seen also from histogram as discussed in the Section 3.1, *Statistical Analysis of Market Data*. It is ambiguous which part is due to the change of the trading scheme and which because of a deep drop in macro economy due to the financial crisis.

4.6 Practical Questions Regarding the Long-Term Perspective

Our approach concentrates mainly on the analytical modelling of the electricity market. However, there might be some major structural changes in the future which will influence the demand and supply of electricity so that models based on historical data will be invalid. Any major changes in the technology or economic can considerably change price dynamics as can be seen in the figures of the electricity forward contracts in Appendix A; the price dynamics of the forward contracts are different before and after price peak due to financial crises of 2008.

The total demand of electricity in the whole world is predicted to grow. U.S. Energy Information Administration (EIA) (2010) forecasts that electricity consumption grows by half from 2007 to 2035 (reference case without prospective legislation or policy changes). Most of this growth comes from developing countries; the increase in OECD counties is only about 14 percent. In the Nordic markets this means that the challenge of the future is not to expand the supply side considerably but shift production to renewable energy sources. If storing or transferring is more economically efficient in future this would link the Nordic market to the global change.

One of the fundamental phenomena is the growing concern about climate change and its consequences. A good example of this is the trading of CO_2 emissions as discussed in Section 4.5, *The Impact of the Evolving CO_2 Market*. This motivates the use of renewable energy sources but also affects consumers and policy makers' opinions. Even though it is impossible to make accurate forecast of future events spanning decades, electricity policy must be considered with long time periods. The most of the near investments to nuclear power and power plants will still be in use in 2050. Also many long-term public and private investments (e.g. traffic and construction) can be done energy efficient way. Some of the new technologies (e.g. electric cars) will eventually increase demand of the electricity because their purpose is to decrease dependency from oil (Finnish Energy Industries, 2009). In addition it is expected that the price of the oil will grow as the amount of untapped oil decreases. If international agreements are not made to prevent use of coal, its use will stay relatively high — most of all in fast growing Asian countries (U.S. Energy Information Administration (EIA), 2010).

The international pressure to reduce CO_2 emissions makes renewable energy sources and nuclear power more and more interesting in the future. In the Nordic countries, as in most developed countries, hydroelectric resources are exploited comprehensively (U.S. Energy Information Administration (EIA), 2010). Thus the more extensive use of nuclear power was considered as a part of the solution, but recent events in Japan may change this trend.

The special characteristics of the Nordic electricity consumption are electricity insensitive industry and need for heating due to cold winters. Approximately 45 percent of electricity is consumed by industry (Finnish Energy Industries, 2009) which is also an important player in the electricity market. As discussed, electricity derivatives are not used in a speculative manner in general, but actually to hedge against volatile spot price. The demand of electricity and activity of the derivatives market will depend on whether the amount of electricity intensive industry decreases or increases in the forthcoming ten years.

Most of the electricity in the Nord Pool area is produced with hydropower but it is not the dominant element in the formation of the electricity prices. It is possible that the price of the electricity will fluctuate more than it has previously done as the competition in the electricity market increases (Fortum, 2007). Especially interesting is the market of long-term forward contracts which can make prices more volatile in the future. Most of imported electricity to Finland comes from Russia. The electricity derivatives market is only just developing there but will probably increase competitiveness of the market in the long run.

5 Conclusions

In this project we have been able to identify and confirm two kinds of problems regarding modelling of long-term electricity prices. Firstly, there are several complications regarding structural model building of the electricity market. Secondly, there are interesting phenomena regarding the behaviour of electricity forward contract data. The aspects of these findings can be summarized as follows:

We suggest there is a structural break happening around summer 2008. This is no wonder due to the financial crisis and the evolving market of both long-term electricity contracts and behaviour of the market. This restricts the use of data prior to this point in estimating parameters for structural models. Notably models in (Povh and Fleten, 2009; Povh, 2009) were estimated on data and assumptions prior to the suggested break.

This also restricts the use of structural models in approximate dynamical modelling of the phenomena behind the market behaviour regarding the electricity forward price. We also suggest the CVAR family of models might fail to capture essential points of the problem: Most notably, if there is no one actual permanent price process to model. Therefore online methods taking into account the changing of the background process, should probably be considered. To be considered in future approaches are hidden Markov model and other incarnations of Bayesian network models (e.g. Bayesian VAR or more sophisticated online methods). Bayesian methods could also be used to incorporate the known uncertainties in the data and future market conditions.

In addition to the restrictions caused by the model structure, a never-ending problem will be the lack of market data in the field. Trustworthy forecasts in the long-term horizon will lack the ability of predicting major changes in market conditions — such as new innovations, political factors and changes in the environment.

As has been suggested in studies before, we also bring forward the thought that there are differences in the long- and short-term contract dynamics. Our data analysis also suggests this. Most interestingly, the cross-correlation of the future prices show a clear lagged correlation pattern structure between the contracts with different times to maturity. This pattern reveals that the longer the time to maturity the slower the adoption to the current market changes. This correlation lag is 1 week for the four year to maturity generic contract and 4 weeks for the five year to maturity generic contract.

There are also clear signs that the contracts with very long time to maturity incorporate quite different dynamics compared to their shorter term counterparts. This phenomenon is suggested to rely on two factors, which are the different clientèle and the low liquidity.

Seasonal factors do not seem to play any evident role in the electricity forward contract prices. We conclude that there probably is some sort of seasonal influence, but it is hidden behind stronger influence from other factors.

To draw conclusions about the very long-term behaviour of electricity forward prices, qualitative methods have to be used instead of relaying on quantitative tools.

We were also able to identify some aspects regarding the risk premium. It appears that the risk premium is not stable over the forward curve. Furthermore we conclude that in the case of electricity two-way hedging can be seen in the risk premium. This seem to change over time and reflect the attitude of both the producers and consumers.

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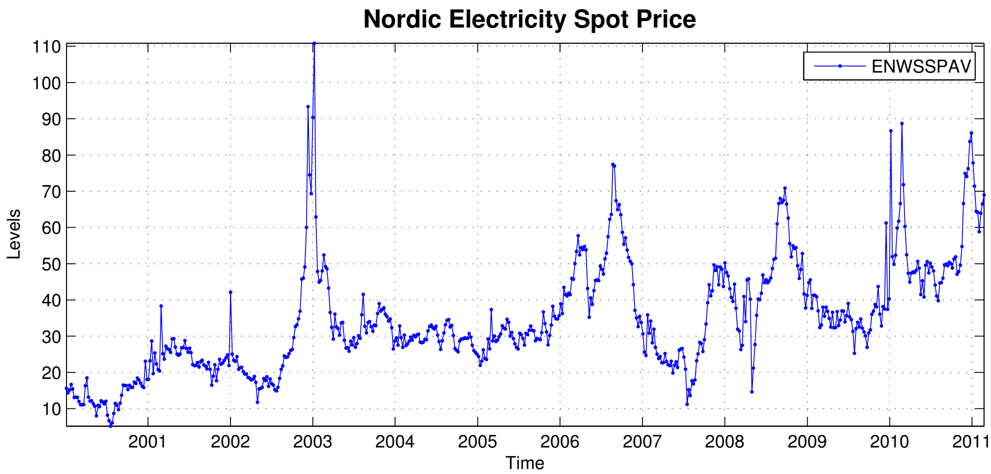
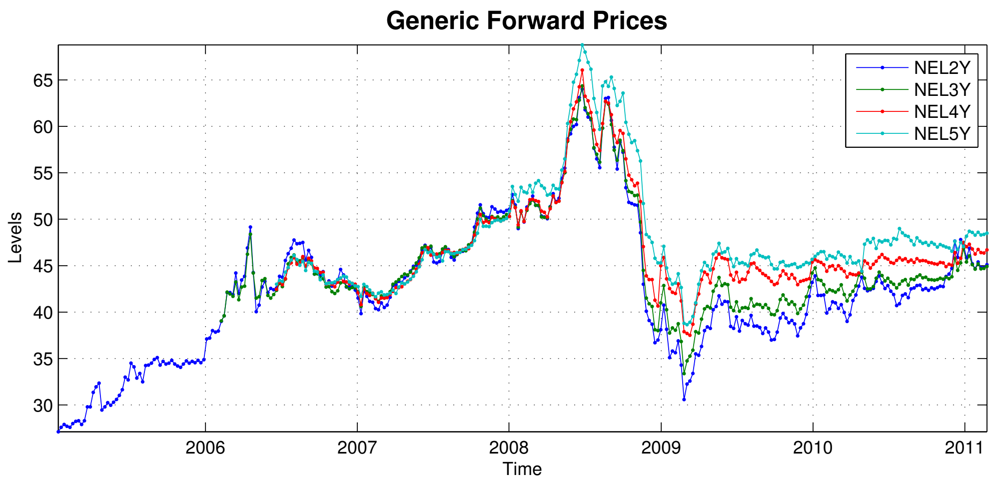
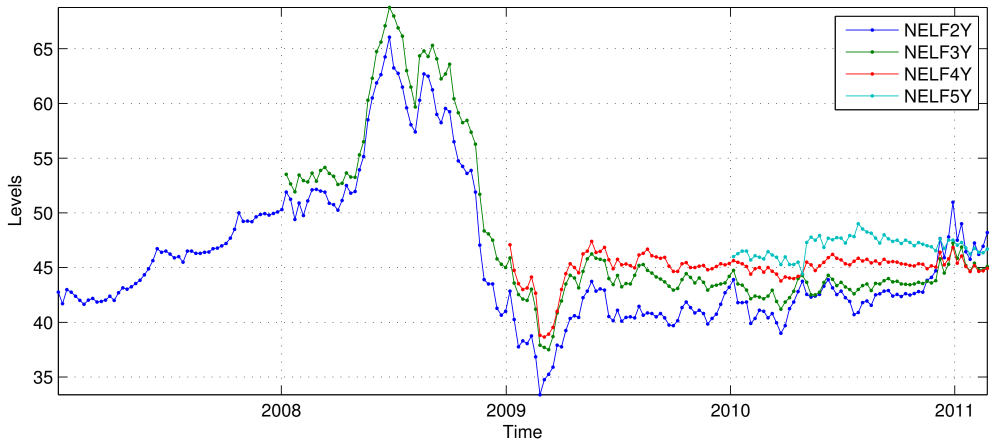
Appendix A:
Market Data

The datasets that were studied in this project are shown in the following time series plots. Similar products are grouped under same labels and shown atop of each other in same graphs. The x-axis values are downsampled to week level using nearest neighbour interpolation, and the length of the series vary from ten years to thirteen months. The y-axis show the unaltered price level. The value is visualized with a dot — the lines connecting the dots are linearly interpolated for visualization purposes.

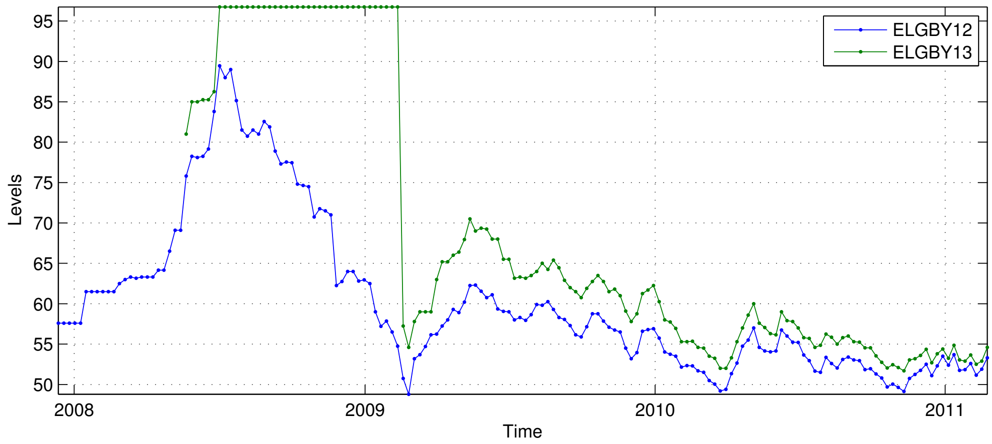




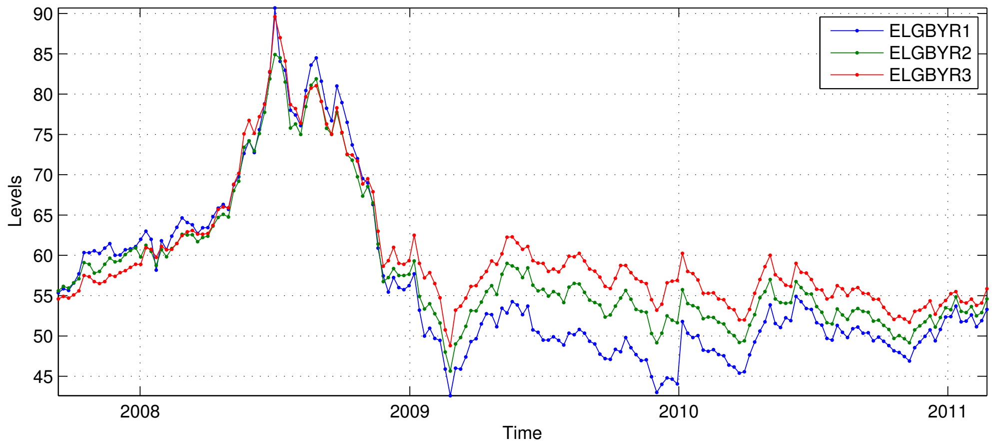
Forward Prices

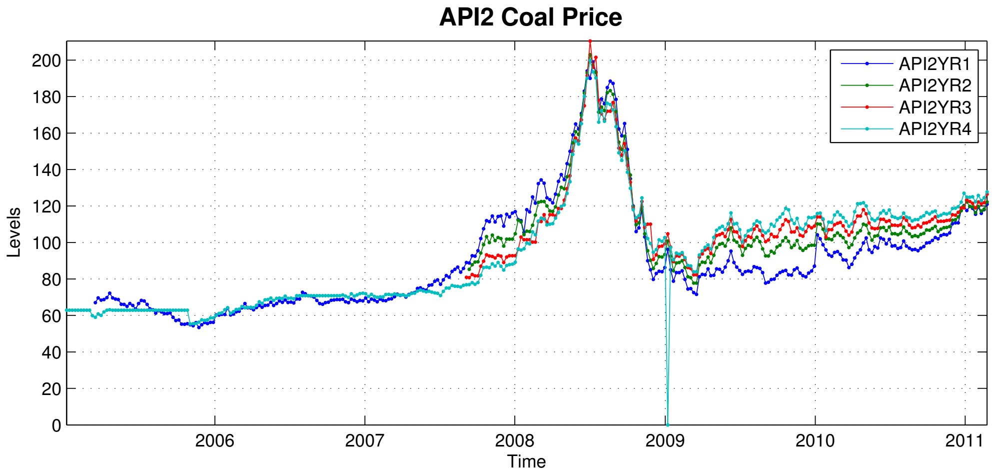


Yearly German Forward Prices



Generic German Contracts





API2 Coal Price
Levels
Time
API2YR1
API2YR2
API2YR3
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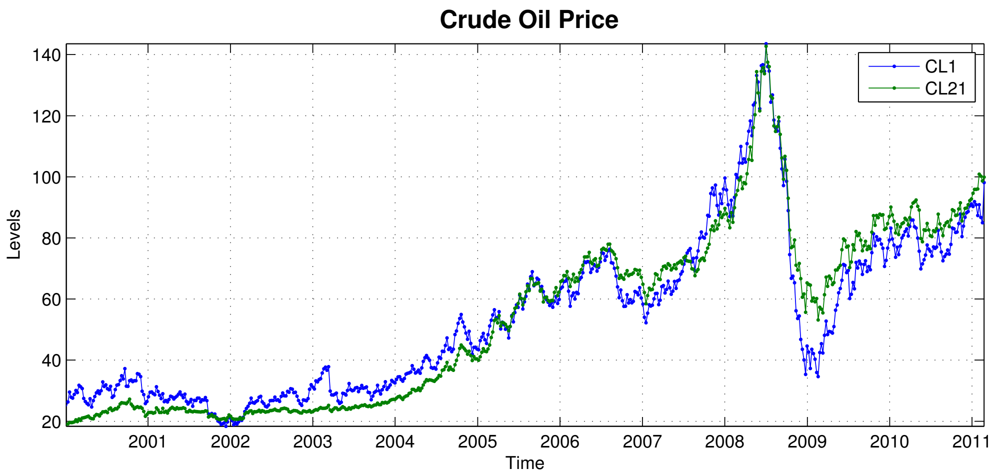
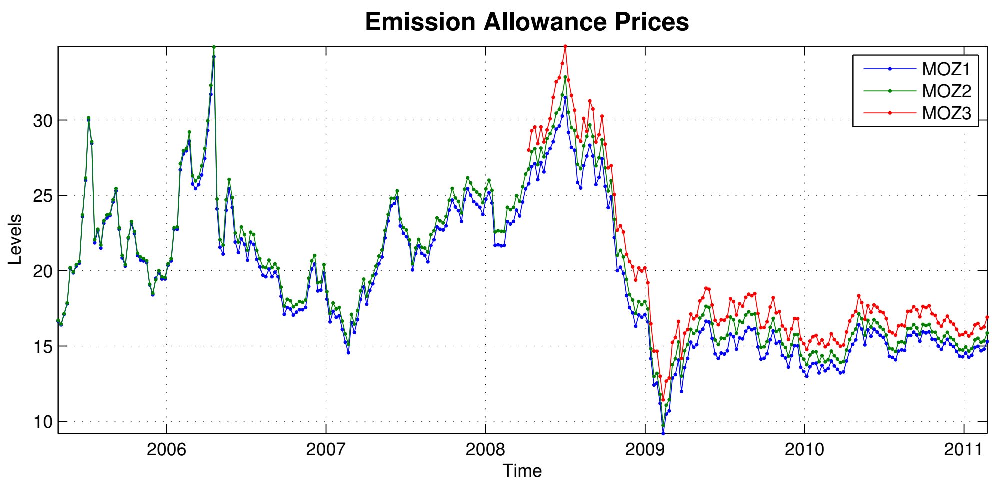
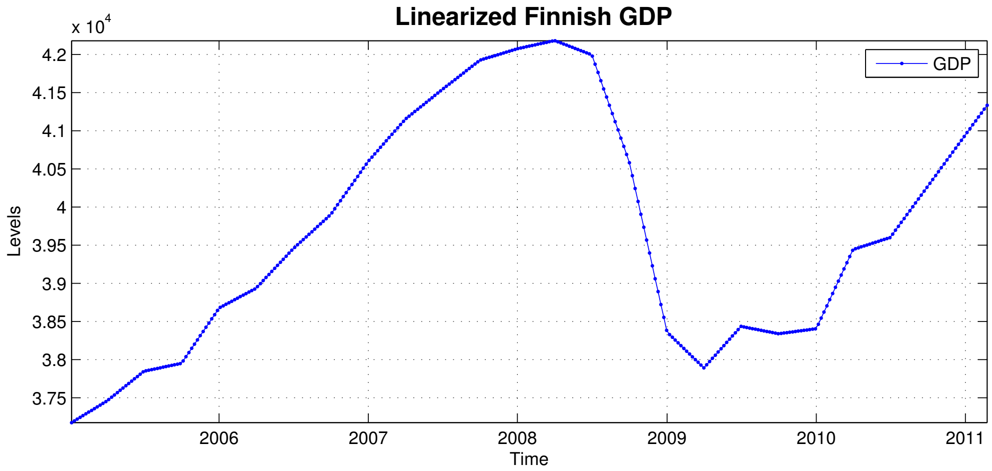
0
20
40
60
80
100
120
140
160
180
200
2006
2007
2008
2009
2010
2011



Crude Oil Price
Levels
Time
CL1
CL21
20
40
60
80
100
120
140
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011



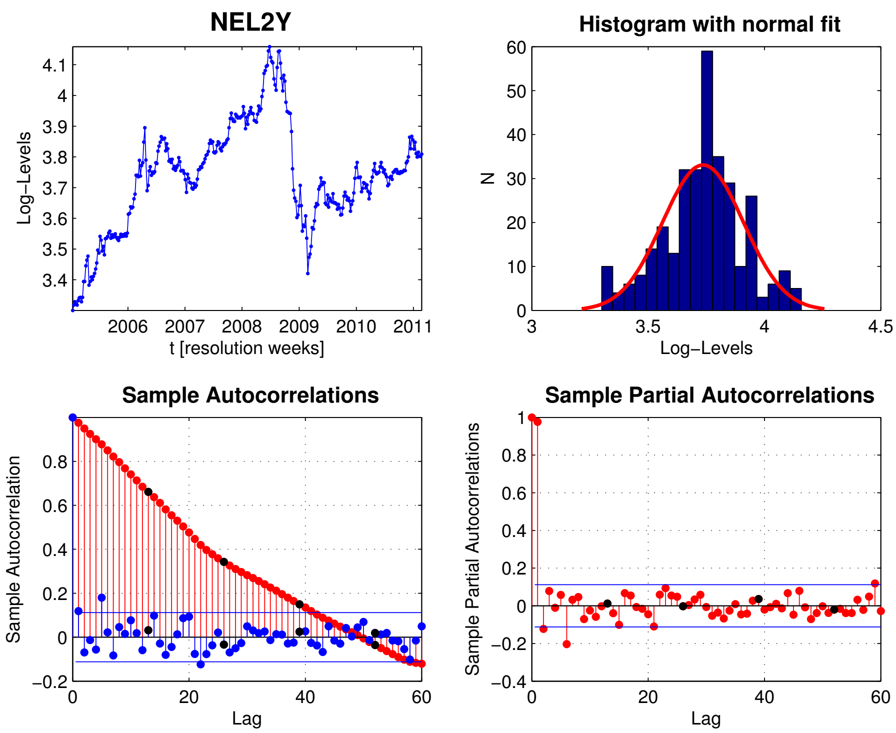
Emission Allowance Prices
Levels
Time
MOZ1
MOZ2
MOZ3
10
15
20
25
30
2006
2007
2008
2009
2010
2011

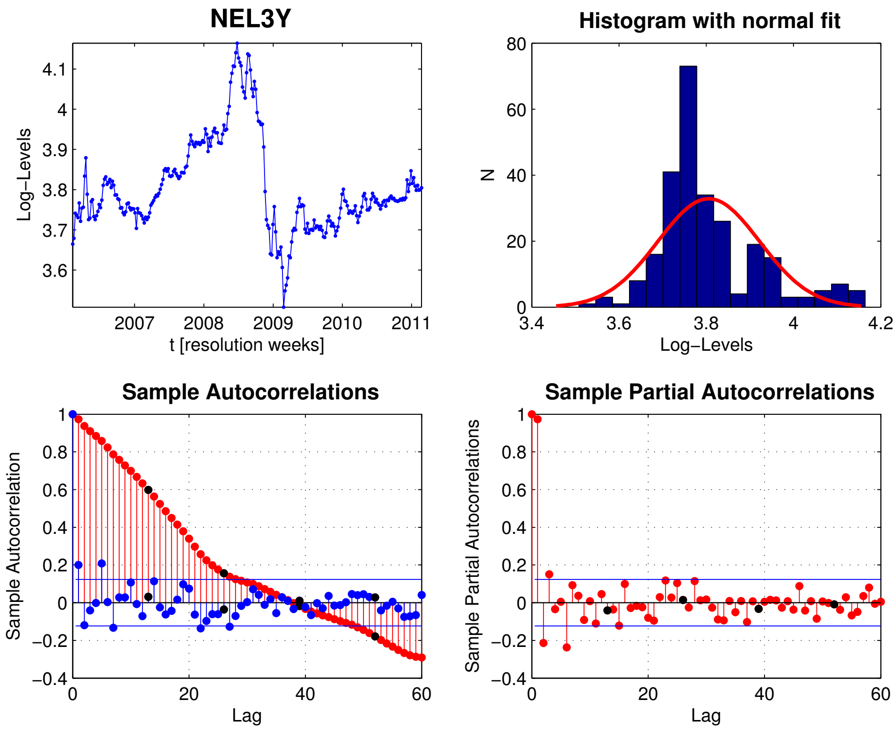

Linearized Finnish GDP
x 10^4
4.2
4.15
4.1
4.05
4
3.95
3.9
3.85
3.8
3.75
Levels
2006
2007
2008
2009
2010
2011
Time
GDP

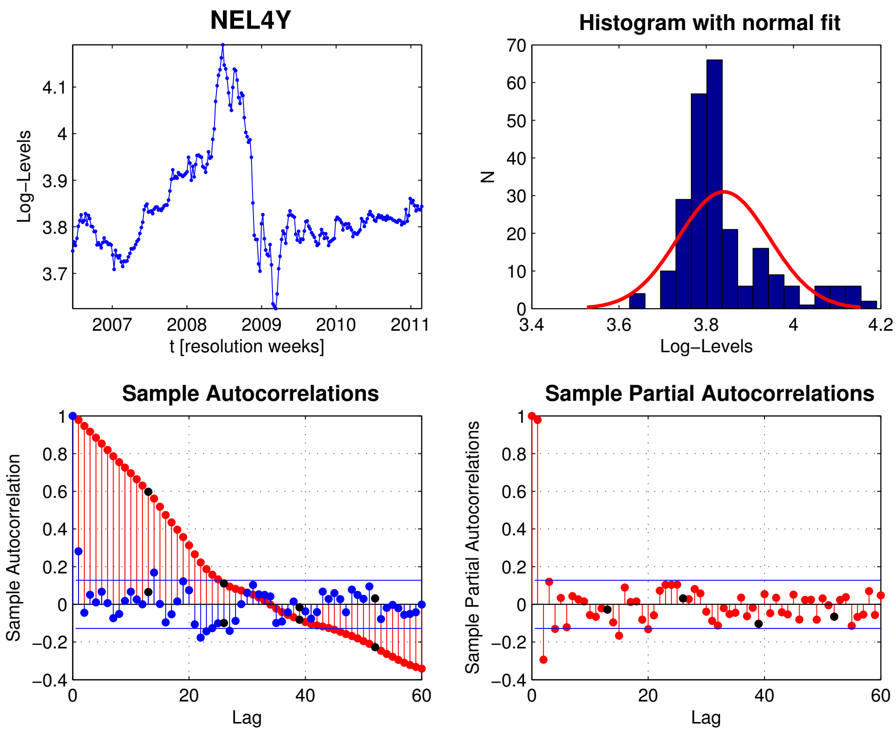
Appendix B:
Figures for Statistical Analysis

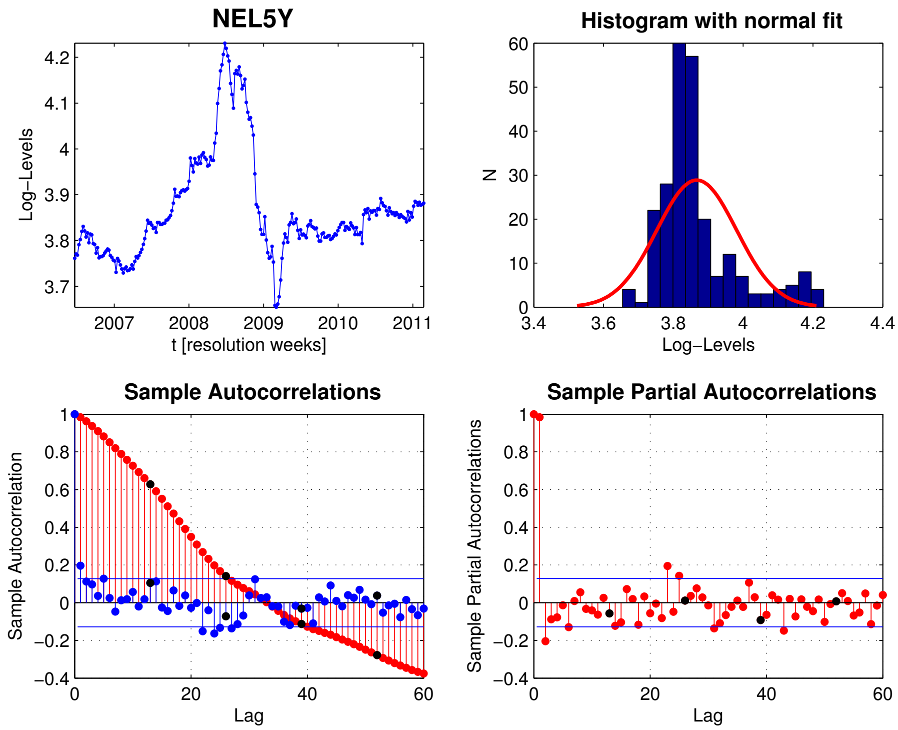
The following figures show some statistical plots for each dataset. The upper left figure shows the data sample values in logarithmic levels. The same data is interpreted as a histogram in the upper right figure together with a fitted Gaussian normal curve for comparison.

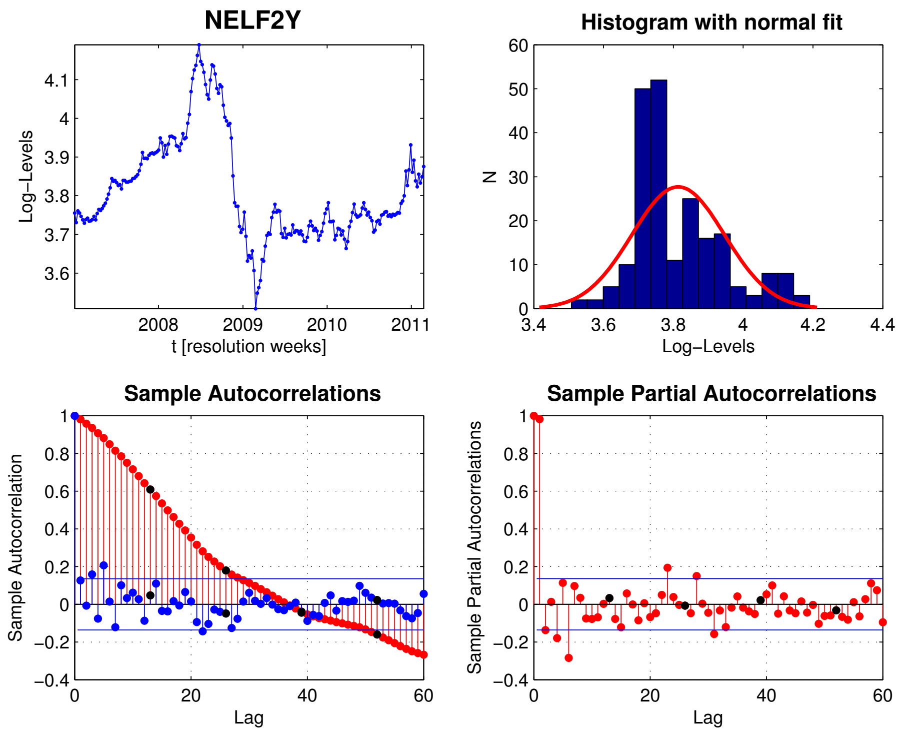
The two lower figures show the sample autocorrelation and partial autocorrelation functions. The autocorrelation function on the left side is shown in red for the actual log-levels and in blue for the differentiated log-level data. This is handy especially in the cases where the autocorrelation plot shows no stationarity for the non-differentiated values. The quarterly lags are highlighted in black dots.

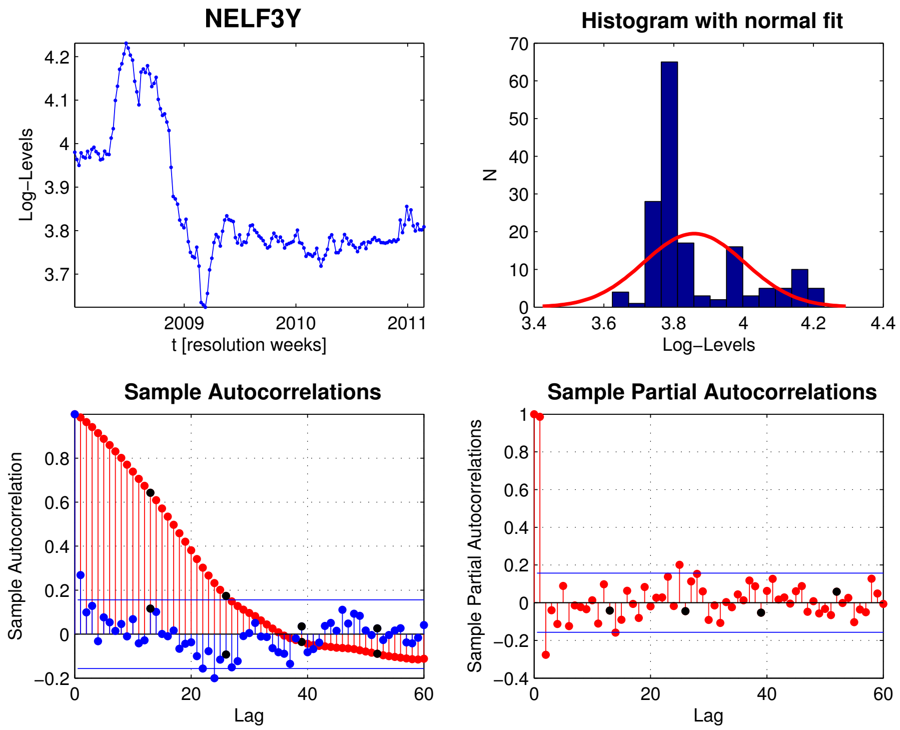


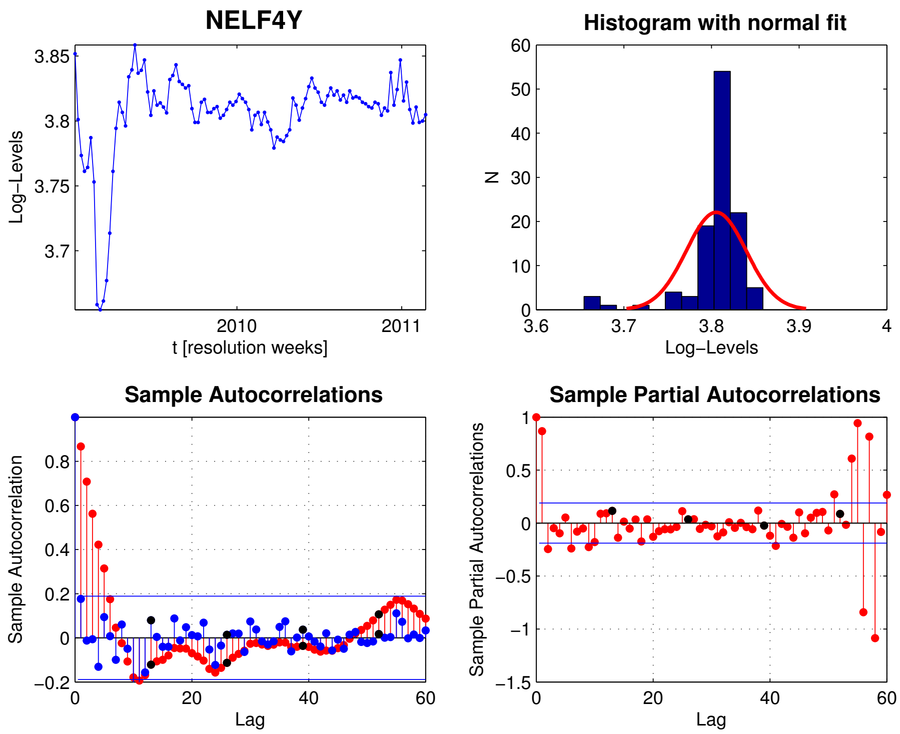

NEL3Y
Log−Levels
t [resolution weeks]
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag

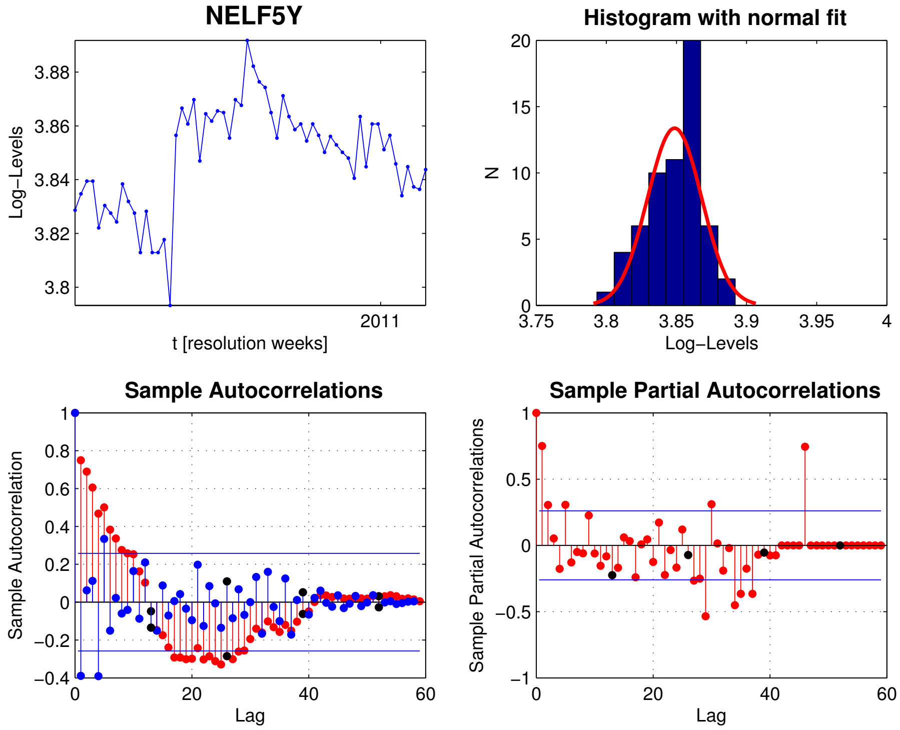

NEL4Y
Log−Levels
t [resolution weeks]
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag

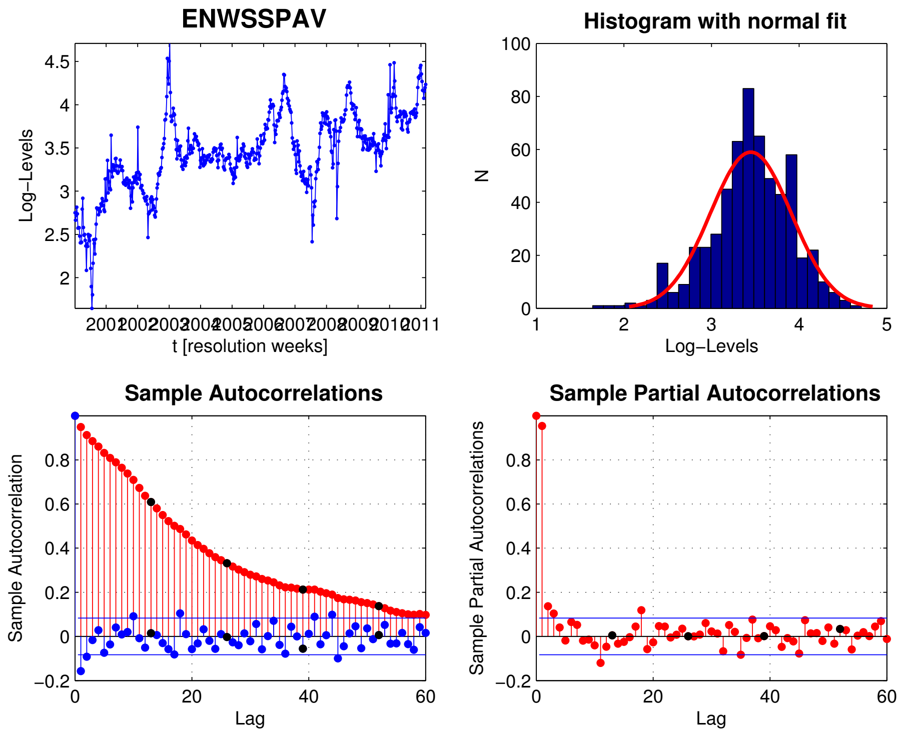

NEL5Y
Log−Levels
t [resolution weeks]
2007
2008
2009
2010
2011
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag

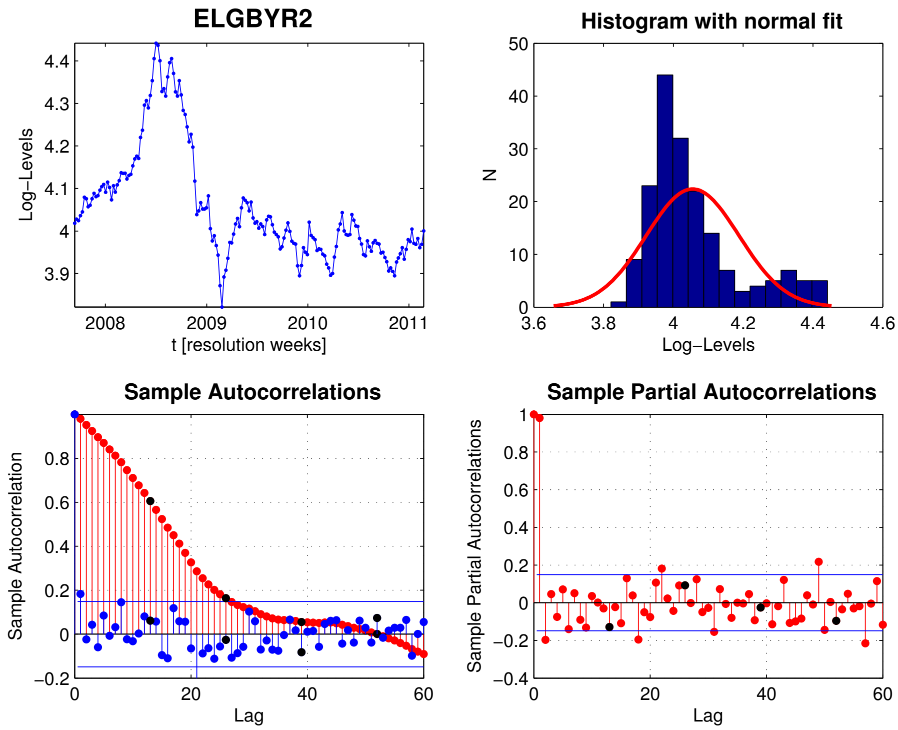

NELF2Y
Log−Levels
t [resolution weeks]
2008
2009
2010
2011
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag

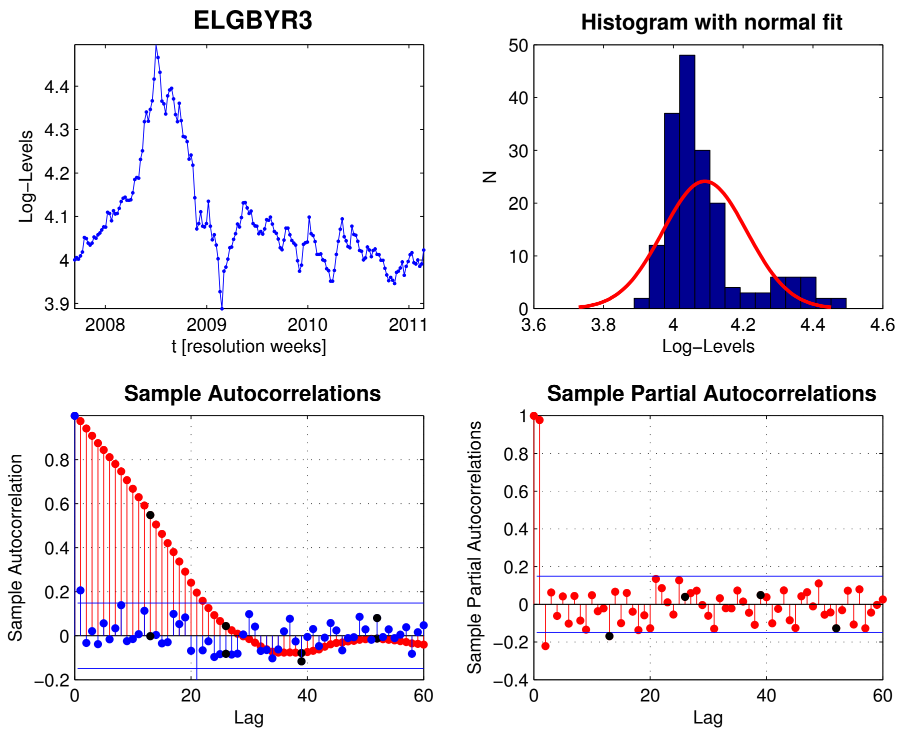

NELF3Y
Log−Levels
t [resolution weeks]
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag

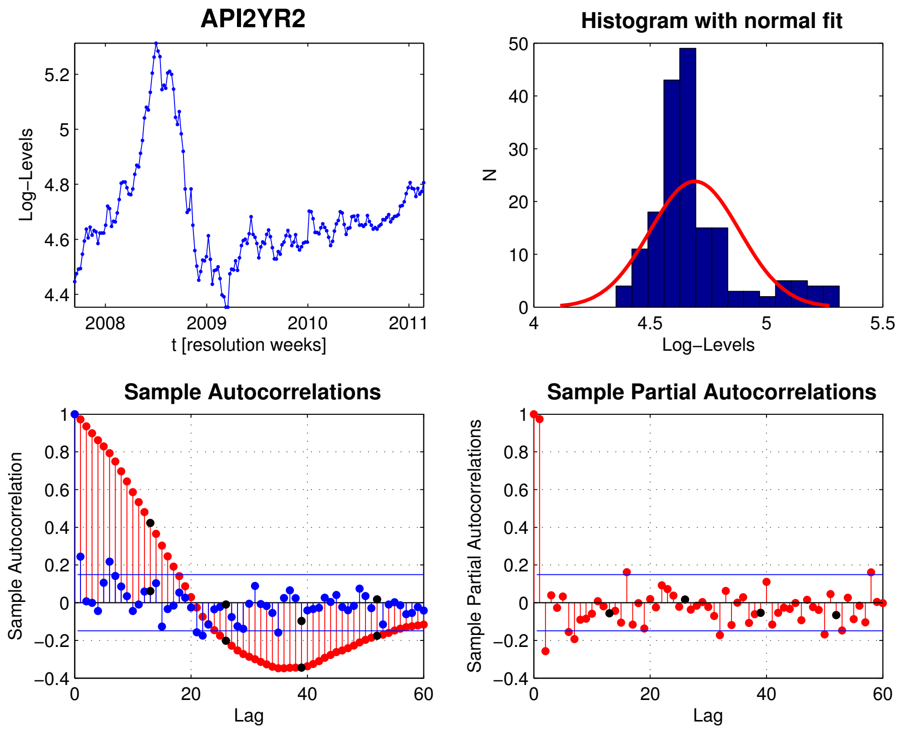

NELF4Y
Log−Levels
t [resolution weeks]
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag

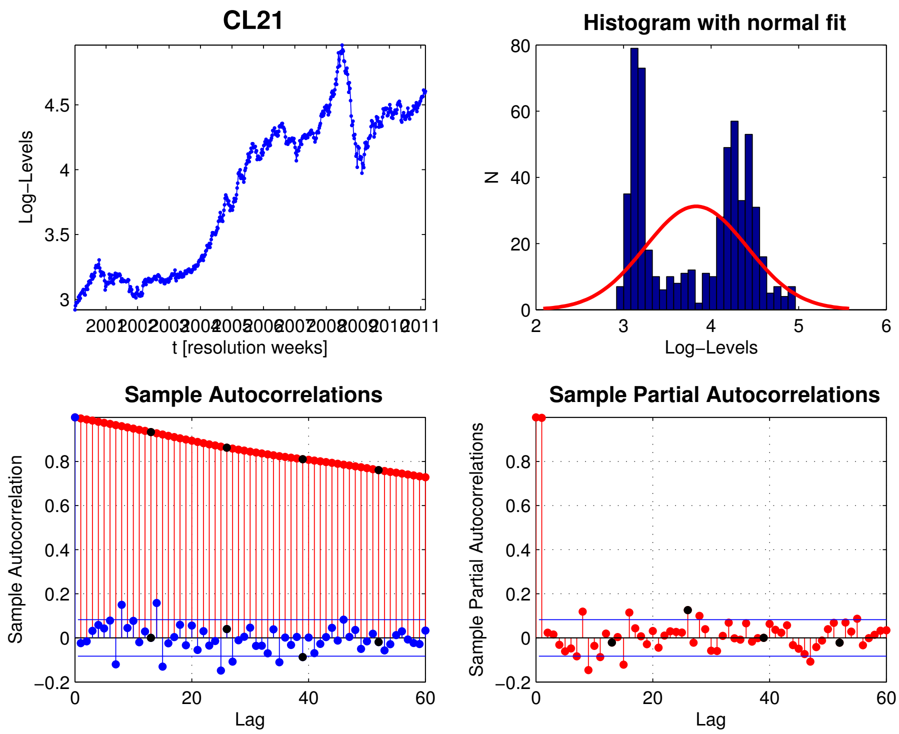

NELF5Y
Log−Levels
t [resolution weeks]
2011
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag

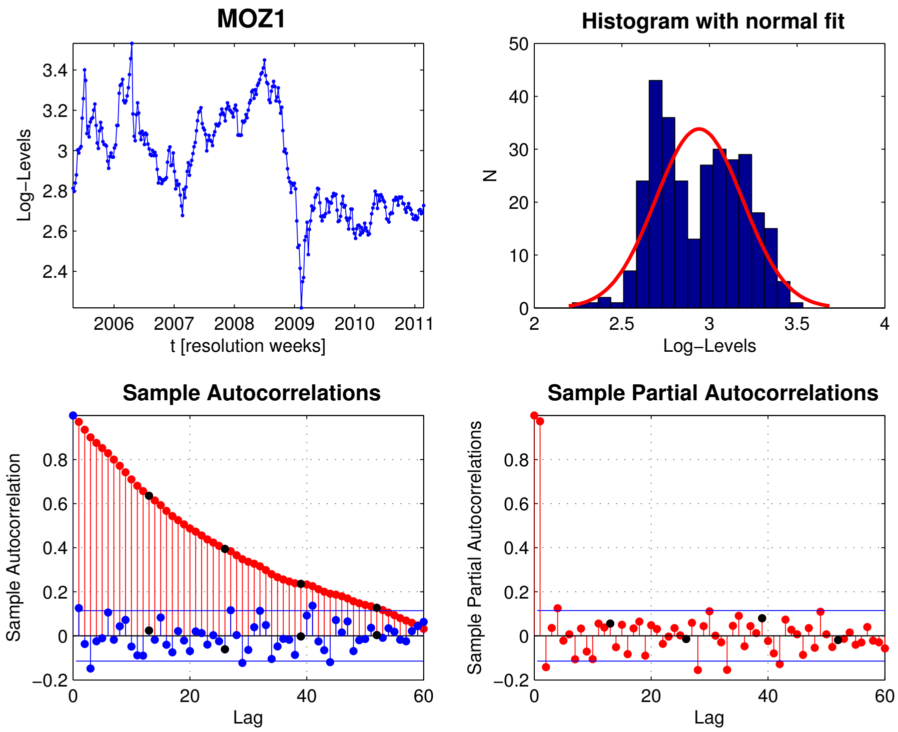

ENWSSPAV
Log−Levels
t [resolution weeks]
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag


ELGBYR2
Log−Levels
t [resolution weeks]
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag


ELGBYR3
Log−Levels
t [resolution weeks]
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag


API2YR2
Log−Levels
t [resolution weeks]
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag


CL21
Log−Levels
t [resolution weeks]
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag


MOZ1
Log−Levels
t [resolution weeks]
Histogram with normal fit
N
Log−Levels
Sample Autocorrelations
Sample Autocorrelation
Lag
Sample Partial Autocorrelations
Sample Partial Autocorrelations
Lag