



**LUND UNIVERSITY**  
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# Futures risk premium characterization and spot price modeling on the German electricity market

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## Abstract

In this thesis it was investigated how accurate the futures predict the spot prices and characterizing the futures risk premium on the German electricity market, which currently undergoes an energy transition. This was conducted twice, with realized data and with data from an own developed model. The realized spot price data and futures were obtained from the European Energy Exchange. The methodology to develop the model was according to conventional financial time series modeling. First, the data was converted from nonstationary to stationary. Then, Box & Jenkins modeling and Akaike information and Schwartz Bayesian criteria were used to determine the lags in the subsequent ARMA model. The model was chosen to be an ARMA(1,1) model. Its parameters were estimated with the maximum-likelihood method and then a 1-step forecasting method was applied to generate data points. Both the realized data and the data from the model, together with the relevant futures, suggest that there is a positive risk premium. This is consistent with financial research. Regarding the accuracy measures, the uncertainty tended to increase gradually for the realized values, meanwhile the model based ones generated a non-consistent pattern.

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## 1. Introduction

Electricity is a crucial commodity for mankind. A special characteristics of it is that storage of it is not possible, in contrast to other commodities, e.g. oil. (Aïd, 2015). Electricity markets have in the past been monopolized. As a result of a gradual deregulation, this market structure has changed and become more competitive. This competitive structure has led to volumetric and price risks. Some electricity markets, e.g. the Nordic and the US, liberalized earlier than other such as the German.

Due to stable and prominent forecasts, the volumetric risk is out of less concern than the price risk, which may possess an extreme volatility. Compared to other commodities, this price risk can sometimes be two orders of magnitude more volatile. An explanation to the price spikes is the non-storability characteristics of electricity, which consequently affects supply and demand. Thus, the role of price forecasts and derivative hedging alternatives, such as forwards and futures, have significantly increased of importance (Weron, 2006).

Forwards and futures are financial derivatives, which both are contracts that have an underlying asset. These types of contract may both have different maturities. The main difference between forwards and futures are that the former is non-standardized and the latter standardized.

Forwards are traded in a non-organized manner, i.e. over-the-counter (OTC), meanwhile futures are traded on organized exchanges. Furthermore, there is a credit risk for the forward contract holders, in contrast to the futures contract holders.

Moreover, futures and forwards are spot price predictors (Byström, 2010). Both forwards and futures have a risk premium included in the prices of their contracts. The risk premium is defined as the futures or the forward prices minus the forecasted spot price. Futures and forwards are highly relevant contracts when managing the risk in the electricity price (Bodie, et al., 2010).

The aims of this thesis are to evaluate how accurate the futures prices, in terms of accuracy measures, predict the spot prices and to characterize the futures risk premium on the German electricity market. This will be conducted twice. First in a pre-study, where realized spot price data will be used, and then in a second part with data from an own-developed spot price model. In the process of developing the own model, conventional time series theory, such as e.g. ARMA modeling, will be used. Microsoft Excel and Matlab, a mathematical software, will be the main tools to conduct the aims of this thesis, e.g. statistical tests will be conducted here.

Due to that the German electricity market liberalized later than other markets, analyses such as the futures forecasting power have not been investigated, in contrast to e.g. Nord Pool, a Nordic power exchange. Torr  (2009) investigated the forecast power of electricity futures at Nord Pool. The results obtained concluded that the forecasting errors of the futures were different from zero. Those errors that were significant could be interpreted as risk premiums. The aim of this thesis to evaluate the forecasting power of futures, in terms of accuracy measures, is thus highly relevant, because such an investigation has not been conducted before, especially if it can be coupled to current energy policy decisions.

Depending on how long the maturity of the futures or forward contract is, the premium may vary and the signs of it may change. Benth et al. (2008) showed, empirically on the German electricity market, that the risk premium, for players with an equal risk aversion, decreases as the maturity time of the contract increases. Furthermore, it was also shown that the sign of the premium changes from positive to negative in the medium and the long run.

Spot price modeling is a common research phenomenon. The first electricity spot price models were developed from Schwartz (1997), which were based on mean reversion, meaning that the price gradually moves to its average. There are e.g. one factor and two factor models, which describes the electricity spot price. These are generally log transformed. A one factor model consists of a deterministic and a stochastic component.

A two factor model contains the same two component as the one factor model, but a second stochastic component is added. The deterministic component generally follows a seasonality pattern. There various applications of these factor models have been conducted (Lucia & Schwartz, 2002). External variables, e.g. temperature, are often included when modeling electricity spot price. Green (2009) used the hydrological balance as an external variable when modeling the electricity spot price on the Nordic Market.

This thesis will be divided into five sections. First, a short overview of electricity markets, the German one in particular, will be presented. A methodology section will then explain, for this thesis, essential mathematical, financial and econometric concept, followed by a data section, result part and conclusion.

## 2. Electricity markets and Risk Premiums

### 2.1 General

The structure of liberalized, competitive energy markets differ from country to country. There are, however, three general structures: the intraday market, the day-ahead market and the forward as well as futures markets. The two former mentioned markets are physical markets and the latter are financial markets. In the intraday market, the electricity is traded on the same day as it is delivered. The electricity in the day-ahead market is traded during the next day. In the forward and futures markets, the electricity is traded for delivery in the future (Aid, 2015).

### 2.2 German electricity market

Today, with an annual electricity consumption of 550 TWh, Germany has the largest electricity market in Europe (Germany Trade & Invest, 2015). During the last two decades, there have been major events that have created today's market structure and environment (Weron, 2006).

The German electricity market was liberalized in 1999. This meant that the consumers could freely choose suppliers. At this time, there were eight leading electricity supplying companies. Due to mergers, this figure became four two years later, consisting of EnBW, Vattenfall Europe, E.ON and RWE (Weron, 2006). Today, there are the same four major companies, but with renaming. RWE is today Amprion, Vattenfall Europe is 50Hertz Transmission and E.ON is Tennet TSO (Germany Trade & Invest, 2015).

Electricity in Germany was almost only traded on an OTC basis until 2000. As a result of increased volumes of traded products throughout the years, two exchanges, the Leipzig Power Exchange and the Frankfurt based European Energy Exchange (EEX), were created in 2000. The two exchanges merged in 2002, creating today's Leipzig based European Energy Exchange (Weron, 2006).

The power spot market of today's EEX operates 24 hours a day and 365 days a year. The trades can either be physically traded as intraday or day-ahead. Renewable energies and their integration are supported in the available products (European Energy Exchange (a), 2015). The market for the derivatives offer a product called the Phelix Future. These financial derivatives are electricity futures in the German and Austrian area. The contracts are available in a daily, weekend based, weekly, monthly, quarterly or annual maturity. In each of these maturities, the

contracts are furthermore available as peak load, base load and off-peak (European Energy Exchange (b), 2015). Peak load contracts are delivered from Monday to Friday from 7 to 20, base load contracts are delivered every hour a week, i.e. 168 hours. Off-peak contracts are equal to the base load minus the peak load (Aid, 2015).

Germany's electricity supply consists of a mixture from various sources, ranging from e.g. renewable energies, coal, wind, nuclear and solar power. The Energiewende is an initiative in Germany with the two main purposes: to gradually make a transition to renewable energies and to conserve energy more effectively. In other words, the German Energiewende is an energy transition.

A major event that led to this energy transition was the nuclear disaster in Fukushima, Japan, 2011, where after German policy makers made the decision to shut down nine out of 17 nuclear reactors in the country. This phase out is continuous and by 2022, Germany aims to be free from nuclear power.

The Energiewende had its origins in the 70s when there was an era of anti-nuclear movements. Furthermore, oil crises and accidents such as the one 1986 in Chernobyl, Ukraine, have contributed to a strong desire of an energy transition.

There are five main reasons that motivates the Energiewende. These are minimizing the climate change, dampening the reliance of energy imports, green energy technology stimulation, eliminate nuclear power risks and making local economies stronger (Morris & Pehnt, 2014).

### 2.3 Risk premiums

Due to the fact that there is an uncertainty in the future electricity spot price, a risk premium is included in futures contracts. The futures market risk premium is defined as:

$$\pi(t, T) = F(t, T) - E(S(T)) \quad (1)$$

where  $\pi$  is the market risk premium,  $F$ , the futures price and  $E(S)$ , the expected spot price. The indices  $t$  is the time when the risk premium is calculated at and  $T$  is the delivery time. The expected spot price is obtained from model-based data. When calculating the realized risk premium, the model-based expected spot price is substituted with realized spot price data (Benth, et al., 2008).

### 3. Methodology

In the following section, the methodology used and its theory are presented in a chronological order, e.g. some of the procedures are dependent on each other. Calculations and tests were performed in Matlab and in Microsoft Excel. The Matlab code is presented in appendix.

#### 3.1 Log returns

Asset returns, especially log returns, sometimes possess more desirable properties than regular price series. Firstly, they generate a summary that is scale-free. Secondly, these returns have prominent statistical properties, e.g. the log returns are independent as well as identical distributed. Log returns,  $r_t$ , are defined as:

$$r_t = \ln \frac{P_t}{P_{t-1}} \quad (2)$$

where  $t$  is the time index,  $P_t$  and  $P_{t-1}$  are prices (Tsay, 2010).

Descriptive statistics of log returns of the weekly mean spot prices are presented in the data section.

#### 3.2 Time series

A time series is a dataset with variables that are available over a certain periods of time (Dougherty, 2011). Financial time series differ from other ones, due to the fact these contain an uncertainty, e.g. asset volatility (Tsay, 2010).

Time series can either be stationary or nonstationary. If regression analysis, which is a common framework, is applied when analyzing these series, nonstationarity generates spurious regression and this will lead to erroneous interpretations. Transforming a nonstationary time series to a stationary one is thus essential (Dougherty, 2011).

Generally, three conditions have to be satisfied, if time series are to be called stationary. The first two conditions are that both the mean and the variance of the distribution should be time independent. The third condition is that the covariance should be time independent and only distance dependent, at any two points of time (Dougherty, 2011).

A common transformation converting a nonstationary time series to a stationary one, is by taking the logarithm of the series. This makes the variability of the series more stable. Another way is to



difference the data. These transformations are usually combined to generate stationary time-series. Time series such as electricity spot price data often possess a seasonality pattern, which follows a trigonometric function. This pattern, like other trends, can be removed (Tsay, 2010).

### 3.2.1 Unit root

To test and determine whether a time series is nonstationary or stationary, a unit-root test is generally conducted. Among unit-root tests, the augmented dickey fuller (ADF) test is widely used. This test has the following null hypothesis:

$$H_0: \rho = 1 \quad (3)$$

$$H_1: \rho < 1 \quad (4)$$

The interpretation of this null hypothesis is that if it is rejected, there is no unit root and the time-series is stationary (Dougherty, 2011) (Tsay, 2010).

### 3.2.2 ARMA-descriptions

An autoregressive moving average (ARMA) model is a combination of an autoregressive (AR) and a moving-average (MA) model. ARMA models are able to describe stationary time series. An advantage of ARMA models is that they reduce the need for models with many parameters, i.e. high-order models. It is possible to introduce exogenous variables in the ARMA model, but it is out of the scope of this thesis.

An AR(1) model has the following structure:

$$s_t = \phi_0 + \phi_1 s_{t-1} + a_t \quad (5)$$

where  $s$  is the spot price,  $t$  is the time interval index, the different  $\phi$  are constants and  $a$  is a white noise time series variable with variance and zero mean. Note that this model has a linear regression form with  $s_t$  as the dependent and  $s_{t-1}$  as the independent variable.

A MA(1) model has the following structure:

$$s_t = c_0 + a_t + \theta_1 a_{t-1} \quad (6)$$

where  $c_0$  and  $\theta_1$  are constants and  $a_t$  the white noise with index  $t$ . Thus, an MA model is a model where the lagged variable is the white noise.

Thus, an ARMA(1,1) model has the following structure:

$$s_t = \phi_0 + \phi_1 s_{t-1} + a_t + \theta_1 a_{t-1} \quad (7)$$

and a general ARMA model the following:

$$s_t = \phi_0 + \sum_{i=1}^p \phi_i s_{t-i} + a_t + \sum_{i=1}^q \theta_i a_{t-i} \quad (8)$$

(Tsay, 2010).

### 3.3 Choice of ARMA model

Whether it is p or q, adding extra lags in an ARMA model will reduce the residual sum of squares. Moreover, irrelevant ones will reduce the forecasting power of the model and degrees of freedom will be lost. There are methods to determine appropriate number of lag, e.g. Box & Jenkins modeling and information criteria (Enders, 2014).

#### 3.3.1 Box & Jenkins

Box & Jenkins modeling consists of several steps. When selecting a model according to these procedures, the autocorrelation function (ACF) and the partial autocorrelation function (PACF) are used.

Both the ACF and the PACF are presented in correlograms with a lower and an upper significance range. Lags are presented on the x-axis and the dependent variables, on the y-axis, are the sample autocorrelation as well as the sample partial autocorrelation. In the ACF, the values going to be analyzed are obtained from the serial correlation between two subsequent time-series point. Regarding the PACF, these values are based on partial autocorrelation. Here, due to its partial characteristics, all shorter lags are controlled, not just the actual one.

The first step in the Box & Jenkins modeling is to check whether the series is stationary or not. A slowly, e.g. above the significance range, decaying sample ACF and/or PACF indicates that the time series is nonstationary. If the time series is nonstationary, a transformation, e.g. taking the logarithm and first difference, is conducted.

The second step is to identify a model (Box, et al., 1994). The PACF is the better of the two autocorrelation functions to identify an AR model and the ACF is the better one to find a MA model. The lag order of the two is graphically determined in the correlograms. Here, the last lag, i.e. where it cuts off, which is above the significance range will be chosen to be either the p or q lag in the ARMA model, depending on which function analyzed.

Information criteria can also be used in this step, in order to confirm the identification (Enders, 2014). After that the chosen model is specified. Furthermore, the parameters of the model are also estimated in this step. Then, a checking of the goodness of fit is conducted. Here, the residuals are evaluated. These should be homoscedastic, have a constant variance and mean, i.e. normally distributed, as well as be uncorrelated (Box, et al., 1994). If the residuals do not have a constant variance, it is possible to apply a GARCH model, in order to obtain constant ones. GARCH distributions also have heavier tails than the conventional normal distribution. GARCH modeling is considered to be without out the scope of this thesis (Tsay, 2010).

### 3.3.2 Information criteria

Akaike information criterion (AIC) and Schwartz Bayesian criterion (SBC) are model selection criteria that determine the number of lags which are optimal. These are described with the following formulas:

$$AIC = T(RSS) + 2n \quad (9)$$

$$SBC = T(RSS) + n \ln T \quad (10)$$

where n is the number of estimated parameters T, the usable observations and RSS, the residual sum of squares. The value of AIC and SBC should be as low as possible, e.g. they can also be negative. Regarding large sample, SBC is preferred over the AIC. Furthermore, adding more regressors results in a higher marginal cost for the SBC, compared to the AIC (Enders, 2014).

### 3.4 Estimation

Unknown parameters in the chosen, AR, MA or ARMA model are estimated with the maximum-likelihood method (ML). The ML method uses a probability distribution, which represent the desired data points, to estimate the parameter values. The values of these estimated parameters are chosen in a way that they maximize the probability of the realized values (Tsay, 2010) (Box, et al., 1994).

### 3.5 Forecast

When the number of lags have been chosen in the ARMA model and its parameters estimated, a 1-step-ahead forecast is applied, in order to obtain a coherent time series of the model. One step in this case means one week. This forecast methodology is obtained from the following equation:

$$\hat{s}_h(1) = E(s_{h+1}|F_h) = \phi_0 + \sum_{i=1}^p \phi_i s_{h+1-i} + a_t + \sum_{i=1}^q \theta_i a_{h+1-i} \quad (11)$$

where some of the nomenclature are already introduced in eq 7. Newly introduced variables are  $h$ , the forecast origin  $F_h$ , available data and  $\hat{s}_h$  the forecasted value (Tsay, 2010).

### 3.6 Accuracy measures

To determine how accurate a value is, compared to its actual one, accuracy measures can be used as evaluations methods. Three commonly used accuracy measures are the mean squared error (MSE), the mean absolute error (MAE) and the mean percentage error (MAPE) (Devore & Berk, 2012) (Makridakis & Hibon, 1995).

MSE is defined as:

$$MSE = \frac{\sum(X_t - F_t)^2}{m} \quad (12)$$

where  $X_t$  is the actual value,  $F_t$ , the forecasted one and  $m$  the number of observations. These variables are also used in the two coming accuracy measures (Devore & Berk, 2012).

MAE is defined as:

$$MAE = \frac{\sum|X_t - F_t|}{m} \quad (13)$$

(Devore & Berk, 2012)

MAPE is defined as:

$$MAPE = \frac{\sum \left| \frac{X_t - F_t}{X_t} \right|}{m} (100) \quad (14)$$

(Makridakis & Hibon, 1995).

## 4. Data

Historical spot and futures prices, ranging from week 12, 2010 to week 13, 2014, were analyzed. The data was obtained from EEX. The historical spot price data was available in a daily format with hourly prices, i.e. 24 hours a day and seven days a week. The weekly mean of these 168 data point was calculated, thus one mean spot price per week.

In the calculated dataset, a negative mean occurred in the end of the year 2012. To facilitate the subsequent developing of an own model, this data point was removed, see figure 1 for an illustrative overview. A reason why it was removed is that it is not possible to take the logarithm of a negative value and, as mentioned in the methodology section, the logarithmic transformation is an important way to convert nonstationary data into stationary. In table 1, descriptive statistics of the weekly mean spot price with the negative value excluded, is presented.

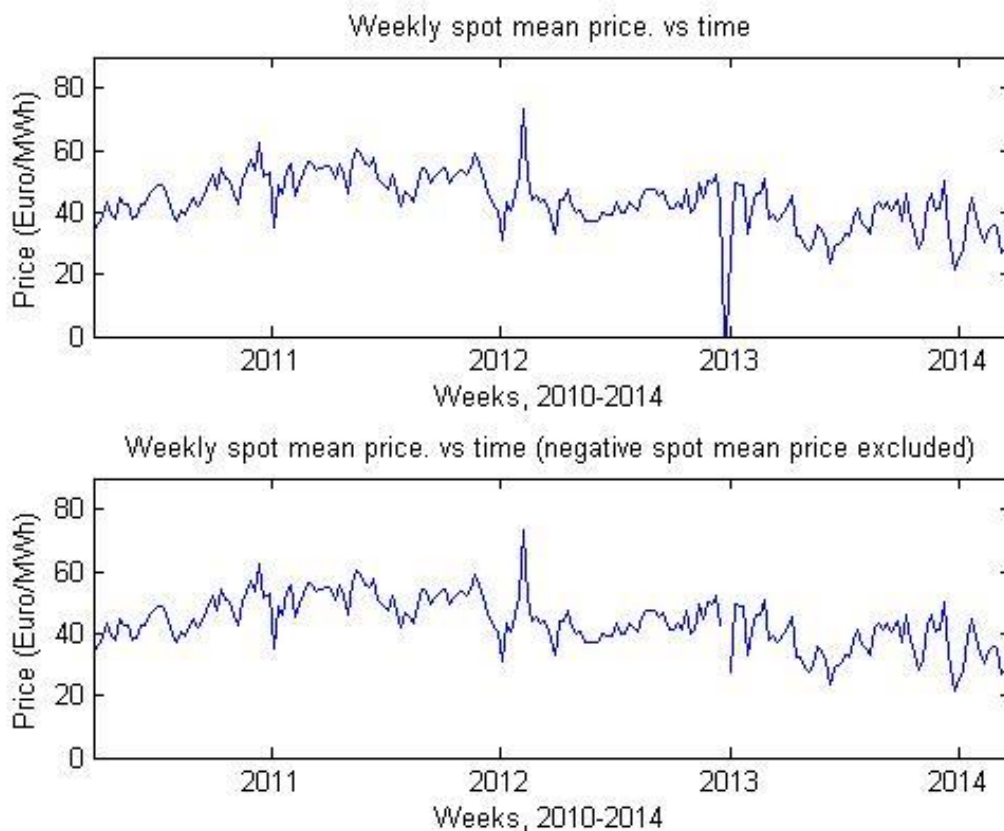


Figure 1. Weekly mean spot price vs. time, both with and without the obtained negative spot price included.

Table 1. Descriptive statistics of the weekly mean spot price, negative data point excluded.

Dataset	Realized price	Realized price Log returns
Mean	43.7278	0.0001
Median	43.5800	0.0011
Skewness	-0.0479	-0.1698
Kurtosis	3.1836	5.3368
Max	72.9600	0.5797
Min	21.2700	-0.4608
Standard deviation	8.1552	0.1410

The futures contracts in the obtained dataset were ranging from daily contracts to weekend based, weekly, monthly as well as quarterly and annual. In each of these maturities, the futures were available in base load, off-peak and peak load contracts. Among these futures contracts, the weekly contracts with one week delivery time with base load were analyzed. The base load was chosen, due to it represents every available hour, in contrast to peak load and off peak. According to the analyzed time span, there were 210 weeks with the negative spot mean price included and 209 with it excluded. The futures were chosen manually.

To be consistent when coupling the futures to the spot prices, a systematic procedure was conducted. During each Friday of the analyzed weeks, the last trading price of a contract delivered during the subsequent week was chosen, e.g. the future contract of week 2 corresponds to the spot price of week 3. As a consequence, there were no overlapping between the futures. Out of the total number of analyzed 210 weeks, there were 163 futures available and 162 when the negative data point was removed.

The logarithm of the weekly spot mean price, with the negative spot price excluded, is illustrated in the upper subplot of figure 2.

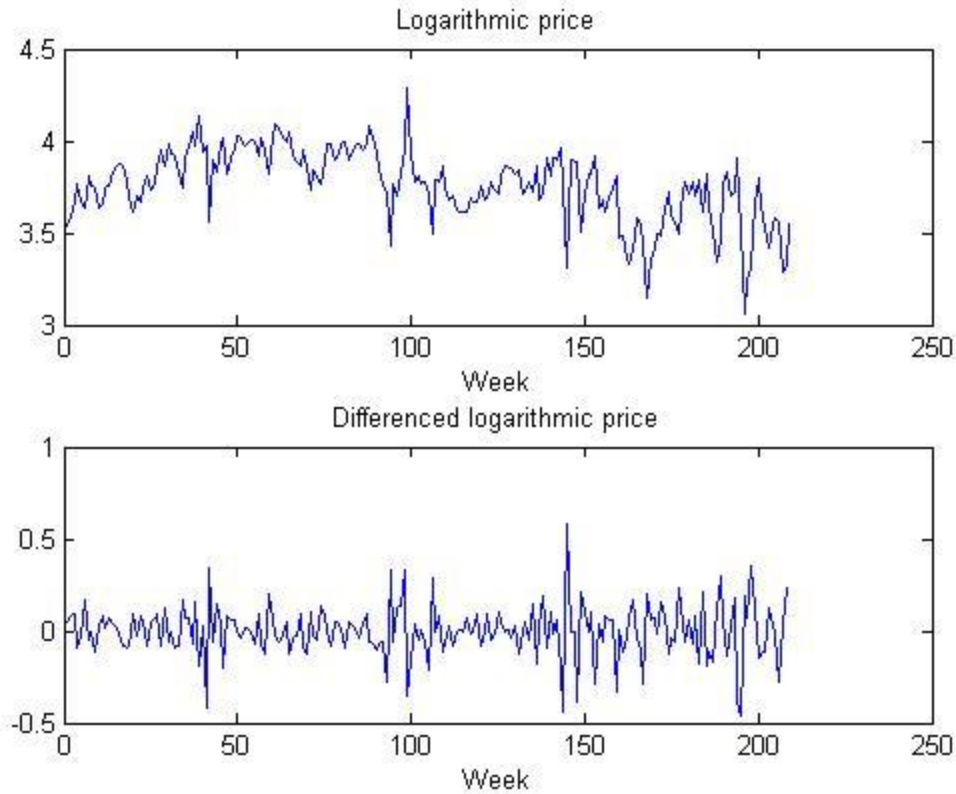


Figure 2. Logarithmic price and the differenced logarithmic price.

According to the conducted ADF-test and based on the obtained p-value, this series was considered to be nonstationary, i.e. the null hypothesis is not rejected, see table 2. When taking the first difference of the logarithmic series, stationarity occurred, due to its p-value. This series is illustrated in the lower subplot in figure 2.

Table 2. ADF-test of the two transformed models.

Data	p-value
Logarithmic price	0.5553
First difference of logarithmic price	0.001

The transition from nonstationarity to stationarity, due to taking the first difference, was also confirmed by plotting the ACF and PACF functions. The logarithmic transformation was considered to be nonstationary, due to its decaying pattern in the ACF plot, see figure 3.

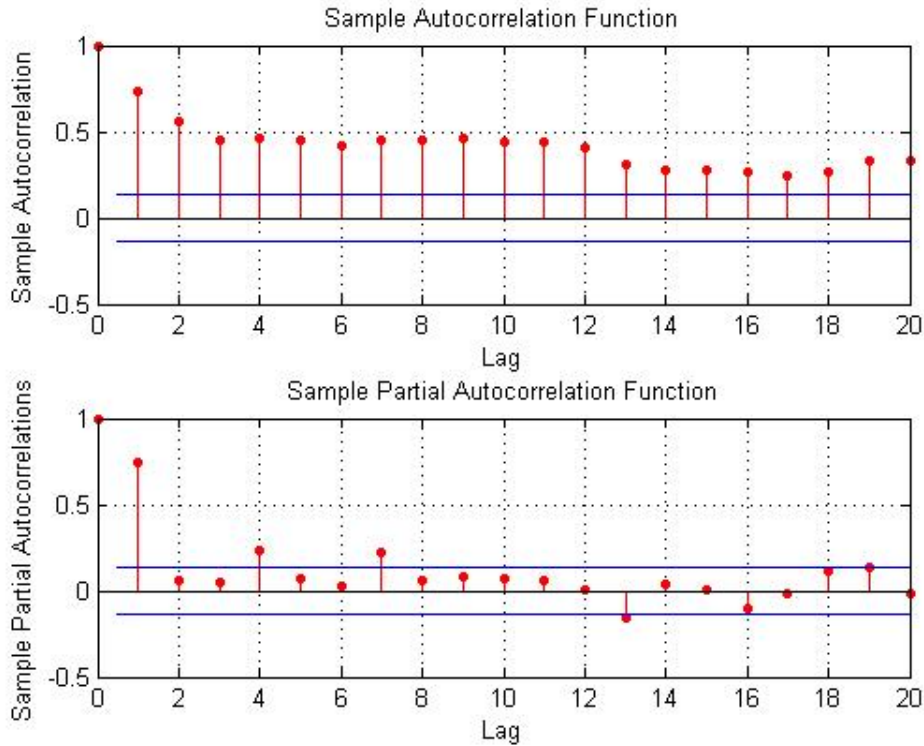


Figure 3. ACF and PACF of the logarithmic model.

Regarding the first-differenced logarithmic model, the more rapid decaying pattern in the ACF plot concluded that the process is stationary, see figure 4.

Although this time series represent electricity spot price, no seasonality could be found. This due to that the time series got stationary after taking the logarithm and the first difference. Thus, no seasonal differencing with a trigonometric function was needed. A reason why there was no seasonality pattern in the series could be that energy mix in Germany is constantly changing due to the Energiewende policy.



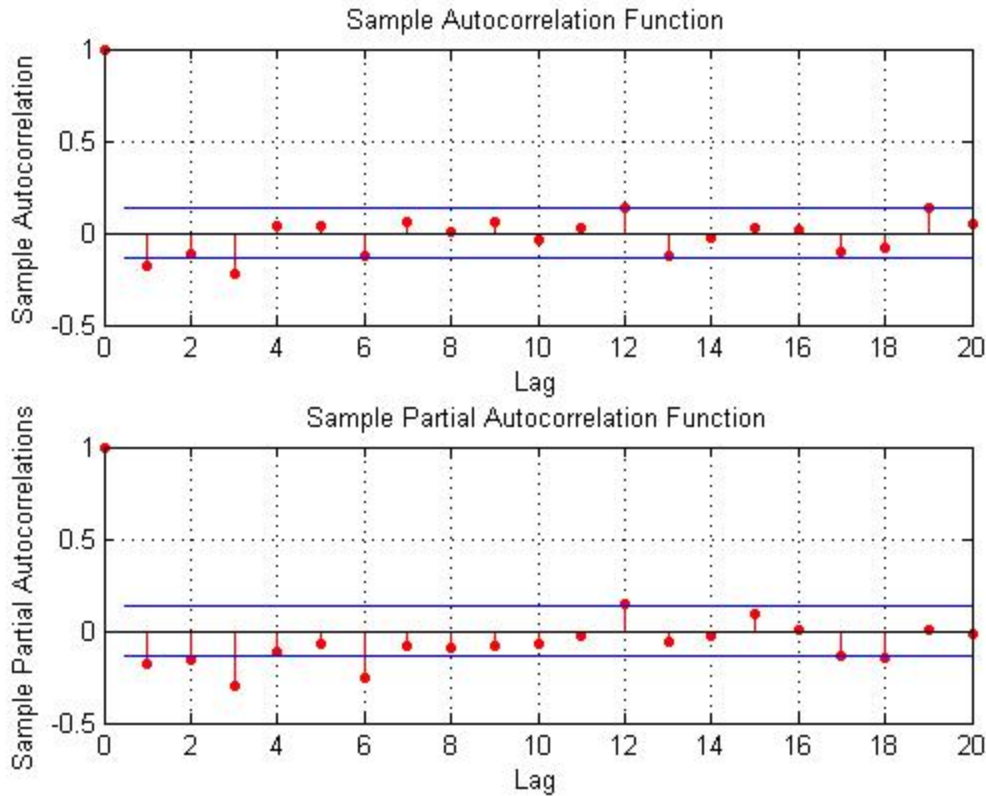


Figure 4. ACF and PACF of the first-differenced logarithmic model.

### Model estimation

Based on the ACF and PCF of the first-differenced logarithmic data, it can be concluded that there are significant lags. Regarding the ACF, lag 1 and 3 are significant. Lag 1, 3 and 6 are significant in the PACF. According to econometrical theory, the model should be an ARMA(6,3). It is improbable that the spot price would depend on the price six weeks ago, compared to e.g. one week ago.

Therefore, several ARMA models were specified and estimated. These estimations together with coefficients are obtained in table 7 and table 8, see appendix. The two information criteria, AIC and SBC are obtained in table 9, see appendix. Based on the estimations and the information criteria, an ARMA(1,1) model was chosen to describe the generated stationary process. The motivation is that the coefficients for this model are significant and that the SBC value is low.

The SBC values were chosen to be preferred over the AIC, since the SBC has large sample properties. Regarding the obtained SBC value for the chosen ARMA model, it is the second lowest. Although it had the second lowest SBC value, it is, due to parsimoniousness, preferred

over the model with the lowest, the ARMA(0,3). Furthermore, it is more reasonable that an electricity price time series follow at least one autoregressive lag than only MA lags. An ARMA(1,1) model seems overall plausible.

The residuals of the chosen ARMA(1,1) model were evaluated and plotted in various ways, see figure 5. From these subplots it is concluded that these residuals seem to be uncorrelated. The variance does not seem to be constant. Furthermore, the residuals do not seem to be normally distributed, due to the occurring heavy tail. GARCH modeling could have solved these two issues, but this is, as also being mentioned in the methodology section, considered to be out of the scope of this thesis. An ADF-test was conducted on the residuals in the model and a p-value of 0.001 was obtained, thus stationary, see table 10, appendix. Although the variance and the normal distribution issues, the ARMA(1,1) model will be the chosen model.

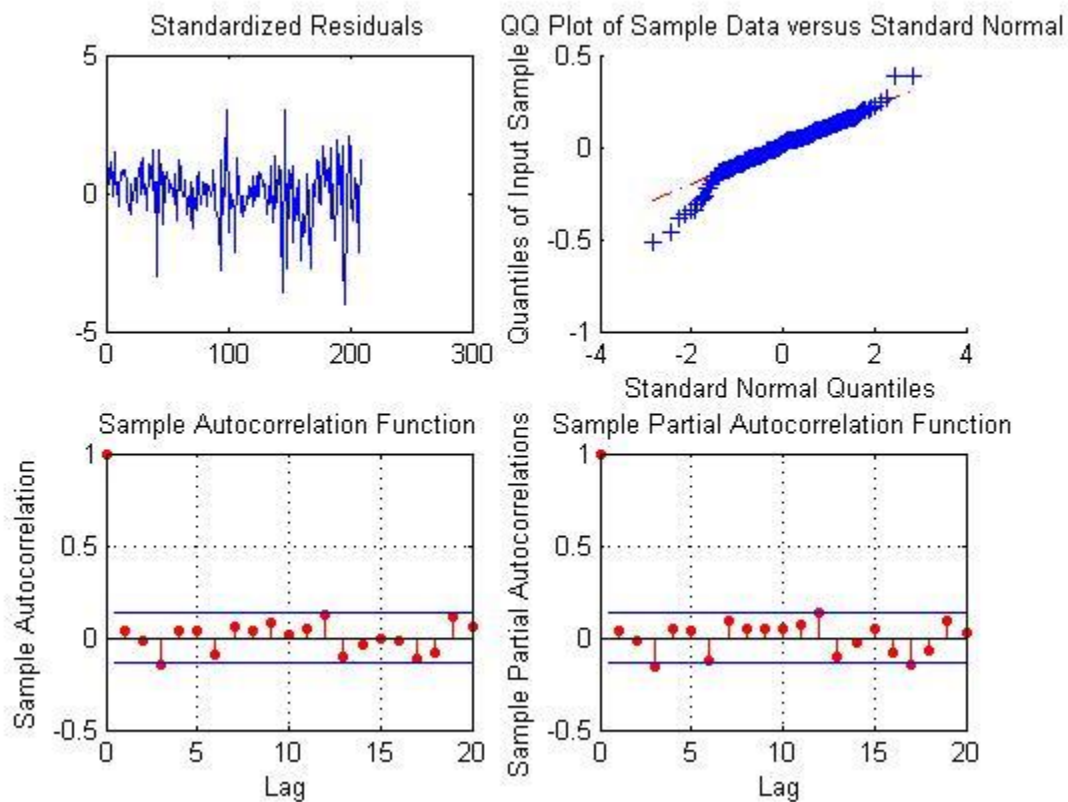


Figure 5. Residual analysis of the chosen model.

Together with the estimated parameters in table 7, appendix, the chosen ARMA(1,1) model is according to the following:

$$s_t = 7.66612s_{t-1} + a_t - 20.2611a_{t-1} \quad (15)$$

Together with the historical data points, the chosen model and a 1-step-ahead forecasting function, a mean for each week was obtained, i.e. 209 data points. This is illustrated in figure 6, where the modeled spot price is compared to the realized one, note that the data values are transformed back to the price.

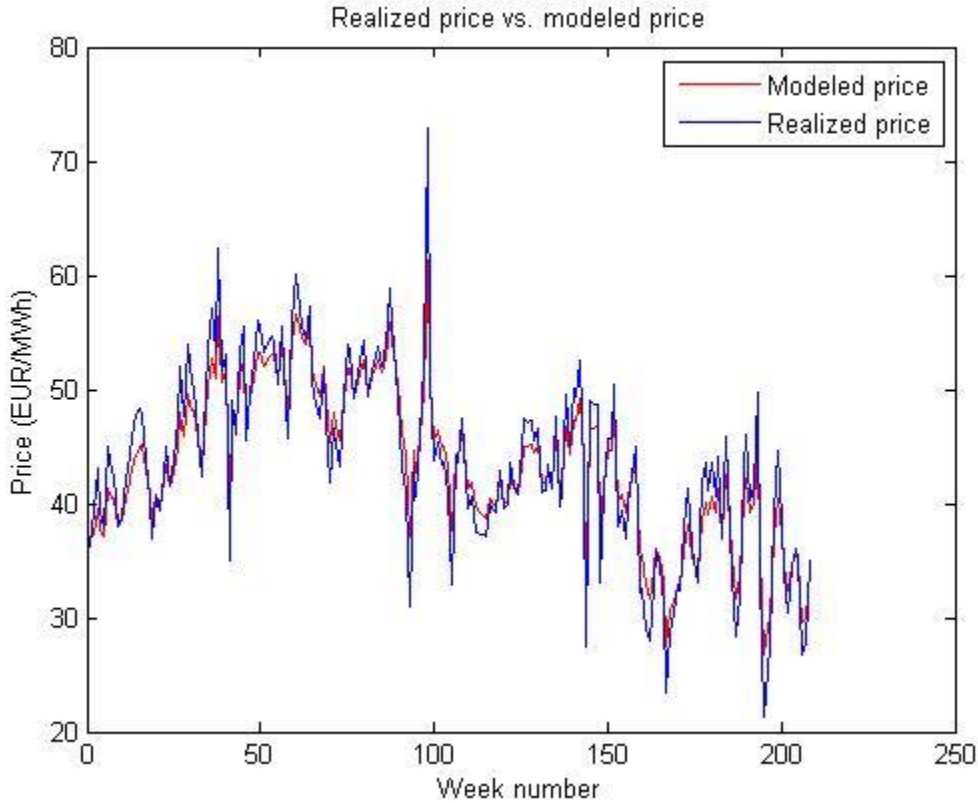


Figure 6. The realized price vs. the modeled price.

In table 3, descriptive statistics of the realized spot price is compared to the model.

Table 3. Descriptive statistics, realized and modeled spot price

Dataset	Realized price	Realized price Log returns	Model	Model Log returns
Mean	43.7278	0.0001	43.4270	-0.0004
Median	43.5800	0.0011	43.2122	0.0006
Skewness	-0.0479	-0.1698	-0.0602	-0.2741
Kurtosis	3.1836	5.3368	2.4742	5.3523

Max	72.9600	0.5797	61.2848	0.3355
Min	21.2700	-0.4608	26.7902	-0.2896
Standard deviation	8.1552	0.1410	6.7227	0.0842

## 5. Results

This result section is divided into two parts. The first part is a pre-study, where realized data is used. In this pre-study, accuracy measures will be evaluated and the realized risk premium characterized. The second part is a model-based part, which is similar to the pre-study, where accuracy measures will be evaluated and the risk premium characterized.

### 5.1 Pre-study

#### 5.1.1 Accuracy measures

The annual and total accuracy measures were calculated, according to eq. 11-13, and are obtained in table 4. The negative weekly mean spot price was included in table 4 and excluded in table 5. Note that only the year of 2012, where the negative price was obtained, and the total value measure are affected, consequently the values of the other years are the same as previously. It is observed that the negative mean spot price value had a major impact on the accuracy measures.

There is a trend that the accuracy measures tend to gradually increase year by year. Furthermore, when the negative price was excluded, the affected measures tend to decrease. An interpretation of this trend is that the uncertainty increases year by year. An explanation to this increasing uncertainty could be the Energiewende policy in Germany, e.g. the nuclear power is gradually phased out and it probably takes time for renewable energies to get established in the power market.

*Table 4. Accuracy measures, negative weekly mean spot price included*

Year/Accuracy measure	MSE	MAE	MAPE (%)
2010	6.3995	2.0635	4.4783
2011	8.3993	2.1735	4.4194
2012	23.6481	2.7733	56.9792
2013	13.7833	2.8343	8.0000

2014	18.4679	3.5625	11.2500
Total	14.9673	2.6355	21.4847

Table 5. Accuracy measures, negative weekly mean spot price excluded.

Year/Accuracy measure	MSE	MAE	MAPE (%)
2012	11.0758	2.3049	5.4468
Total	11.2662	2.4988	6.3148

5.1.2 Realized risk premium

Together with the identified futures, their corresponding realized spot prices and according to eq. 1, 90 positive premium were calculated out of 162. The distribution of the calculated premium is illustrated in figure 7.

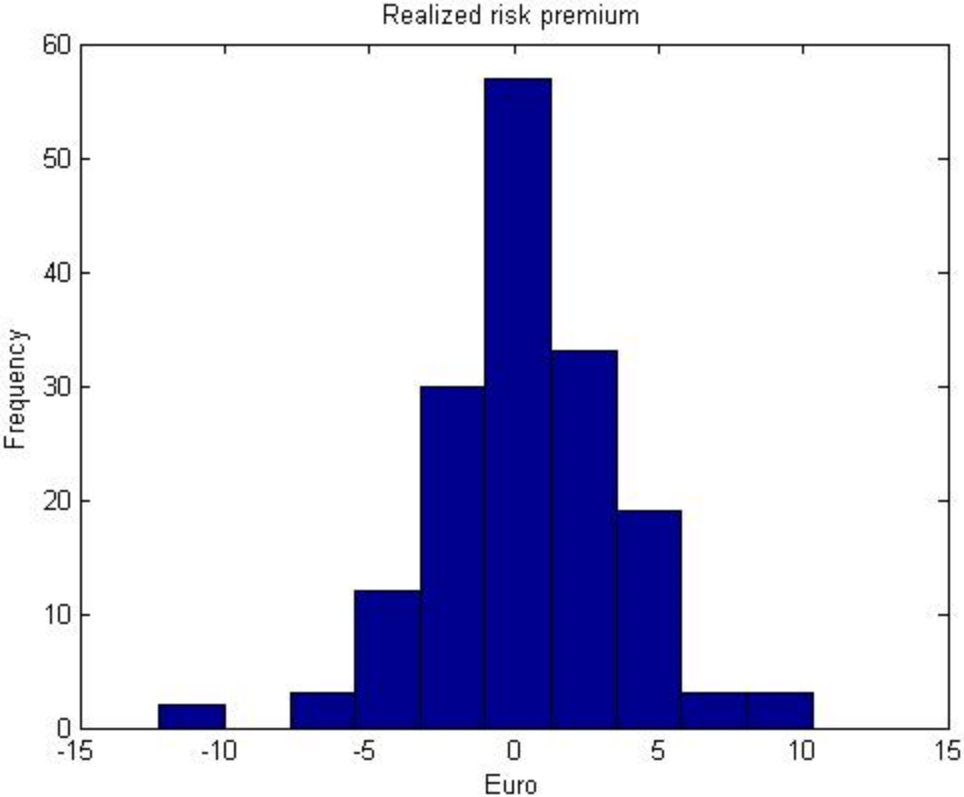


Figure 7. Risk premium weekly futures contracts, pre-study. Here is the negative weekly mean spot price excluded.

To conclude what sign the risk premium,  $\pi$ , possesses in this case, a t-test, based on these figures, was conducted, according to the following null hypothesis:

$$H_0: \pi = 0 \quad (16)$$

$$H_1: \pi > 0 \quad (17)$$

The obtained p-value was 0.0394 and consequently, the null hypothesis is rejected at a 5% significance level. Thus, the weekly realized risk premium is positive. This result is consistent with the result that Benth et al. (2008) obtained.

## 5.2 Model-based part

### 5.2.1 Accuracy measures

The annual and total accuracy measures were calculated in the same manner as in the pre-study. The obtained results do not show such a clear trend as in table 6. Neither of the measures are gradually increasing, compared to in the pre-study. As a consequence, it cannot be concluded that the Energiewende, the nuclear power phasing out in particular, contributes to an increasing uncertainty. Furthermore, the nature of the developed model could also be a reason. The model is simplified, because no exogenous variables are implemented in it. Thus, it can be improved and perhaps the accuracy measures would have been more consistent.

Table 6. Accuracy measures, based on data values from the model

Year/Accuracy measure	MSE	MAE	MAPE (%)
2010	11.9759	3.0357	6.5509
2011	11.1419	2.7369	5.3766
2012	7.1079	1.9934	4.5594
2013	17.7611	2.8518	7.8738
2014	12.1251	2.5640	7.5623
Total	12.1649	2.5856	6.2235

### 5.2.2 Risk premium

Together with the identified futures, their corresponding realized spot prices and according to eq. 1, 99 positive premium were calculated out of 162. The distribution of the calculated premium is illustrated in figure 8.

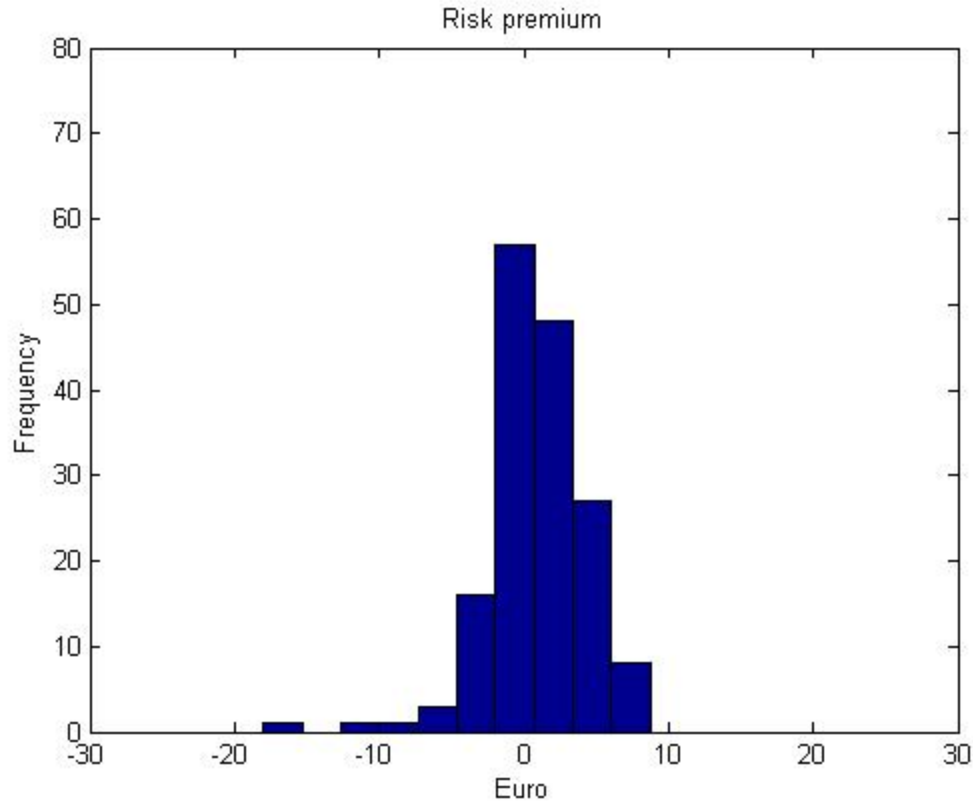


Figure 8. Risk premium weekly futures contracts, pre-study. Here is the negative weekly mean spot price excluded.

To conclude what sign the risk premium,  $\pi$ , possesses, a t-test, based on these figures, was conducted, according to the following null hypothesis:

$$H_0: \pi = 0 \quad (18)$$

$$H_1: \pi > 0 \quad (19)$$

The obtained p-value was  $2.9082e-04$  and consequently, the null hypothesis is rejected at a 5% significance level. Consequently, in similarity to the pre-study, there is a positive risk premium. This result is consistent with the result that Benth et al. (2008) obtained.

## 6. Conclusion

Since the 70s, Germany has had a desire for an energy transition, phasing out nuclear energy in particular. After the nuclear disaster in Fukushima, Japan, 2011, nine out of 17 nuclear power reactors were closed and by 2022 Germany aims to be nuclear-free. This is a part of an energy transition called the Energiewende and the thought is that renewable energies will replace the nuclear energy.

Due to the fact that nuclear energy is a relatively inexpensive way of producing energy, this replacement will most likely result in a market uncertainty to some degree. In this thesis this uncertainty, in terms of accuracy measures, was investigated. The accuracy measures were based on electricity futures forecasting power of the spot price. This was conducted twice, both with realized and model-based data.

The results from the realized data suggest annually increasing accuracy measures. This pattern is plausible, due to the fact that more and more renewable energies are introduced into Germany's energy mix. The model based data did not show such a clear pattern. A possible reason could be that the model is simplified. Exogenous variables could have been introduced into the model, but this was considered to be out. In this thesis, the futures market risk premium was also characterized. The results, both for the risk premium and its realized equivalent, showed positive premiums and this is consistent with financial research. This result is also logically plausible.

An interesting feature that can be coupled to the Energiewende is that no seasonal trend was found in the electricity spot price time series. Once more, the reason could be the occurring market environment with renewable energies, which possibly reduce the influence of seasonal factors such as e.g. the temperature.

Future research could be analyzing several futures maturities, e.g. monthly, quarterly and annual, and evaluate the sign of the risk premium. Moreover, introducing exogenous variables to the ARMA model could also be an additional thing for future research. In the obtained spot price data, there was a negative value, which was excluded. This seems acceptable, since the aim of the thesis was not to develop a model that is supposed to be used in industry. Future research could include negative prices, by e.g. implementing constants which adjust for the matter. A GARCH model could also be introduced to solve the two residual issues of the ARMA model.



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## 8. Appendix

### 8.1 Tables

Table 7. Estimated ARMA model coefficients and their p-values. Significant p-values are marked with blue color.

Parameter	ARMA(1,0)	ARMA(0,1)	ARMA(1,1)	ARMA(2,0)	ARMA(0,2)	ARMA(2,1)
Constant	-0.0150414 0.988047	-0.0414492 0.967336	-0.242863 0.809022	-0.0461132 0.963275	-0.160274 0.873039	-0.199484 0.842461
AR(1)	-3.88406 0.000138		7.66612 < 0.00001	-4.34486 2.2E-05		7.91284 < 0.00001
MA(1)		-7.90044 < 0.00001	-20.2611 < 0.00001		-7.82649 < 0.00001	-15.8648 < 0.00001
AR(2)				-2.29242 0.022921		-1.27817 0.202702
MA(2)					-5.27052 < 0.00001	
Variance	14.6621	14.6752	13.5875	14.4073	13.0483	13.0956

Table 8. Estimated ARMA model coefficients and their p-values. Significant p-values are marked with blue color.

Parameter	ARMA(1,2)	ARMA(2,2)	ARMA(3,0)	ARMA(0,3)	ARMA(3,3)	ARMA(1,3)
Constant	-0.211592 0.833098	-0.152868 0.879338	-0.0917665 0.927582	-0.184192 0.854196	-0.387099 0.699166	-0.179058 0.858116
AR(1)	2.23693 0.026375	3.70724 0.00027	-5.46373 < 0.00001		2.25519 0.025205	-1.09444 0.275251
MA(1)	-4.05343 7.2E-05	-4.53659 < 0.00001		-6.30701 < 0.00001	-10.2647 < 0.00001	-0.509884 0.611305
AR(2)		-3.30345 0.00113	-2.98871 0.003153		-20.3691 < 0.00001	
MA(2)	-0.776244 0.438648	2.07435 0.039313		-2.66548 0.008315	24.9465 < 0.00001	-2.34337 0.020097
AR(3)			-5.03398		6.16146	

			< 0.00001		< 0.00001	
MA(3)				-4.1038 5.9E-05	-18.5558 < 0.00001	-4.70953 < 0.00001
Variance	13.0875	13.5499	13.9343	13.3601	13.0655	13.2263

Table 9. AIC and SBC information criteria. The lowest values are marked in red and the four lowest values are ranked in parenthesis.

Model	AIC	SBC
ARMA(1,0)	-227.6466	-217.6196
ARMA(0,1)	-233.2072	-223.1802
ARMA(1,1)	-257.3620 (4)	-243.9927 (2)
ARMA(2,0)	-230.6282	-217.2589
ARMA(0,2)	-252.5774	-239.2081
ARMA(2,2)	-257.0777	-237.0237
ARMA(2,1)	-256.8785	-240.1668 (4)
ARMA(1,2)	-256.2897	-239.5780
ARMA(3,0)	-247.7080	-230.9963
ARMA(0,3)	-262.3099 (2)	-245.5982 (1)
ARMA(3,3)	-263.8261 (1)	-237.0874 (7)
ARMA(1,3)	-261.6368 (3)	-241.5828 (3)

Table 10. ADF-test, residuals of the estimated models

Model	p-value
ARMA(1,0)	0.001
ARMA(0,1)	0.001
ARMA(1,1)	0.001
ARMA(2,0)	0.001
ARMA(0,2)	0.001
ARMA(2,2)	0.001

ARMA(2,1)	0.001
ARMA(3,0)	0.001
ARMA(0,3)	0.001
ARMA(3,3)	0.001
ARMA(1,3)	0.001

## 8.2 Matlab code

```
% This script is dedicated to the weekly mean values of the available spot
% prices. The mean values were calculated in Excel.

% Year 2010
p2010 = [53.11 51.60 62.45 53.31 57.18 53.34 49.93 42.41 45.81 50.22 50.61
53.95 47.71 51.96 ...
    47.24 43.87 41.63 45.00 42.51 39.35 40.56 37.00 40.20 44.01 47.86 48.42
47.73 45.90 42.92 ...
    42.35 38.84 37.97 42.46 42.88 44.93 38.07 39.13 43.03 39.34 36.18 34.31];
% Converting to chronological order
P10=p2010(end:-1:1);

% Year 2011
p2011 = [40.89 43.28 46.44 51.64 55.72 58.93 53.90 51.96 53.78 52.93 51.73
49.43 ...
    54.23 53.52 51.50 49.17 53.48 53.95 49.45 43.29 45.23 46.52 41.86 47.52
51.84 ...
    47.46 48.66 50.67 57.36 54.55 55.50 58.71 60.09 56.07 45.77 51.84 55.57
50.48 ...
    54.16 54.60 54.21 53.27 55.48 56.06 52.54 49.57 45.50 55.54 53.43 46.03
49.03 34.98];
% Converting to chronological order
P11=p2011(end:-1:1);

% Year 2012
p2012 = [-1.04 42.84 52.47 49.36 50.03 44.93 49.52 41.03 39.75 47.69 41.30
...
    43.49 41.21 41.00 46.54 45.53 47.22 47.15 47.49 45.01 40.78 41.61 43.59
...
    39.84 39.63 42.96 39.28 39.32 40.00 37.10 37.30 37.26 37.46 40.70 39.56
...
    42.13 47.41 43.64 44.04 32.97 40.97 43.64 43.34 45.33 43.85 51.15 72.96
52.30 45.90 40.58 43.28 31.00];
% Converting to chronological order
P12=p2012(end:-1:1);

p20122 = [42.84 52.47 49.36 50.03 44.93 49.52 41.03 39.75 47.69 41.30 ...
    43.49 41.21 41.00 46.54 45.53 47.22 47.15 47.49 45.01 40.78 41.61 43.59
...
    39.84 39.63 42.96 39.28 39.32 40.00 37.10 37.30 37.26 37.46 40.70 39.56
...
    42.13 47.41 43.64 44.04 32.97 40.97 43.64 43.34 45.33 43.85 51.15 72.96
52.30 45.90 40.58 43.28 31.00];
% Converting to chronological order
P121=p20122(end:-1:1);

% Year 2013
p2013 = [21.27 33.72 49.80 41.48 40.29 46.10 43.25 32.03 28.36 33.66 37.85
...
    45.87 36.94 44.21 40.69 43.55 41.15 43.58 41.88 32.99 35.07 36.38 41.37
...
    37.94 32.45 32.87 30.48 28.67 23.37 31.19 34.70 35.92 30.28 27.91 29.05
...]
```

```

    32.48 32.17 45.02 42.50 39.93 37.00 39.44 38.03 50.50 45.73 45.78 41.08
33.13 48.68 48.77 49.10 27.50];
% Converting to chronological order
P13=p2013(end:-1:1);

% Year 2014
p2014 = [34.95 27.75 26.71 35.29 36.03 34.61 30.43 33.95 38.48 44.58 39.13
27.41 25.60];

P14=p2014(end:-1:1);
% Converting to chronological order

% Total number of weeks
xx = 1:1:(41+52+52+52+13);

start_date = datenum('22-Mar-2010');
end_date = datenum('24-Mar-2014');
% Vector with the weeks in time format
date = (start_date:7:end_date);

% Vector with the spot mean prices in chronological order
p1112 = [P10 P11 P12 P13 P14];

% To exclude the negative price
start_date1 = datenum('22-Mar-2010');
end_date1 = datenum('17-Dec-2012');
start_date2 = datenum('31-Dec-2012');
end_date2 = datenum('24-Mar-2014');
% Vector with the weeks in time format
date1 = (start_date1:7:end_date1);
numel(date1);
date2 = (start_date2:7:end_date2);
numel(date2);
% Vector with the spot mean prices in chronological order
p1 = [P10 P11 P12];
p2 = [P13 P14];

% The spot mean values are plotted
figure(1)
subplot(2,1,1) % first subplot
plot(date,p1112)
datetick();
xlabel('Weeks, 2010-2014')
ylabel('Price (Euro/MWh)')
title('Weekly spot mean price. vs time')
axis([min(date),max(date),0,90])
subplot(2,1,2) % second subplot
plot(date1,p1)
hold on
plot(date2,p2)
hold off
datetick();
axis([min(date1),max(date2),0,90])
xlabel('Weeks, 2010-2014')

```

```

ylabel('Price (Euro/MWh)')
title('Weekly spot mean price. vs time (negative spot mean price excluded)')

%% Log data and differencing
datee = [date1 date2];
pdone1 = [p1 p2];
pdone2 = log(pdone1);
pdone3 = diff(pdone2);
x1=numel(datee);
x2=1:1:x1;
x3=numel(datee)-1;
x4=1:1:x3;

figure(2)
subplot(2,1,1) % first subplot
plot(x2,pdone2)
xlabel('Week')
title('Logarithmic price')
subplot(2,1,2) % second subplot
plot(x4,pdone3)
xlabel('Week')
title('Differenced logarithmic price')

%% Tests

% ADF test - log.
[h1, pval1] = adftest(pdone2)

% ADF test - log. + first diff.
[h2, pval2] = adftest(pdone3)

%% Forecast and Box-Jenkins
%
figure(3)
subplot(2,1,1)
autocorr(pdone2)
subplot(2,1,2)
parcorr(pdone2)
%
figure(4)
subplot(2,1,1)
autocorr(pdone3)
subplot(2,1,2)
parcorr(pdone3)

py = pdone2';
Mdl = arima(1,1,1);
EstMdl = estimate(Mdl,py)
model = EstMdl;

res = infer(EstMdl,py);

figure(5)
subplot(2,2,1)

```



```

plot(res./sqrt(EstMdl.Variance))
title('Standardized Residuals')
subplot(2,2,2)
qqplot(res)
subplot(2,2,3)
autocorr(res)
subplot(2,2,4)
parcorr(res)

% 1-step-forecasting

for i = 2:209
[yFA(i)] = forecast(model,1,'Y0',py(1:i));
end

aa=length(py);
xxx = length(xx);
xxx1 = 1:(xxx-2);
aaa = 1:(aa-1);
yFAA = exp(yFA);
figure(6)
plot(aaa,yFAA(2:end),'r')
hold on
plot(xxx1,pdone1(2:end))
hold off
xlabel('Week number')
ylabel('Price (EUR/MWh)')
legend('Modeled price','Realized price')
title('Realized price vs. modeled price')

% Evaluating realized risk premium - realized data
% This script is dedicated to analyzing the risk premium - this data was
% calculated from raw data in Microsoft Excel. This data is the difference
between the spot and futures
% price

yr10 = [4.60 -0.30 -2.69 2.43 -0.66 0.43 -5.59 0.31 -3.39 0.95 -1.79 3.96 -
0.51 -0.88 -3.12 -1.00 -1.49 -2.15 1.46 -3.00 -3.99 -1.58 -1.18];
yr11 = [-4.21 -4.22 -2.78 -1.07 -0.35 1.38 -2.32 -0.52 -1.77 0.60 0.70 -0.43
-8.64 -1.98 0.84 -3.44 -2.33 1.61 -0.89 2.34 1.77 -3.42 -0.34 ...
-6.90 3.21 -0.52 4.36 0.54 -0.68 1.04 2.18];
yr12 = [-3.66 -3.43 -0.89 1.43 -4.07 3.12 -3.47 -5.00 2.19 -4.26 0.46 -4.50 -
0.46 -0.47 -0.03 -3.51 1.76 0.28 3.11 3.59 -0.16 -0.12 ...
1.41 0.28 0.72 0.25 -1.15 1.80 -2.24 -0.24 -0.30 1.06 -0.87 0.41 -5.28 -
2.03 0.24 -1.06 -1.67 2.15 -2.35 10.46 -1.70 0.40 -8.02 -1.97 -10.30];
yr13 = [5.02 -4.28 1.10 0.58 -0.21 -0.40 5.00 -0.97 -1.89 -2.34 -5.65 2.62
0.37 -0.39 3.44 0.05 3.85 2.58 3.10 1.92 -1.87 0.87 5.44 0.16 ...
3.48 1.17 -6.13 -1.06 -1.30 7.22 -1.27 1.16 1.05 -1.77 -5.33 0.77 5.93
0.25 -5.31 -3.47 6.30 2.98 2.53 0.58 -2.37 -2.07 -5.48 3.55 12.25];
yr14 = [0.45 -5.59 3.04 2.53 0.11 -3.07 -0.55 -5.47 3.58 -4.37 -8.59 -5.40];

% Constructing a coherent vector
done = [yr10 yr11 yr12 yr13 yr14];

% The vecor is multiplied with -1 to obtain the risk premium, i.e. futures

```

```

% - spot
RiskPrem = -1.*done;

% How many of the differences that are positive, i.e. upward biased
% estimator
count1 = numel(RiskPrem( RiskPrem(:)>0 ))

% A histogram is generated of the difference values, looks normal
% distributed
hist(RiskPrem)
title('Realized risk premium')
xlabel('Euro')
ylabel('Frequency')

%Null hypothesis that the data comes from a population with mean equal to 0,
against the alternative that the mean is greater than 0.
% h = 1 = reject the null hypothesis
[h3, p3] = ttest(RiskPrem,0,'Tail','right')

%% Accuracy measures - realized data
% The mean square error and the mean absolute error.
% differences, spot-futures (actual-forcecasted) are calculated in Excel
% and imported from there.

% Year 2010
ya10 = [4.60 -0.30 -2.69 2.43 -0.66 0.43 -5.59 0.31 -3.39 0.95 -1.79 3.96 -
0.51 -0.88 ...
-3.12 -1.00 -1.49 -2.15 1.46 -3.00 -3.99 -1.58 -1.18];
% The differences are squared
ya1=ya10.^2;
yma1=abs(ya10);
% Year 2011
ya11 = [-4.21 -4.22 -2.78 -1.07 -0.35 1.38 -2.32 -0.52 -1.77 0.60 0.70 -0.43
-8.64 -1.98 ...
0.84 -3.44 -2.33 1.61 -0.89 2.34 1.77 -3.42 -0.34 -6.90 3.21 -0.52 4.36
0.54 -0.68 1.04 2.18];
% The differences are squared
ya2=ya11.^2;
yma2=abs(ya11);
% Year 2012 with negative price excluded
ya12 = [-3.66 -3.43 -0.89 1.43 -4.07 3.12 -3.47 -5.00 2.19 -4.26 0.46 -4.50 -
0.46 ...
-0.47 -0.03 -3.51 1.76 0.28 3.11 3.59 -0.16 -0.12 1.41 0.28 0.72 0.25 -
1.15 1.80 -2.24 ...
-0.24 -0.30 1.06 -0.87 0.41 -5.28 -2.03 0.24 -1.06 -1.67 2.15 -2.35 10.46
-1.70 0.40 -8.02 -1.97 -10.30];
% Year 2012 with negative price included
ya121 = [-24.79 -3.66 -3.43 -0.89 1.43 -4.07 3.12 -3.47 -5.00 2.19 -4.26 0.46
-4.50 -0.46 ...
-0.47 -0.03 -3.51 1.76 0.28 3.11 3.59 -0.16 -0.12 1.41 0.28 0.72 0.25 -
1.15 1.80 -2.24 ...
-0.24 -0.30 1.06 -0.87 0.41 -5.28 -2.03 0.24 -1.06 -1.67 2.15 -2.35 10.46
-1.70 0.40 -8.02 -1.97 -10.30];
% The differences are squared
ya3=ya12.^2;

```

```

ya31=ya121.^2;
yma3=abs(ya12);
yma31=abs(ya121);
% Year 2013
ya13 = [5.02 -4.28 1.10 0.58 -0.21 -0.40 5.00 -0.97 -1.89 -2.34 -5.65 2.62
0.37 -0.39 ...
3.44 0.05 3.85 2.58 3.10 1.92 -1.87 0.87 5.44 0.16 3.48 1.17 -6.13 -1.06
-1.30 7.22 ...
-1.27 1.16 1.05 -1.77 -5.33 0.77 5.93 0.25 -5.31 -3.47 6.30 2.98 2.53
0.58 -2.37 -2.07 -5.48 3.55 12.25];
% The differences are squared
ya4=ya13.^2;
yma4=abs(ya13);
% Year 2014
ya14 = [0.45 -5.59 3.04 2.53 0.11 -3.07 -0.55 -5.47 3.58 -4.37 -8.59 -5.40];
% The differences are squared
ya5=ya14.^2;
yma5=abs(ya14);

% A vector of all the newly squared values is constructed
doneMSE = [ya1 ya2 ya3 ya4 ya5];
doneMSE1 = [ya1 ya2 ya31 ya4 ya5];
doneMAE = [yma1 yma2 yma3 yma4 yma5];
doneMAE1 = [yma1 yma2 yma31 yma4 yma5];

% Annual and total MSE are calculated - negative price included
MSE10 = mean(ya1)
MSE11 = mean(ya2)
MSE12 = mean(ya31)
MSE13 = mean(ya4)
MSE14 = mean(ya5)
MSEtot = mean(doneMSE1)

% negative price excluded
MSE12E = mean(ya3)
MSEtotE = mean(doneMSE)

% Annual and total MAE are calculated - negative price included
MAE10 = mean(yma1)
MAE11 = mean(yma2)
MAE12 = mean(yma31)
MAE13 = mean(yma4)
MAE14 = mean(yma5)
MAEtot = mean(doneMAE1)

% negative price excluded
MAE12E = mean(yma3)
MAEtotE = mean(doneMAE)

% Mean absolute percentage error
% These values do not include the multiplication of 100 and taking the
% absolute measure

% year 2010

```

```

yb10 = [0.09 0.00 -0.05 0.04 -0.01 0.01 -0.13 0.01 -0.07 0.02 -0.04 0.08 -
0.01 ...
-0.02 -0.07 -0.02 -0.04 -0.05 0.04 -0.08 -0.09 -0.03 -0.03];
% Annual absolute percentage errors are generated
ymp1 = abs(yb10)*100;
% year 2011
yb11 = [-0.10 -0.10 -0.05 -0.02 -0.01 0.03 -0.04 -0.01 -0.03 0.01 0.01 -0.01
-0.21 ...
-0.04 0.02 -0.07 -0.05 0.03 -0.02 0.04 0.03 -0.07 -0.01 -0.13 0.06 -0.01
0.08 ...
0.01 -0.01 0.02 0.04];
% Annual absolute percentage errors are generated
ymp2 = abs(yb11)*100;
% year 2012 with negative price excluded
yb12 = [-0.09 -0.07 -0.02 0.03 -0.09 0.06 -0.08 -0.13 0.05 -0.10 0.01 -0.11 -
0.01 ...
-0.01 0.00 -0.07 0.04 0.01 0.07 0.08 0.00 0.00 0.03 0.01 0.02 0.01 -0.03
0.05 -0.06 ...
-0.01 -0.01 0.03 -0.02 0.01 -0.16 -0.05 0.01 -0.02 -0.04 0.05 -0.05 0.14
-0.03 0.01 -0.20 -0.05 -0.33];
% Year 2012 with negative price included
yb121 = [-24.79 -3.66 -3.43 -0.89 1.43 -4.07 3.12 -3.47 -5.00 2.19 -4.26 0.46
-4.50 -0.46 ...
-0.47 -0.03 -3.51 1.76 0.28 3.11 3.59 -0.16 -0.12 1.41 0.28 0.72 0.25 -
1.15 1.80 -2.24 ...
-0.24 -0.30 1.06 -0.87 0.41 -5.28 -2.03 0.24 -1.06 -1.67 2.15 -2.35 10.46
-1.70 0.40 -8.02 -1.97 -10.30];
% Annual absolute percentage errors are generated
ymp3 = abs(yb12)*100;
ymp31 = abs(yb121)*100;
% year 2013
yb13 = [0.24 -0.13 0.02 0.01 -0.01 -0.01 0.12 -0.03 -0.07 -0.07 -0.15 0.06
0.01 -0.01 0.08 ...
0.00 0.09 0.06 0.07 0.05 -0.05 0.02 0.14 0.00 0.11 0.04 -0.26 -0.03 -0.04
0.20 -0.04 ...
0.04 0.04 -0.05 -0.17 0.02 0.15 0.01 -0.13 -0.09 0.12 0.07 0.06 0.01 -
0.07 -0.04 -0.11 0.07 0.45];
% Annual absolute percentage errors are generated
ymp4 = abs(yb13)*100;
% year 2014
yb14 = [0.01 -0.21 0.09 0.07 0.00 -0.10 -0.02 -0.14 0.08 -0.11 -0.31 -0.21];
% Annual absolute percentage errors are generated
ymp5 = abs(yb14)*100;
% A vector of the values is constructed
vector = [yb10 yb11 yb12 yb13 yb14];
vector1 = [yb10 yb11 yb121 yb13 yb14];
% The MAPE values are obtained
doneMPE = abs(vector)*100;
doneMPE1 = abs(vector1)*100;

% Annual and total MAPE are calculated - negative price excluded
MAPE10 = mean(ymp1)
MAPE11 = mean(ymp2)
MAPE12 = mean(ymp3)
MAPE13 = mean(ymp4)
MAPE14 = mean(ymp5)
MAPEtot = mean(doneMPE)

```

```

% negative price included
MAPEE12 = mean(ymp31)
MAPEtotE = mean(doneMPE1)

%% Evaluating risk premium - model based data

% the available weekly base load futures
forward = [44.10 50.00 48.00 40.00 39.10 41.50 44.00 46.00 44.75 44.75 47.75
48.00 49.50 ...
53.00 54.00 45.50 48.00 49.50 54.00 54.75 56.00 62.75 47.00 51.25 54.50 50.25
52.00 51.70 ...
56.00 51.00 61.50 54.50 53.90 54.30 57.75 59.60 55.75 53.00 52.10 51.00 49.50
50.50 46.95 ...
48.75 50.90 56.00 52.25 55.25 52.40 54.25 60.00 58.50 47.50 45.10 41.30 45.25
48.60 45.50 ...
54.00 62.50 53.50 41.70 47.00 44.40 43.40 43.00 38.25 47.00 43.00 38.50 41.00
37.70 39.50 ...
35.50 38.25 39.75 38.60 39.00 41.55 39.75 40.00 40.00 38.50 40.50 43.25 51.00
47.25 46.00 ...
47.00 45.50 40.75 47.75 45.50 44.75 44.50 46.40 49.00 48.60 50.25 55.90 46.50
15.25 ...
45.55 54.25 50.75 35.50 40.50 43.25 42.75 44.20 41.50 44.75 36.75 34.00 44.25
37.50 34.25 ...
28.00 26.75 31.55 28.70 36.00 32.25 29.50 27.50 27.00 32.29 32.50 40.50 38.25
33.15 38.78 ...
41.00 37.30 43.50 37.25 44.60 36.57 43.25 43.50 36.00 30.25 33.00 38.25 46.50
40.50 40.90 ...
48.70 38.00 16.25 31.00 36.00 43.50 41.00 43.95 34.50 33.50 34.50 33.50 32.25
32.30 34.50];

% The indices to the corresponding spot price values
index = [13 16 18 20 21 22 23 24 25 26 27 28 29 30 31 33 34 35 36 37 38 39 40
44 45 ...
47 48 49 50 52 53 54 55 59 60 61 64 65 66 68 69 70 71 74 78 80 82 83 84 86 87
88 91 92 94 ...
95 96 97 98 99 100 101 102 103 104 105 106 109 110 111 112 113 114 115 116
117 118 119 120 ...
121 122 123 124 125 126 127 129 130 131 132 133 134 136 137 138 139 140 141
142 143 144 ...
145 146 147 148 149 150 151 152 153 154 155 156 157 159 160 161 162 163 164
165 166 167 168 ...
169 170 171 172 173 174 176 178 179 180 181 182 183 184 185 186 187 188 189
190 191 192 193 ...
194 195 196 197 198 199 200 201 202 203 204 205 206 207 209];

RiskPrem = forward - yFAA(index);

% How many of the differences that are positive, i.e. upward biased
% estimator
count2 = numel(RiskPrem( RiskPrem(:)>0 ))

```

```

% A histogram is generated of the difference values, looks normal
% distributed
hist(RiskPrem)
axis([-30 30 0 80])
title('Risk premium')
xlabel('Euro')
ylabel('Frequency')

%Null hypothesis that the data comes from a population with mean equal to 0,
against the alternative that the mean is greater than 0.
% h = 1 = reject the null hypothesis
[h4, p4] = ttest(RiskPrem,0,'Tail','right')

%% Accuracy measures - model based data

% This script is dedicated to calculate the mean square error. The
% differences, spot-futures (actual-forcecasted)

% Furthermore, the largest number is erased

vector = (RiskPrem*-1);

% Annual and total MSE are calculated

MSEtot = vector.^2;

y11 = MSEtot(1:23);
y21 = MSEtot(24:54);
y31 = MSEtot(55:101);
y41 = MSEtot(102:150);
y51 = MSEtot(151:162);
MSE10 = mean(y11)
MSE11 = mean(y21)
MSE12 = mean(y31)
MSE13 = mean(y41)
MSE14 = mean(y51)
MSEtot = mean(MSEtot)

% Annual and total MAE are calculated

MAEtot = abs(vector);

y12 = MAEtot(1:23);
y22 = MAEtot(24:54);
y32 = MAEtot(55:101);
y42 = MAEtot(102:150);
y52 = MAEtot(151:162);

MAE10 = mean(y12)
MAE11 = mean(y22)
MAE12 = mean(y32)
MAE13 = mean(y42)

```

```

MAE14 = mean(y52)
MAEtot = mean(MAEtot)

% Annual and total MAPE are calculated

MAPEtot = abs(vector)./yFAA(indx);

y13 = MAPEtot(1:23);
y23 = MAPEtot(24:54);
y33 = MAPEtot(55:101);
y43 = MAPEtot(102:150);
y53 = MAPEtot(151:162);

MAPE10 = mean(y13)*100
MAPE11 = mean(y23)*100
MAPE12 = mean(y33)*100
MAPE13 = mean(y43)*100
MAPE14 = mean(y53)*100
MAPEtot = mean(MAPEtot)*100

% %% Model vs realized.... actual - model
%
% vectorr = pdone(2:209)-yFAA(2:209);
% square = vectorr.^2;
% MSEmodel = mean(square)
% MAEmodel = mean((abs(vectorr)))

%% Descriptive statistics
% descriptive statistics, realized price
DescrAct = [mean(pdone1) median(pdone1) skewness(pdone1) kurtosis(pdone1)
max(pdone1) min(pdone1) std(pdone1)]

% log returns, realized price
for i = 2:209
ActR(i) = log(pdone1(i)/pdone1(i-1));
end
% descriptive statistics, log returns
DescrActR = [mean(ActR) median(ActR) skewness(ActR) kurtosis(ActR) max(ActR)
min(ActR) std(ActR)]

% descriptive statistics, modeled price
DescrMod = [mean(yFAA(2:209)) median(yFAA(2:209)) skewness(yFAA(2:209))
kurtosis(yFAA(2:209)) max(yFAA(2:209)) min(yFAA(2:209)) std(yFAA(2:209))]

% log returns, modeled price
for i = 3:209
ModR(i) = log(yFAA(i)/yFAA(i-1));
end

% descriptive statistics, modeled price, log returns

```

```

DescrModR = [mean(ModR) median(ModR) skewness(ModR) kurtosis(ModR) max(ModR)
min(ModR) std(ModR)]

```

```

%% Information criteria - aic and bic

```

```

py = pdone2';
Mdl1 = arima(1,1,0);
Mdl2 = arima(0,1,1);
Mdl3 = arima(1,1,1);
Mdl4 = arima(2,1,0);
Mdl5 = arima(0,1,2);
Mdl6 = arima(2,1,2);
Mdl7 = arima(2,1,1);
Mdl8 = arima(1,1,2);
Mdl9 = arima(3,1,0);
Mdl10 = arima(0,1,3);
Mdl11 = arima(3,1,3);
Mdl12 = arima(1,1,3);

```

```

logL = zeros(12,1); % Preallocate loglikelihood vector
[~,~,logL(1)] = estimate(Mdl1,py,'print',false);
[~,~,logL(2)] = estimate(Mdl2,py,'print',false);
[~,~,logL(3)] = estimate(Mdl3,py,'print',false);
[~,~,logL(4)] = estimate(Mdl4,py,'print',false);
[~,~,logL(5)] = estimate(Mdl5,py,'print',false);
[~,~,logL(6)] = estimate(Mdl6,py,'print',false);
[~,~,logL(7)] = estimate(Mdl7,py,'print',false);
[~,~,logL(8)] = estimate(Mdl8,py,'print',false);
[~,~,logL(9)] = estimate(Mdl9,py,'print',false);
[~,~,logL(10)] = estimate(Mdl10,py,'print',false);
[~,~,logL(11)] = estimate(Mdl11,py,'print',false);
[~,~,logL(12)] = estimate(Mdl12,py,'print',false);

```

```

T = length(py);

```

```

% Calculating the aic and bic values

```

```

[aic,bic] = aicbic(logL, [3; 3; 4; 4; 4; 6; 5; 5; 5; 5; 8; 6], T*ones(12,1))

```

```

% several models are estimated

```

```

EstMdl1 = estimate(Mdl1,py);
EstMdl2 = estimate(Mdl2,py);
EstMdl3 = estimate(Mdl3,py);
EstMdl4 = estimate(Mdl4,py);
EstMdl5 = estimate(Mdl5,py);
EstMdl6 = estimate(Mdl6,py);
EstMdl7 = estimate(Mdl7,py);
EstMdl8 = estimate(Mdl8,py);
EstMdl9 = estimate(Mdl9,py);
EstMdl10 = estimate(Mdl10,py);

```



```

EstMdl11= estimate(Mdl11,py);
EstMdl12 = estimate(Mdl12,py);

% the estimated models' residuals are calculated

res1 = infer(EstMdl1,py);
res2 = infer(EstMdl2,py);
res3 = infer(EstMdl3,py);
res4 = infer(EstMdl4,py);
res5 = infer(EstMdl5,py);
res6 = infer(EstMdl6,py);
res7 = infer(EstMdl7,py);
res8 = infer(EstMdl8,py);
res9 = infer(EstMdl9,py);
res10 = infer(EstMdl10,py);
res11 = infer(EstMdl11,py);
res12 = infer(EstMdl12,py);

% Unit root test of the estimated models' residuals

[h5 p5] = adftest(res1);
[h6 p6] = adftest(res2);
[h7 p7] = adftest(res3);
[h8 p8] = adftest(res4);
[h9 p9] = adftest(res5);
[h10 p10] = adftest(res6);
[h11 p11] = adftest(res7);
[h12 p12] = adftest(res8);
[h13 p13] = adftest(res9);
[h14 p14] = adftest(res10);
[h15 p15] = adftest(res11);
[h16 p16] = adftest(res12);

nullhyp = [h5 h6 h7 h8 h9 h10 h11 h12 h13 h14 h15 h16]

pvalues = [p5 p6 p7 p8 p9 p10 p11 p12 p13 p14 p15 p16]

```