Extreme Value Strategies in the FX-market

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Preface

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Abstract

The foreign exchange market is known as one of the most efficient markets in the world, has a daily turnover of approximately $1.9 trillion and is open 24 hours a day seven days a week. In difference to what most people belive 80-95% of the market activity is of purely speculative behaviour. In order to speculate in market movements the investor needs to make a prediction of the future spot rate. There are many ways to do this and in this thesis we investigate methods using historical data to make predictions of future values. When using historical data which is sampled we lose information. This information can be partly restored using the high and low price samples. We investigate if it is possible to restore the lost information by using the high and low price samples and construct strategies that use this information to evaluate them against strategies that does not use the information. Our results shows that the extra information can be used to make more profitable strategies.

Contents

1 Introduction

1.1 Background

The foreign exchange market has a $1.9 trillion daily turnover, is open 24-hours a day and is known as one of the most efficient markets in the world. There are many participants in the foreign exchange market, some are none profit seeking but the majority, 80-95%, of the participants are pure speculative in their behavior [2]. This means that in order to make money out of the market, one important factor for success is to be able to forecast the currency exchange rates. Banks, companies, financial institutions and other participants are all trying to forecast the future prices, and they are using a variuos number of techniques. These techniques have traditionally been different kinds of time series models, especially the ARIMA-model proposed by Box and Jenkins, 1976. Later on, techinques, like Artificial Neural Networks, Genetic algorithms, Fuzzy logic etc. have been used for prediction. No mather of which technique that is used, the traditional approach has been to predict using the opening price and/or the closing price.

In order to extract excess returns from the market the speculator have to make some assumptions of the market's future behavior, and determine a way to enter and exit the market. This can be done in many different ways and results in many different strategies. To be able to construct more complex and profitable strategies one could predict the highest and lowest value during the next time step, and use this new information for building strategies.

1.2 Purpose

Where other papers have focused on forecasting of currency exchange rates using different techniques on opening prices, our focus lies in the prediction of the process hourly extremes and construction and evaluation of trading strategies. The main objective is to explore if it is possible to receive higher returns on a strategy when using extreme value predictions compared to a strategy using only the prediction of the hourly close price.

1.3 Limitations

In this thesis we have focused on the Foreign exchange market, but a similar study can be made on any other financial time series, whether it is equities or any other asset. Another limitation is that we have chosen to work with hourly data. This will influence the strategies and results due to the heavy costs of trading at a high frequency. When holding a position in a cross rate overnight, you are to receive a payment based on the differential between the interest rates of the two countries. The interest rate differential could be negative and this implies that you are charged instead. When performing our calculations we are not adjusting the results based on the interest rate differential since it will only influence the results insignificantly. We are calculating the predictions under the assumption that the closing price and opening price for the next hour are the same. Usually the opening and closing price differs in some sense and this will reflect our results.

1.4 Disposition

The thesis continuous with a short description of the Foreign Exchange market in Chapter 2. In Chapter 3 we present the Efficient Market Hypothesis. Then we look at different ways of constructing a Trading Model in Chapter 4. In Chapter 5 we turn to the Markowitz Portfolio Theory. When measuring the portfolio performance the Key Ratios gives us the information, these are defined in Chapter 6. In Chapter 7 basic statistical concepts and time series modeling are discussed. Chapter 8 explains the different strategies and Chapter 9 describes the methodology and our approach in detail. In Chapter 10 the portfolio results of our different strategies are presented. Finally our conclusions and proposals for future research are presented in Chapter 11.

2 The Forex market

2.1 Build up and Participants

The Foreign Exchange market or the FX-market as it also is called, is not physically located at one location. It is considered an Over-The-Counter market or Interbank market. This means that instead of having centralized exchange it is built up from a network of dealing rooms.

The dealing rooms' main objectives are to receive customer orders, give prices to customers, net currency deals with other deals, offload risk on other banks and offload other banks' risk as well.

The participants of the FX-market include central banks, commercial banks, investment banks, large multinational corporations, global money managers, registered dealers, international money brokers, futures, options traders and private speculators.

The FX-market is a 24 hour global market. This means that it never closes. Market activity is though limited on the weekends and highly dependent on which countries that's awake for the moment.

2.2 Daily Turnover

The FX-market daily turnover was estimated at $1.9 trillion in April 2004, with an increase of 57% since april 2001 measured with current exchange rates.[1] The FX-market turnover by location is shown in the table below and shows that the largest activity is taking place in the UK and UK literally means London.

Location	*Market Shares (%)*
UK	32 %
US	16 %
Japan	9 %
Singapore	6 %
Germany	5 %
Switzerland	4 %
Hong Kong	4 %
Australia	3 %
France	3 %
Canada	3 %
Other	15 %

2.3 Cross rates, Spreads and Commissions

When trading on the FX-market you place your positions in something called a cross rate. The cross rate consists of two currencies which forms a pair, a cross rate pair. When taking the trade you sell one currency and buy the other. For example if expecting that the Euro is getting stronger and the USD weaker you would take a long position in the cross rate EUR/USD, this means that you buy Euro and sell US dollar for the same amount.

Approximately 85% of all daily trading is done in the cross rates of the major currencies, the Majors are: US Dollar, Yen, Euro, Sterling, Swiss Franc, Canadian Dollar and the Australian Dollar.

The FX-market is almost entirely free of commissions, the only cost is due to the bid-offer spread. The bid-offer spread is the difference between the rate the market maker sells and the rate he buys. This means that if you buy and sell at the same time you will end up loosing the spread. The spread can be viewed as the price the customer pays to the market maker for entering a position.

3 Efficient Market Hypothesis - EMH

EMH, formulated by Eugene Fama in 1970, is an investment theory that states that it is impossible to "beat the market", because all relevant information that reflects the prices is already incorporated in the price. This theory is also known under the name "market efficiency", and it is related to the Random Walk Theory. When money is put into the Forex market, or any other market, it is usually done with the purpose of generating a return on the invested capital. Many investors try not only to make a profitable return but also to "beat" the market. To their help they may use fundamental and/or technical analysis, but that is impossible if the EMH theory holds. There are three different forms of market efficiency, the weak form, the semi-strong form and the strong form

3.1 The weak form

This form of efficiency reflects the situation where prices follow a "Random Walk". This means that prices move up or down on a random basis without regard to what has happened in the previous days, with other word the process has "no memory" (e.g. a Markov process). This also implies that there is no predictable pattern in price time series, so it's useless to look at historical prices to predict future prices. The weak form of efficiency suggests that current prices fully reflect any information contained in historical prices. There are some investors who try to identify patterns occurring in the prices, this is known as technical analysis. However, this type of analysis will not be profitable for investors in a capital market that has weak form efficiency, because according to the theory there are no predictable patterns to detect.

3.2 Semi-strong form

The semi-strong form extends the weak form a little further and describes the situation where any public information relating to the certain asset will be reflected in its price. There are some investors who spend time analyzing for example a company's annual report, announcements, industry trends, economic forecasts and so on, this is known as fundamental analysis. However, this type of analysis will not be profitable for investors in a capital market that has semi-strong form efficiency, because according to the theory this information has already been incorporated into the price of a certain asset. Moreover there is an assumption that new information comes unpredictably and is incorporated very fast in the price. Once again there will not be any (predictable) patterns after, for example new reports. So these investors will be wasting their time as this information is already incorporated in the price.

3.3 Strong form

This last form of efficiency is the most complete form of efficiency in the sense that it describes the situation where all relevant information, whether it is public or private information, where the later one means "insider" information. This means that even if an investor has access to "inside" information, it's impossible to make superior returns. This is due to that even the "insider" information is already incorporated in the price.

The EMH is a controversial and often disputed theory. Supporters of this model believe it's pointless to search for undervalued stocks or try to predict trends in the market through any technique from fundamental to technical analysis. Academics point to a large volume of evidence in support of EMH.

But most traders use some form of technical analysis, and most analysts and fund managers use some kind of fundamental analysis. If that did not work for them they probably would not be in the business.

Our purpose with this thesis is not investigate whether the EMH holds or not, but rather to have it in mind when we are developing trading models.

4 Trading Models

A trading model aims at describing the future behavior of the exchange rate. This forecast is then used to make active management decisions. Most models forecasts the direction of the market movements instead of a precise future rate.

One way of categorizing trading models, according to James Binny at ABN Amro [3] ,is to organize them according to the following aspects.

1. Time Horizon
2. Degree of judgement employed
3. Modeling technique
4. Source of alpha

4.1 Time Horizon

The time horizon has the following suborder

Long term: measured in years
Medium term: measured in months
Short term: measured in days, weeks
Very short term: measured in hours

When moving along the time horizon from the long to the very short term the models and the techniques used to forecast move from fundamental research models in the long term to forecasts using time series in the shorter term. One problem with taking long term positions is that when the forecast finally is achieved the client may already have withdrawn his money due to under performance. The models that we are investigating in this thesis is categorized under the very short time horizon.

4.2 Degree of judgement

When talking about: The degree of judgement employed we focus on how a currency manager manages the investment process. On one end of the scale we find an investment process which is managed completely by human judgement and on the other side we find a automatic investment process driven without human interference.

The degree of judgement employed can be subordered as follows

4.2.1 Pure discretionary

Those managers that has a pure discretionary process uses fundamental, political and other factors to make a prediction of the future exchange rate.

4.2.2 Flexible decision support

Flexible decision support can be describe as a manager that uses many different models to make decisions and uses them according to what he feels is suitable at the moment.

4.2.3 Systematic investment process

The systematic investment process is a model based on a set of rules that gives the manager recommended positions to trade, though he has the full control of what trades to take, the level of risk and how to time the market.

4.2.4 Pure Black-Box

The pure Black-Box system is a system that's almost independent of human contact. The Black-Box is often self updating and uses advanced statistical methods extract returns from the market. The models we are using and investigating is typical Black-Box models.

4.3 Modeling Technique

When choosing modeling technique there are many different ways to proceed. We have chosen to use Auto Regressive Moving Average models to model the time series. Other techniques are Neural networks, Genetic algorithms and fuzzy logic to name a few. When trying to solve the problem of modeling the returns of a financial asset with time series models there are different situations that can appear. If we denote the asset time series as $Y(k)$ then the different situations that can occur are:

$\{Y(k)\}$ is independent, identically distributed with a unknown distribution. This gives us the opportunity, given the observed process, to estimate the probability function and receive a approximate knowledge about the process future value, in terms of a point estimate or a confidence interval for $Y(k+1)$.

If $\{Y(k)\}$ is independent, identically distributed with a known distribution. Then the observations do not give us any further information about the process statistical properties.

If there is a dependence between different $Y(k)$ which are completely known, we can use this to enhance the accuracy of predictions. The greater the dependencies are the better predictions we can make.

4.4 Source of alpha

In portfolio theory Alpha is a measure of the excess returns in comparison to the market portfolio. The higher your Alpha, the better your portfolio has done in achieving excess returns. It is generally considered the higher the alpha, the better the trading model performs. An Alpha model is solely a trading model that tries to perform better than the market portfolio. When speaking of 'The source of alpha' it refers to the different techniques used to gain the excess returns. Two of the most common techniques are PPP and Trend following.

4.4.1 PPP

Purchasing-power-parity(PPP) states that the price of a good in one country should equal the price of an equal good in an other countries currency. If this is not true you should expect the currencies to move in a direction such that they eventually reach equilibrium.

4.4.2 Trend following

Technical analysis was originally based on visual pattern recognition of the price charts. When using pattern recognition as a source of alpha the assumption, of that the market has a memory and that patterns occurs repeatedly, is made. An other form of technical analysis is based on using advanced statistical methods on the price time series and this is what we are using.

5 Portfolio Theory

5.1 Minimum Variance Portfolio

The Portfolio Selection Theory explains how to combine a group of assets in a portfolio in the best way in response to estimated return and variance. If we plot all possible portfolio constructions that can be attained according to estimated return and variance, and select the portfolios that have the lowest variance(risk) given a particular level of expected return, we get a perimeter called the minimum variance set. The minimum variance set's top half is known as the efficient set and represents the highest attainable expected return portfolios for different levels of risk. The portfolio that has the lowest risk of all attainable portfolios is know as the global minimum variance portfolio (MVP).

5.2 Finding the MVP

Finding the minimum variance portfolio for a given level of expected return can be approached as follow. If we introduce the following variables:

$w = [w_1, ..., w_N]$, Array of portfolio weights, N assets.

$\sum_{i=1}^{N} abs(w_i) = 1$, N assets.

$r = [r_1, ..., r_N]$, Array of expected rate of return of N assets.

C, Covariance matrix.

Then

$E(r_P) = wr^T$, Portfolio expected rate of return.

$\sigma_P^2 = wCw^T$, Portfolio variance.

Minimize $\sigma_P^2 = wCw^T$ on the restrictions

$E(r_p^*) = wr^T$

5.3 Power Mapping

When estimating the covariance matrix for the Markowtiz portfolio calculations you should not use the standard (random sample covarians) according to [5], you should instead use a different estimation method such as Power Mapping to receive better results.

Power mapping is a technique developed by [7] to reveal the true correlations buried under the noise in a correlation matrix. If the time series are long enough the true correlations become visible under the noise, the Power mapping technique is an procedure to prolong the time series and thereby enables us to identify the noise in a given correlation matrix.

The power mapping transformation of the correlation matrix is used as follows:

$$C_{kl}^{(q)}(T) = sign(C_{kl}(T)) \mid C_{kl}(T) \mid^{q}$$

where the best separation is obtained when q=1.5.

6 Key ratios

In order to determine the internal rank of different strategies there are several different measures to use: average annual return, turnover, success ratio, Sharpe ratio, maximum drawdown and Calmar ratio.

6.1 Average return

The average return is a good indicator of the performance. Inevitably is has some flaws, an high average return can be misleading if the returns are driven by additional risk taking or if the returns are influenced by outliers.

6.2 Average Turnover

The average turnover is defined as the average number of position changes during a year. Every change of direction in a position results in a transaction cost and it is therefor an important aspect in the evaluation process.

6.3 Success ratio

The success ratio measures the amount of profitable trades relative to the amount of loosing trades.

6.4 Sharp Ratio

The Sharpe Ratio i defined as follow:

$S = \frac{r_p - R_f}{\sigma_p}$

where r_p is the realized return, R_f is the risk free rate and σ_p is the realized volatility.

6.5 Information Ratio

The Information Ratio i defined as follow:

$IR = \frac{r_p}{\sigma_p}$

where r_p and σ_p is defined as above.

6.6 Maximum Drawdown

The maximum drawdown is defined as the largest consecutive loss during the portfolios lifetime and is an indication of the drawdown risk involved in the portfolio.

6.7 Calmar Ratio

The Calmar ratio is defined as follows:

$C = \frac{r_p}{MaximumDrawdown}$

The higher the Calmar Ratio the better. A portfolio can show large annual returns but also have significant draw down risks. The Calmar Ratio is a measure of returns but is adjusted to the draw down risk as well.

6.8 Problems with overoptimization

Problems with overoptimization, overfitting or data mining as it's also called, appears when the model is optimized in such a way that the performance is due solely to the fit of the available data. To keep our models from this problem we are using two consecutive data sets, one that we use for building the models and one for use when simulating the trades of the portfolios. This enables us to give more realistic results that is not influenced by over optimization.

7 Time Series Analysis

Before the models that will be used are presented, some basic statistical concepts will be described. First of all a *stochastic process* is defined. A stochastic process with parameter space Z is a family

$$X(t), t \in Z \tag{1}$$

of stochastic variables defined on one single sample space Ω. At a specific time point t, X_t is a random variable with a specific density function. Given a specific $\omega \in \Omega$, $X_t = \{X_t(\omega), t \in Z\}$ is a realization or a path of the process.

7.1 Characteristics of the stochastic process

When modeling stochastic processes it is essential to have some information about the characteristics of the process. This usually means that the density functions or the moment functions are known. With knowledge about these functions it is possible to make more accurate predictions. So before going further describing different kinds of stochastic processes, these functions will be defined.

7.1.1 Density functions

The *joint cumulative probability function* (cdf) is defined as

$$F_{t_1,\ldots,t_n}(x_1,\ldots,x_n) = P(X_{t_1} \le x_1,\ldots,X_{t_n} \le x_n) \tag{2}$$

The *conditional cdf* of a stochastic process X_t for any $t_1,\ldots,t_n \in$ Z with $t_1 < t_2 \ldots < t_n$ is defined as

$$F_{t_n|t_1,\ldots,t_n}(x_1,\ldots,x_n) = P(X_{t_n} \le x_n | X_{t_{n-1}} = x_{n-1},\ldots,X_{t_1} = x_1) \tag{3}$$

7.1.2 Moment functions

Next the moment functions of a stochastic process are defined. It's assumed that the moments exists, otherwise the corresponding function is not defined.

The *mean function* of a stochastic process is defined as

$$\mu(t) = E[X(t)] \tag{4}$$

Usually, the mean function depends on time t, e.g. processes have a deterministic trend or a seasonal or periodical structure. The variance function of a stochastic process is defined as

$$var(t) = V[X(t)] \tag{5}$$

The *auto covariance function* of a stochastic process is defined as

$$\gamma(s,t) = C[X(s), X(t)] \tag{6}$$

The *correlation function* of a stochastic process is defined as

$$\rho(s,t) = \rho[X(s), X(t)] \tag{7}$$

The functions defined above depends on each other as:

$$\gamma(t,t) = var(t) = V[X(t)] \tag{8}$$

$$\rho(s,t) = \frac{C[X(s), X(t)]}{\sqrt{V[X(s)]V[X(t)]}} = \frac{\gamma(s,t)}{\sqrt{\gamma(s,s)\gamma(t,t)}} \tag{9}$$

The *cross covariance function* is an other important moment function, it describes how two different stochastic processes, X and Y depends on each other, and is defined as

$$\gamma_{X,Y}(s,t) = C[X(s), Y(t)] \tag{10}$$

7.2 Stationarity

The dependency between different X(s) and X(t) for a stochastic process can be shown in many different ways, it is therefore necessary to make some simplified assumptions about the process. There are mainly three such assumptions, which reduces the difficulties with dependencies. The first one is the *Markov-principal*, which is close connected to the concept state space variables. The Markov-principal says that the events which will occur in the interval (t,t+h] depends on what has happened in the interval (0,t] solely by the value on X(t). The second assumption is a variant of the first assumption, it says that the expected value of a future change of the process is zero, no matter what has occurred in the past. Processes with this property is called a *martingale* and they are frequently used within Financial statistics. The third assumption which makes the dependency of the stochastic process easier to handle with is called the *Stationary-principal*. It is this one that we will use in our thesis.

A stochastic process X is *weakly stationary* if both following conditions holds

$$\mu(t) = \mu \tag{11}$$

$$\gamma(t, t-\tau) = \gamma(\tau) \tag{12}$$

where τ=t-s and s < t. The second conditions means that the auto covariance function only depends on time interval τ and not on time t.

A stochastic process X, is *strictly stationary* if for any $t_1, \ldots, t_n$ and for all n,s $\in$ Z, the following condition holds

$$F_{t_1,\ldots,t_n}(x_1, \ldots, x_n) = F_{t_{1+s},\ldots,t_{n+s}}(x_1, \ldots, x_n) \tag{13}$$

A short notice, is that a stochastic process may be strictly stationary without being weakly stationary when the variance (or covariance) function is not defined. But if the two first moment functions exist, then weakly stationary follows from strictly stationary. The strictly stationarity condition is often a too hard assumption for financial time series, so in this thesis we rest our stationarity tests to the weaker form.

7.3 Some Stochastic Processes

After a short description of some basic statistical concepts that describes the properties of stochastic processes it is now time to look at some elementary examples of stochastic processes. A stochastic process X is *white noise* if the two following conditions hold

$$\mu(t) = 0 \tag{14}$$

$$\gamma(\tau) = \begin{cases} \sigma^2, & when \tau = 0 \\ 0 & when \tau \neq 0 \end{cases} \tag{15}$$

A stochastic process X, follows a *Random walk* if it can be represented as

$$X(t) = c + X(t-1) + \epsilon(t) \tag{16}$$

where c is an constant and ϵ is white noise. If c is a nonzero constant then the variables

$$Z(t) = X(t) - X(t-1) = c + \epsilon(t) \tag{17}$$

have a nonzero mean, and we call this process a random walk with drift. The random walk has historically been a very popular model, ever since it was introduced 1900 by Louis Bachelier. The random walk as it is defined here can be seen as the boundary case for an AR(1)-process, as $a \to 1$. The AR(p)-process is defined below.

7.3.1 Auto Regressive Processes

A weak stationary process $Y(t)_{-\infty}^{\infty}$ is an AR(p)-process, of order p, if the sequence $X(t)_{-\infty}^{\infty}$, which is given by

$$X(t) + a_1 X(t-1)+, \ldots, +a_p X(t-p) = e(t), \tag{18}$$

is white noise, and if e_t is uncorrelated with X(t-1), X(t-2),. . . .

7.3.2 Moving Average Processes

An intuitive and simple way to introduce a dependency for a stationary process $X(t)_{-\infty}^{\infty}$, is to look at it as a weighted sum of uncorrelated stochastic variables. This leads us to the introduction of the MA(q)-process. It is defined as

$$X(t) = e(t) + c_1 e(t-1)+, \ldots, +c_q e(t-q), \tag{19}$$

7.3.3 Auto Regressive Moving Average Processes

A natural generalization is to connect in series an AR(p)-filter and a MA(q)-filter to obtain an ARMA(p,q)-process, it is defined as

$$X(t) + a_1 X(t-1)+, \ldots, +a_p X(t-p) = e(t) + c_1 e(t-1)+, \ldots, +c_q e(t-p), \tag{20}$$

7.4 Transformation

Forex data is a good example of non-stationary time series, and to model such data with stationary models, one must first transform it so that it becomes stationary. For example, if the data has a trend component, the model will have a dependency on several lagged values, this will then make the model slow to new chocks. It will take a quit a long for the model to fit the data again. One of the most commonly used transformations on financial data is the so called Box-Cox-transformation, i.e logarithm the data and then differentiate it once, or equivalently take the ratio between X(t) and X(t+1) and then logarithm this new time series, where X is the cross rate between two foreign exchanges.

$$Y = ln(X(t+1)) - ln(X(t)) = ln(\frac{X(t+1)}{X(t)}) \tag{21}$$

This transformation is the one that we will use in our thesis.

7.5 Choice of Model structure

There are several approaches to choose the model structure. A commonly used method is to do a hypothesis test. An other approach is use to different kind of information criterions. We have chosen Akaike's *Final Prediction Error* (FPE).

7.5.1 Akaike's FPE

FPE is used for comparing different models and it rewards their ability of prediction and at the same time punishes higher order models with more parameters. FPE is defined as

$$FPE = \hat{\sigma}^2 \frac{1 + \frac{p}{N}}{1 - \frac{p}{N}} \tag{22}$$

where p is the number of parameters to be estimated, N is the number of estimation data and $\hat{\sigma}^2$ is the asymptotic variance of the prediction error. By minimizing FPE as a function of n, the order of the process is decided. The FPE is a general method, this means that the AR-models can be compared with the ARMA-models by comparing the FPE's for respectively model.

7.5.2 Model validation

A general assumption when dealing with time series models is that the process {e(t)} is white noise. Where {e(t)} is the insignal to the models defined in **??**. To test if this assumption holds one can look at the residuals from the models. This is called Residual Analysis. The residuals are defined as

$$\epsilon(t) = y(t) - x^T(t)\hat{\Theta} \tag{23}$$

and if the model is fairly correct, ϵ(t)$\approx$ e(t).

There are many different types of Residual Analysis. One of the most important ones, is the *estimation and test of the correlation function* and is defined as

$$\rho^*_\epsilon = \frac{\gamma^*_\epsilon(k)}{\gamma^*_\epsilon(0)} \tag{24}$$

where

$$\gamma_\epsilon^*(k) = \frac{1}{N-n}\sum_{t=n+1}^{N-k} \epsilon(t,\hat{\Theta})\epsilon(t+k,\hat{\Theta}) \tag{25}$$

If $\epsilon(t,\hat{\Theta})$ is white noise, i.e, $\rho_\epsilon(k)$=0 for k=1,2,..., then the estimation $\rho_\epsilon^*(k)$ is approximately N(0,$\frac{1}{\sqrt{N'}}$) for these k, where N is the number of data in the time series and n is the number of lagged values in the model. One may then check if the values $\rho_\epsilon(1)$=0, $\rho_\epsilon(2)$=0,..., are significantly different from to zero, which then indicates dependency. If one test many values $\rho_\epsilon(k)$ then there may be some significant results that can appear because of randomness.

8 Strategies

8.1 Benchmark Strategies

8.1.1 Strategy 1

The opening price predictions are used to determine the direction of the next position, i.e we look at the sign of the next prediction and takes a position accordingly. The position is then closed at the end of the time period if the predicted direction changes.

8.1.2 Strategy 2

The opening price predictions are used as target levels, i.e the position is closed if the spot reaches the target level. If not the position is closed at the end of the time period.

8.2 Extreme Value Strategies

8.2.1 Strategy 3

The high predictions are used as a target level and the position is closed if the spot reaches the level. If not the position is closed at the end of the time period.

8.2.2 Strategy 4

The low predictions are used as target levels and we take a position accordingly. If the spot reaches the target level the position is closed. If the target level is not reached the position is closed at the end of the time period.

8.2.3 Strategy 5

The high and low predictions are used as target levels but only one position is taken in the direction of the largest prediction. If the position does not reach the level it is closed at the end of the time period.

8.2.4 Strategy 6

The high and low predictions are used as sell and buy signals. If the spot reaches the predicted high we sell and if the predicted low is reached we buy. If only one of the levels is reached during the time period the position is closed at the end of the period. If no level is reached we do nothing.

9 Methodology

9.1 Data

The data we are using are composed of five different Foreign Exchange cross rates; Eur/Usd, Eur/Gbp, Eur/Chf, Usd/Chf and Usd/Jpy and is downloaded from FINAM Investment Holding's home page www.fin-rus.com. FINAM is a Russian full service investment company located in Moscow. The different cross rates consists of Open, High, Low and Close values sampled on an hourly basis. The data set is 14,000 values long and starts in February 16, 2001 and ends at December 03, 2003. The data set has been divided in two parts with 7,000 values in both data sets. The first data set is used for model estimation and the second data set is used for model validation and finally for the trading simulation.

In the plots below (figures 2-5) the different cross rates are presented for the last 7,000 values, i.e the second data set. After these plots the mean and the standard deviation are put together in a table.

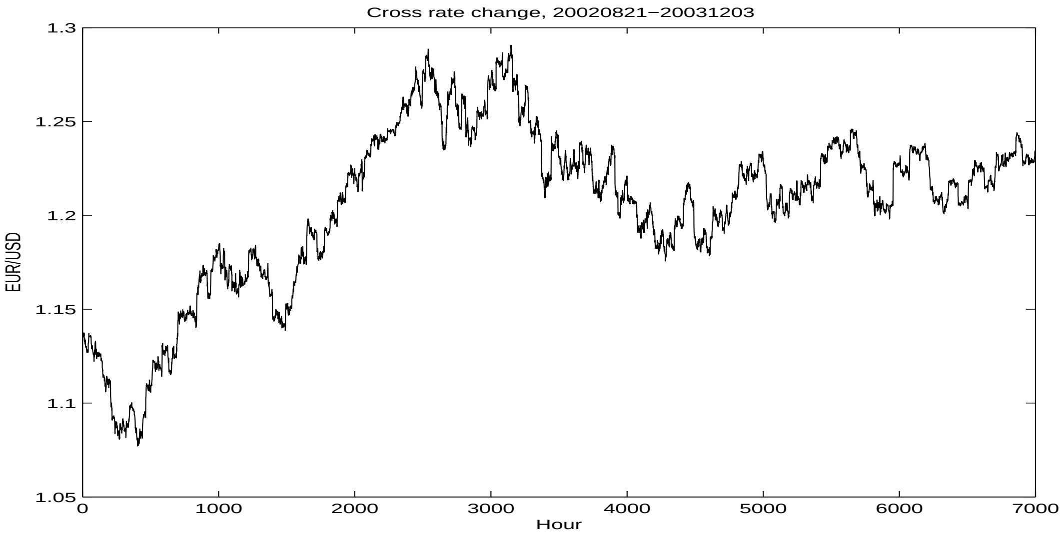

Figure 1: Cross rate change, EUR/USD, 20020821-20031203

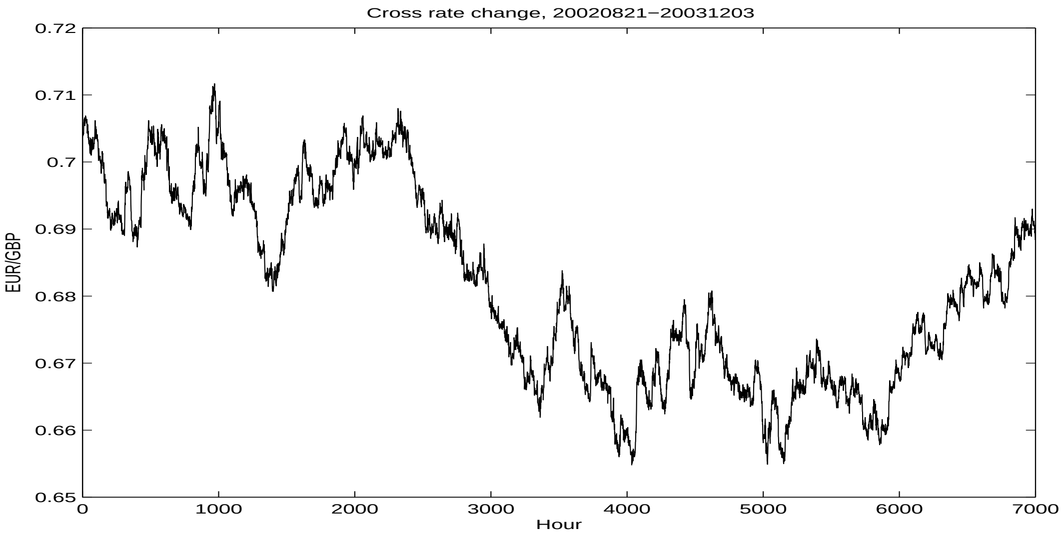

Figure 2: Cross rate change, EUR/GBP, 20020821-20031203

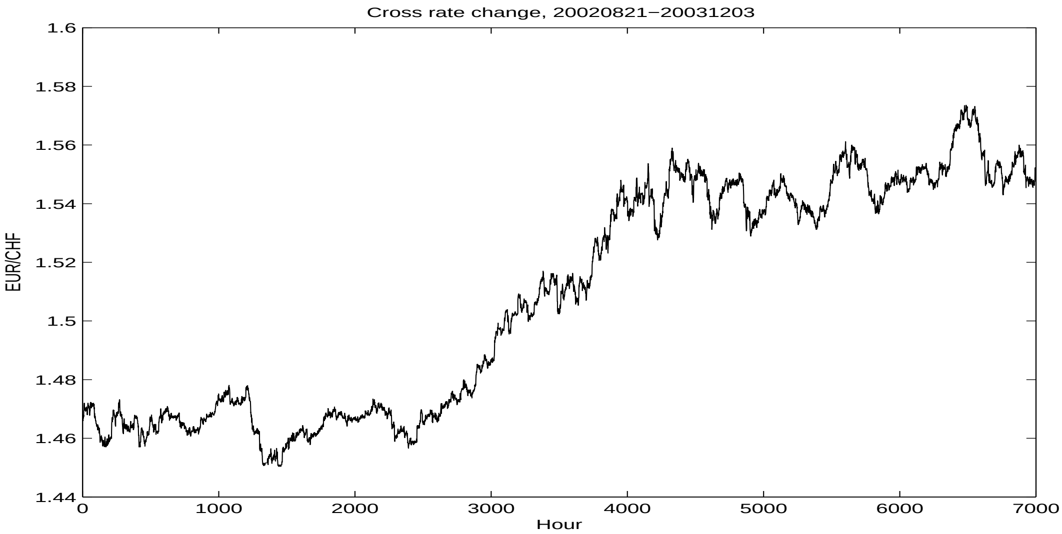

Figure 3: Cross rate change, EUR/CHF, 20020821-20031203

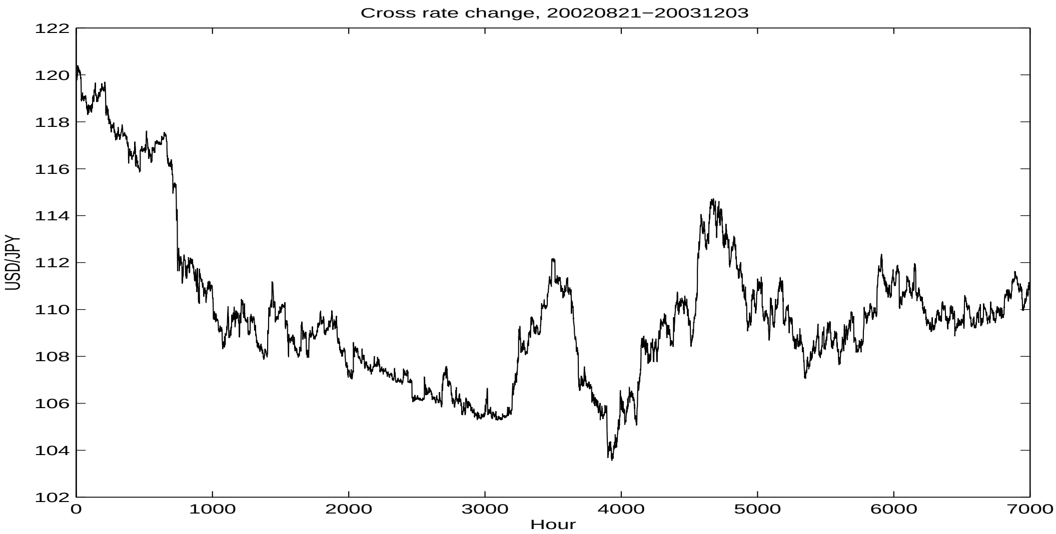

Figure 4: Cross rate change, USD/JPY, 20020821-20031203

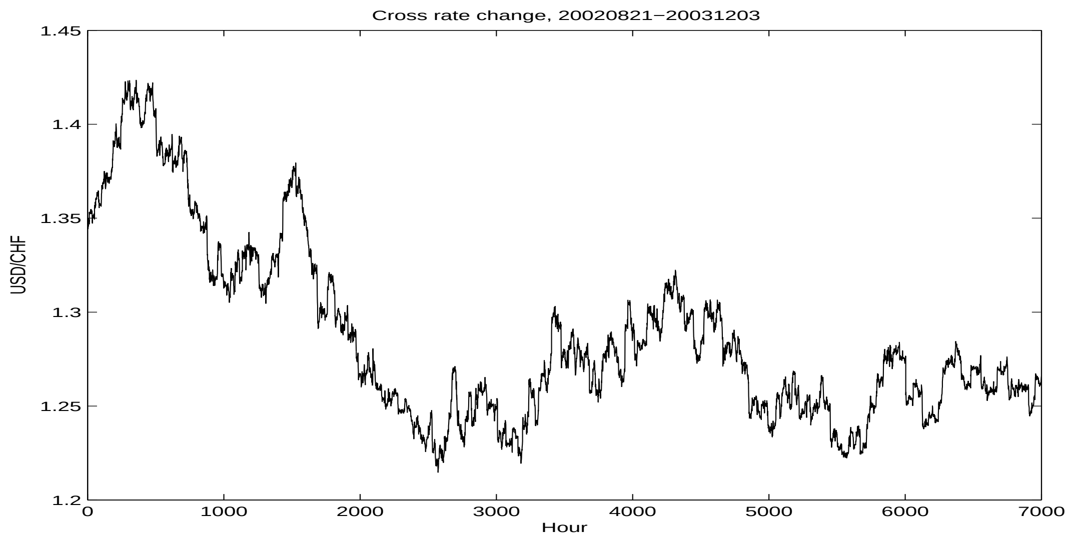

Figure 5: Cross rate change, USD/CHF, 20020821-20031203

Data Statistics	*Mean*	*Standard deviation*
EUR/USD	1.2052	0.0442
EUR/CHF	1.5079	0.0385
EUR/GBP	0.6815	0.0144
USD/CHF	1.2867	0.0478
USD/JPY	109.8809	3.3012

In practice, observed financial data often has properties which a stationary model has difficulties to achieve. To deal with this problem one can use nonstationary models or transform the data, if possible, so that it becomes stationary. In this thesis we have, as mentioned above, chosen stationary models so in order to make the data stationary we have used one of the commonly used Box-Cox-transformations, see Transformation 7.4.

In figure 6, one hour of tick quotes for the Eur/Usd is highlighted. When sampling the process with 1 hour samples. Point A is defined as the Open price. The maximum price level during the hour is marked B and is defined as the High price. The minimum price level, C, is defined as Low and the price at the end of the time period , D, is defined as the Close price.

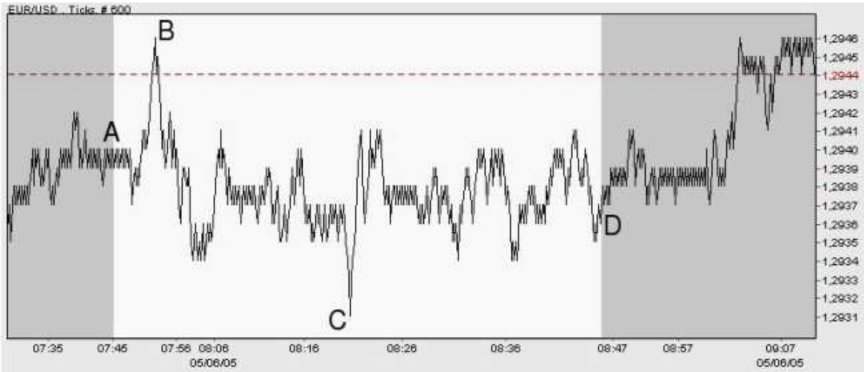

Figure 6: A: Open, B: High, C: Low, D: Close

9.2 Model Selection

The next step is to choose an appropriate model structure, and for this purpose we have used the MATLAB functions ARX and ARMAX which computes the LS-estimates (Least Squares) of the AR- and ARMA-parameters respectively. The resulting models that are estimated are stable, i.e the poles and zeros are within the unit circle. ARX and ARMAX also computes confidence intervals for the estimated parameters with 95% significance level. To choose an appropriate model, one must first check whether the estimated parameters are sigificantly different from zero, otherwise the parameter(s) should not be in incorporated in the model. When the models has been rejected, for which the Hypothesis H_0 : parameter(s) $= 0$ holds, one choose the model which has the lowest FPE.

When the model structure has been chosen, the parameters have been estimated and the order number for the model has been decided it is time for the model validation. The purpose of the model validation is to check that the data are consistent with the chosen model.

9.3 Auto correlation

As mentioned in Time Series Analysis chapter, it is important to first transform the data to eliminate nonstationarities and dependencies in the data. The results of these transformations can be seen in the plots below (figures 2-4). The untransformed data show (figure 2) evidence of strong autocorrelation, this will give us slow models which takes long time to react on new chocks. This kind of dependency is not desirable therefore we have transformed the data with an ordinary Box-Cox transformation, i.e first the logarithm of the data and then a differentiation. As can bee seen in the plot below (figure 3), the auto correlation is eliminated. In the third plot (figure 4) one can easily see that the data has been over-differentiated, we have now introduced dependency in the transformed data again. The last transformation was a variant of the Box-Cox transformation used in the the first transformation, but here we have differentiated it one more time.

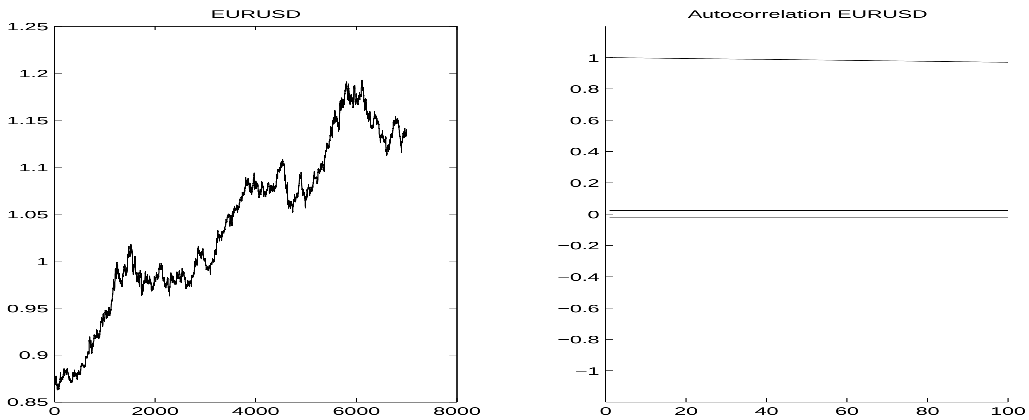

Figure 7: EURUSD-untransformed and its Autocorrelation function

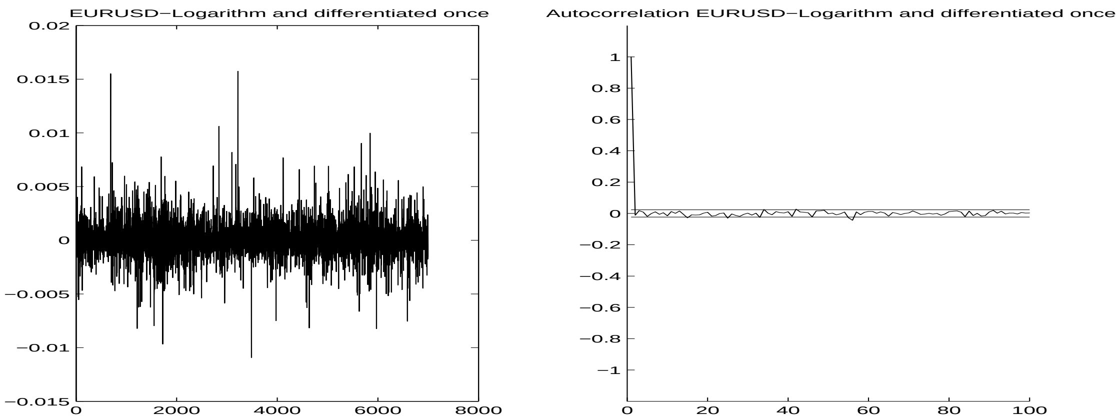

Figure 8: EURUSD-Logarithm and differentiated once and its Autocorrelation function

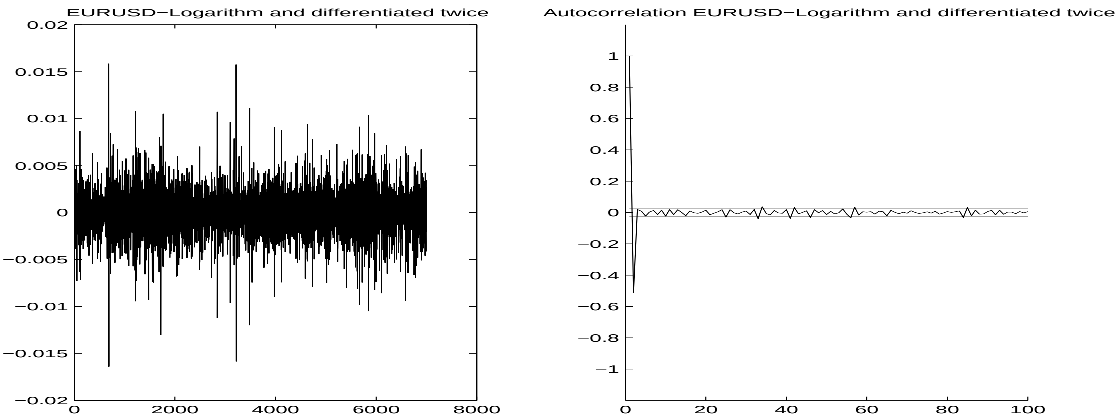

Figure 9: EURUSD-Logarithm and differentiated twice and its Autocorrelation function

9.4 Estimation and Validation of Models

In the tables in the Appendix 13.1, the result of the hypothesis tests of the model parameters and the FPE measures are presented for respectively model. We have estimated the parameters for AR(1),. . . , AR(4) and ARMA(1,1), ARMA(1,2), . . . , ARMA(4,4). In these tables we have only included those model for which the hypothesis

$$H_0 : a_i, c_i = 0, \forall i$$

does not holds, the other have been discarded. When the hypothesis test is done, the models are ranked according to Akaike's Final Prediction Error. The model with the lowest value on the FPE is the best model for predicting new values. The result of the Hypothesis test and the choice of best model is presented in these tables as well. The models with the best (lowest) FPE for respectively time series is indicated with bold letters.

In the table below we have put together the best models for respectively time series from the tables above and also presented the estimated parameter values.

EURUSD	*Model*	*A(q)-polynomial*	*C(q)-polynomial*
OPEN	ARMA(2,2)	$A(q) = 1 + 0.7519q^-1 + 0.3695q^-2$	$C(q) = 1 + 0.7186q^-1 + 0.3396q^-2$
HIGH	AR(1)	$A(q) = 1 - 0.09356q^-1$	-
LOW	AR(1)	$1 - 0.1057q^-1$	-
EURCHF	*Model*	*A(q)-polynomial*	*C(q)-polynomial*
OPEN	ARMA(1)	$A(q) = 1 + 0.01219q^-1$	-
HIGH	ARMA(2,2)	$A(q) = 1 - 1.465q^-1 + 0.6722q^-2$	$C(q) = 1 + 1.473q^-1 + 0.6875q^-2$
LOW	ARMA(1,1)	$A(q) = 1 + 0.9314q^-1$	$C(q) = 1 + 0.9377q^-1$
EURGBP	*Model*	*A(q)-polynomial*	*C(q)-polynomial*
OPEN	AR(3)	$A(q) = 1 + 0.1105q^-1 + 0.03426q^-2+$ $+0.01933q^-3$	-
HIGH	AR(1)	$A(q) = 1 - 0.02797q^-1 + 0.02338q^-2+$ $+0.01925q^-3$	-
LOW	AR(1)	$A(q) = 1 - 0.02921q^-1 + 0.0498q^-2+$ $+0.01996q^-3 - 0.02089q^-4$	-
USDCHF	*Model*	*A(q)-polynomial*	*C(q)-polynomial*
OPEN	ARMA(2,2)	$A(q) = 1 + 1.102q^-1 + 0.5733q^-2$	$C(q) = 1 + 1.085q^-1 + 0.5535q^-2$
HIGH	AR(1)	$A(q) = 1 - 0.1234q^-1$	-
LOW	AR(1)	$1 - 0.09426q^-1$	-
USDJPY	*Model*	*A(q)-polynomial*	*C(q)-polynomial*
OPEN	ARMA(2,1)	$A(q) = 1 + 0.7796q^-1 + 0.0232q^-2$	$C(q) = 1 + 0.7507q^-1$
HIGH	AR(1)	$A(q) = 1 - 0.0972q^-1$	-
LOW	AR(1)	$1 - 0.06183q^-1$	-

9.5 Residual Analysis

As can be shown in the plots (figure 5-19) showing the autocorrelation for the residuals, they are mostly inside the 95% confidence interval. There are a few values that are just outside the limits. As mentioned earlier in the Model Validation 7.5.2, there may appear some significant values just because of randomness. An other aspect to have in mind is that the we have used 7,000 values which makes the confidence limits very tight. Recall that the standard deviation is approximately N(0,$\sqrt{\frac{1}{N'}}$), where N' is the number of residuals. The last aspect is a result of our big data set, we are using hourly data over a time period of 16 months. When doing a residual analysis one shall divide the data set in parts, the first part is for model estimation and the second part for model validation according to [9].

9.6 Back transformation

The models have been estimated on transformed data and to be able to make a prediction of next value in the original data series one must back transform the data. First we have made a prediction of the transformed time series and then we have transformed it back. The plot below (figure 20) is an example of how this looks like.

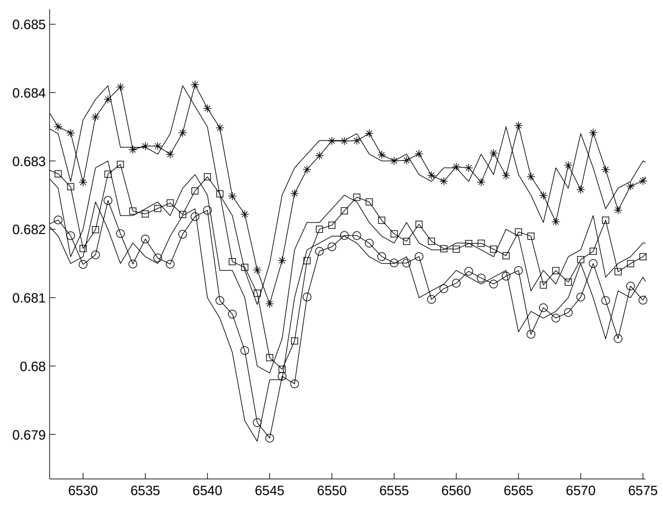

Figure 10: Prediction EURGBP

When the prediction models have been estimated and validated we now turn to the investigation of the different strategies.

9.7 Trading the Strategies and Combining the Portfolios

For every time period of length one hour, the time series models of the high, low and closing prices are used to make predictions of the future behavior of the cross rate. The predictions are used in combination with the strategies to make estimations of the expected returns. When combining the portfolio we first take into account the expected profit for each position, if it is larger than the spread cost we take the position in the cross rate. This means that we are neutral in the market if we do not expect to profit from entering the positions. The portfolio is then combined with the selected cross rates using Markowitz Portfolio Theory and Power Mapping technique. The portfolio can solely at every time period consist of zero to five cross rates. This method of predicting, choosing and combining is used for every sample of the validation dataset and the results are calculated as Key Ratios. The reinvested portfolio, i.e. the cumulative product of all returns, is plotted in the results plot. In order to be able to reveal how the strategies perform on every cross rate and not just in the combined portfolio we also calculate the evolvement of the individual cross rate. This time series is weighted in every data point according to its weight in the portfolio and plotted in as Traded Assets. The Assets plot in the results shows the cumulative product of the true assets returns in the validation dataset.

10 Presentation and analysis of results

10.1 Results Benchmark Strategies

10.1.1 Strategy 1

Key Ratios	*Results Strategy 1*
Total Return	-80.08 %
Days Profitable	7.32 %
Months Profitable	0 %
Highest Daily Return	0.69 %
Lowest Daily Return	-1.42 %
Average Daily Return	-0.29 %
Highest Monthly Return	-1.85 %
Lowest Monthly Return	-12.07 %
Average Monthly Return	-4.99 %
Monthly Standard Deviation	2.99 %
Information Ratio	-6.676
Maximum Drawdown	-80.06 %
Calmar Ratio	-1.0

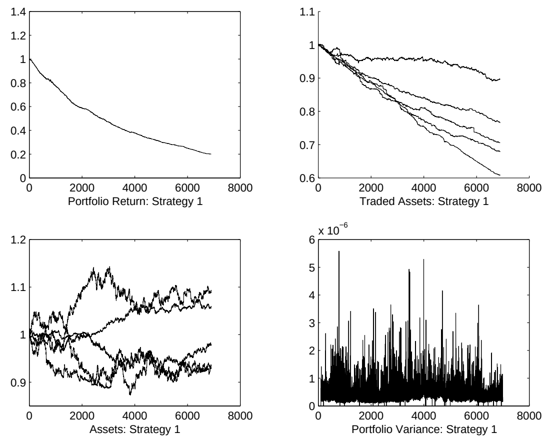

Figure 11: Strategy 1

Strategy 1 is used as a benchmark strategy. The opening price prediction is used to determine in which direction the market is moving and we place a postion accordingly, if the predicted direction changes we close the postion and take a new in the new direction. The results shows that the portfolio has ha total return of -80.08% and a monthly standard deviation of 2.99 %. All the traded assets have negative performance and during no time during the test period the portfolio shows positive returns. An probable explanation of the bad performance lies in the heavy costs of trading every hour.

10.1.2 Strategy 2

Key Ratios	*Results Strategy 2*
Total Return	38.82 %
Days Profitable	65.51 %
Months Profitable	81.25 %
Highest Daily Return	1.21 %
Lowest Daily Return	-1.41 %
Average Daily Return	0.14 %
Highest Monthly Return	6.34 %
Lowest Monthly Return	-4.41 %
Average Monthly Return	2.34 %
Monthly Standard Deviation	3.05 %
Information Ratio	3.04
Maximum Drawdown	-6.47 %
Calmar Ratio	5.99

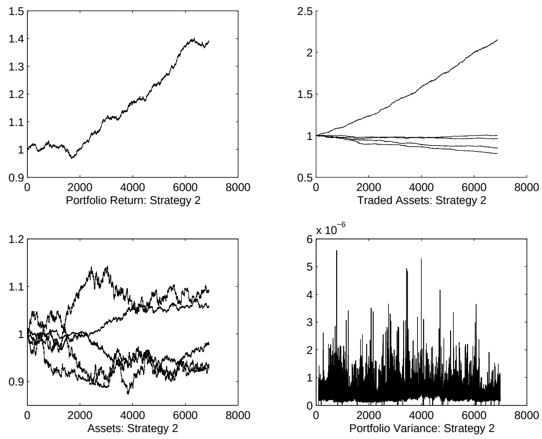

Figure 12: Strategy 2

Strategy 2 predicts the close price and sets a target at this level, if the target is reached the position is closed, otherwise the position closes at the end of the time period. The strategy results shows positive returns of approximately 38.82%. This is obviously a very high performance but the portfolio is strictly dominated by the EUR/GBP and the performance is heavily influenced by this. Maximum Drawdown shows -6.47 % and the monthly standard deviation show 3.05 %. The model we developed to describe the EUR/GBP behavior works very well and is the only asset that contributes to the portfolio with positive returns. Looking at the other cross rates we can see that the they all have negative performance.

10.2 Results Extreme Value Strategies

10.2.1 Strategy 3

Key Ratios	*Results Strategy 3*
Total Return	-3.72 %
Days Profitable	48.08 %
Months Profitable	37.50 %
Highest Daily Return	1.26 %
Lowest Daily Return	-0.92 %
Average Daily Return	-0.014 %
Highest Monthly Return	3.51 %
Lowest Monthly Return	-2.96 %
Average Monthly Return	-0.19 %
Monthly Standard Deviation	1.61 %
Information Ratio	-0.42
Maximum Drawdown	-6.73 %
Calmar Ratio	-0.55

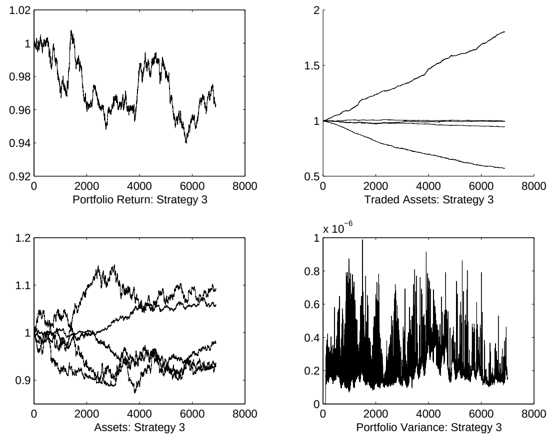

Figure 13: Strategy 3

Strategy 3 uses the predicted high price as a target level, we take a buy position in every time step, if the target level is reached we close the position. If the target level is not reached we close the postion at the end of the time period. Strategy 3 shows a negative total return of -3.72 % with a monthly standard deviation of 1.61 %. The strategy is dominated by two cross rates, the EUR/GBP and the EUR/CHF. The EUR/GBP adds value to the portfolio and the EUR/CHF drains it from profitability. The other cross rates have negative performance. One conclusion to be drawn is that in strategy 2 the EUR/GBP performs better than in strategy 3. One reason for this is that Strategy 3 always trades in the belief that the High target will be reached, independent of the direction of the trend.

10.2.2 Strategy 4

Key Ratios	*Results Strategy 4*
Total Return	-67.29 %
Days Profitable	10.1 %
Months Profitable	0 %
Highest Daily Return	0.33 %
Lowest Daily Return	-0.92 %
Average Daily Return	-0.24 %
Highest Monthly Return	-1.44 %
Lowest Monthly Return	-7.33 %
Average Monthly Return	-4.17 %
Monthly Standard Deviation	1.9 %
Information Ratio	-8.76
Maximum Drawdown	-67.40 %
Calmar Ratio	-0.99

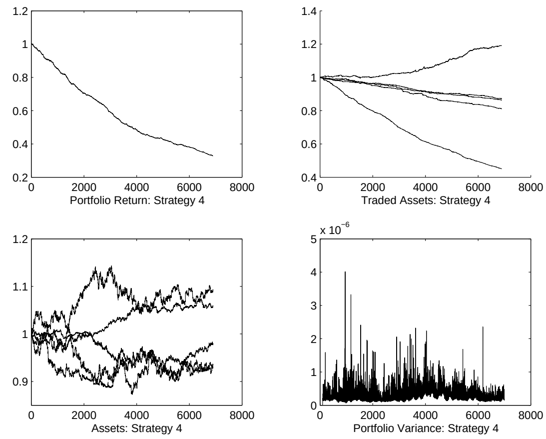

Figure 14: Strategy 4

Strategy 4 uses the low price prediction as a target level, and we take a sell postion in every time step. If the target level is reached we close the position. If the target level is not reached we close the postion in the end of the time period. Strategy 4 shows a total return of -67.29% and a monthly standard deviation of 1.9%. Stragtegy 4 is dominated by two assets, the EUR/GBP that performs positive and the EUR/CHF that performs negative. The other cross rates performance show that they are negative. The portfolio does not show any positive returns for the hole time period. One reason for this could be that the strategy only take sell positions independent of the trend.

10.2.3 Strategy 5

Key Ratios	*Results Strategy 5*
Total Return	24.24 %
Days Profitable	55.40 %
Months Profitable	75 %
Highest Daily Return	1.26 %
Lowest Daily Return	-0.95 %
Average Daily Return	0.08 %
Highest Monthly Return	8.45 %
Lowest Monthly Return	-3.99 %
Average Monthly Return	1.54 %
Monthly Standard Deviation	3.36 %
Information Ratio	1.84
Maximum Drawdown	-10.10 %
Calmar Ratio	2.40

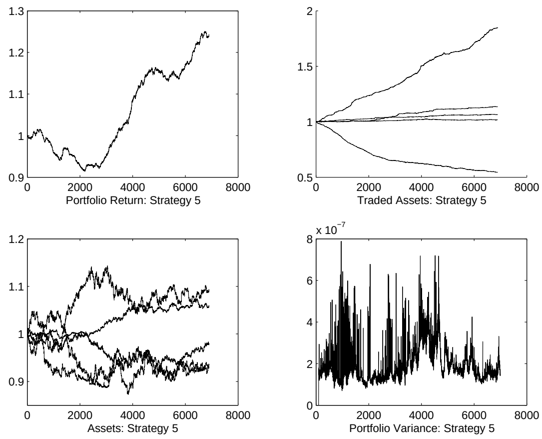

Figure 15: Strategy 5

Strategy 5 uses both the high price and low price predictions as target levels but takes a position only in the direction where the estimated profit is the largest. If the spot reaches the target level we close the position, otherwise we close the position in the end of the timeperiod. Strategy 5 shows a total return of 24.24 % with a monthly standard deviation of 3.36 % and a maximum drawdown of -10.1%. When combining strategy 3 & 4 and trading in the direction of the largest profit we can see that four out of five cross rates performs positive and actually adds value to the portfolio. This is a good indicator that strategy 5 is more reliable than strategy 2 since strategy 2 had all it's profit coming from only one cross rate. We can observe that almost all profit comes from the EUR/GBP and that this heavily influences the performance.

10.2.4 Strategy 6

Key Ratios	*Results Strategy 6*
Total Return	242.32 %
Days Profitable	94.08 %
Months Profitable	100 %
Highest Daily Return	3.30 %
Lowest Daily Return	-0.55 %
Average Daily Return	0.88 %
Highest Monthly Return	32.26 %
Lowest Monthly Return	3.50 %
Average Monthly Return	14.72 %
Monthly Standard Deviation	9.18 %
Information Ratio	6.4
Maximum Drawdown	-1.01 %
Calmar Ratio	240.52

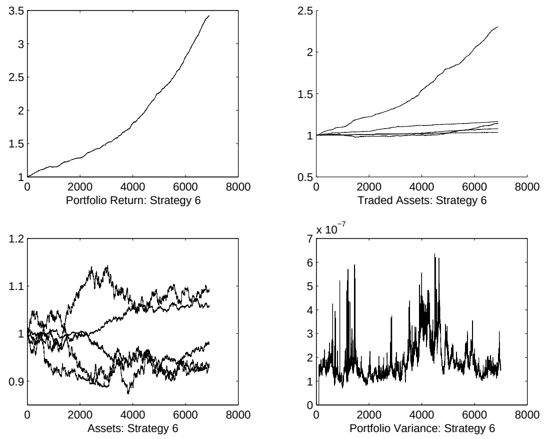

Figure 16: Strategy 6

In strategy 6 we use the high and low price predictions as sell and buy levels respectively. If the spot reaches the high level we sell and if it reaches the low level we buy. If only one of the levels is reached during the time period we close the postion at the end of the time period. If no level is reached we do nothing. Strategy 6 shows a very high performance of 242.32 % with a monthly standard deviation of 9.18 % and a maximum drawdown as low as -1.01 %. Once again the portfolio is heavily dominated by a single currency and once again it's the EUR/GBP. Positive is that all cross rates shows good performance and this in by far the most profitable strategy we have tested. You should always raise one's eyebrows when getting results like this. Things that could influence the results are first of all the slippage cost and secondly that the data we are using could be non tradable. The performance of this strategy is heavily influenced by the variance, the larger the noise we have in the market the better the strategy performs. The strategy 6 results gives us clear view that further investigation and development of the strategy is supported.

The following table summarize the strategies performance.

Results	*Strategy 1*	*Strategy 2*	*Strategy 3*	*Strategy 4*	*Strategy 5*	*Strategy 6*
Total Return	-80.08 %	38.82 %	-3.72 %	-67.29 %	24.24 %	242.32 %
Average Daily Return	-0.29 %	0.14 %	-0.014 %	-0.24 %	0.08 %	0.88 %
Information Ratio	-6.676	3.04	-0.42	-8.76	1.84	6.4
Maximum Drawdown	-80.06 %	-6.47 %	-6.73 %	-67.40 %	-10.10 %	-1.01 %
Calmar Ratio	-1.0	5.99	-0.55	-0.99	2.40	240.52

11 Conclusions and Future research

The aim of this paper was to investigate if it is possible to gain extra returns by using a prediction of the extreme values instead of the predictions of the close price. The conclusions to be drawn is that when using AR and ARMA models to predict the High, Low and Open price of the FX-rates EUR/GBP,EUR/USD,USD/JPY,EUR/CHF and USD/CHF, a strategy that combines and uses the High and Low prediction levels gives better results than strategies based on the open price predictions when combined and traded in portfolios. One aspect to consider when analyzing the results is that they are heavily influenced by one traded asset that performs very well. What is noticeable is that the overall performance is better in strategy 5 compared to strategy 2 when looking at the amount of positive returns on the traded assets. One aspect that influences our results are the fact that the data is not live data which is tradeable, this means that our models can not be used as they are to realize a live trading system. What we can do with the data is to examine different strategies and show that extreme value strategies gives interesting results worth to develop further.

The problem with dominating assets in our portfolios cam be solved in different ways. One way would be to chose by random which assets that should be included in our portfolios, the technique would work if we had more than 20 assets to chose from. An other way would be to just eliminate those assets that dominates one or several portfolios. The drawback with this technique is the same as the one mentioned above, we only have five assets. If we then eliminate a couple of assets, the portfolio selection would be unnecessary. It would make no sense to do a portfolio selection with just two or three assets.

This is the reason why we have kept all the assets even if there are a couple of assets that dominates the results of portfolio, both positively and negatively.

Future research areas could be to investigate: Due to the heavy cost of trading in the interval of 1 hour the results are heavily impacted. In order to make the trading costs less influential one could look at a larger sample interval.

The trading volume differs during the day depending on which countries awake for the moment. It is probable to assume that larger returns is more common when trading volume is high. Further research could investigate the hourly extremes dependencies of the time during the day.

The fat-tails of the return distribution implies large jumps in the process. These jumps should be investigated further in order to be able to capitalize on them as well.

12 Appendix

12.1 Over Trading

There is one big problem with trading at very high frequencies and that is the cost of placing so many trades. When placing one trade approximately every hour in every cross rate in your evenly balanced portfolio, the costs sums up e.g. 5 cross rates traded every hour at a pip cost of 0.0005 gives an yearly expense of 5*24*0.0005*250 = 150000 pips, which means that you need to perform very well just to break even. This means that if you are able to develop techniques that minimizes the amounts of trades made, there are plenty of costs to be saved.

12.2 How we calculate the spread cost

Every pair trades at a different cost, the costs we use when calculating the trading profits are as follows.

Eur/Usd: 3 pips
Usd/Chf: 5 pips
Usd/Jpy: 4 pips
Eur/Gbp: 3 pips
Eur/Chf: 7 pips

And using the Average of the Cross rate for the first 7000 values to calculate the cost in percent.

Eur/Usd: 1.0369
Usd/Chf: 1.4398
Usd/Jpy: 121.04
Eur/Gbp: 1.5725
Eur/Chf: 1.5350

12.3 Model Estimation and Validation

EURUSD

Open		*High*		*Low*	
Model	*FPE*	*Model*	*FPE*	*Model*	*FPE*
ARMA(1,1)	2.0308e-006	**AR(1)**	1.6721e-006	**AR(1)**	1.74551e-006
ARMA(2,2)	2.03023e-006	ARMA(1,2)	1.67442e-006	ARMA(1,1)	1.74793e-006
ARMA(2,3)	2.03158e-006	ARMA(2,3)	1.67436e-006	ARMA(1,2)	1.74654e-006
-	-	-	-	ARMA(2,3)	1.74736e-006
-	-	-	-	ARMA(3,1)	1.74933e-006

EURGBP

Open		*High*		*Low*	
Model	*FPE*	*Model*	*FPE*	*Model*	*FPE*
AR(1)	1.27633e-006	AR(1)	9.72636e-007	AR(1)	1.02242e-006
AR(2)	1.2754e-006	AR(2)	9.71384e-007	AR(2)	1.01977e-006
AR(3)	1.27431e-006	**AR(3)**	9.71252e-007	AR(3)	1.01908e-006
ARMA(1,1)	1.27591e-006	ARMA(1,1)	9.73109e-007	**AR(4)**	1.01893e-006
ARMA(2,3)	1.27625e-006	ARMA(1,2)	9.72885e-007	ARMA(1,1)	1.0221e-006
ARMA(3,2)	1.27633e-006	ARMA(1,3)	9.73558e-007	ARMA(1,2)	1.02046e-006
ARMA(3,3)	1.27588e-006	ARMA(2,1)	9.72806e-007	ARMA(2,1)	1.02031e-006
ARMA(4,2)	1.2761e-006	ARMA(3,1)	9.73091e-007	-	-

EURCHF

Open		*High*		*Low*	
Model	*FPE*	*Model*	*FPE*	*Model*	*FPE*
AR(1)	4.25508e-007	AR(1)	3.33556e-007	**ARMA(1,1)**	3.63951e-007
ARMA(2,1)	4.25923e-007	ARMA(1,2)	3.33786e-007	ARMA(1,2)	3.64742e-007
ARMA(4,4)	4.26948e-007	**ARMA(2,2)**	3.33536e-007	ARMA(1,3)	3.64654e-007
-	-	ARMA(3,1)	3.33827e-007	ARMA(2,1)	3.64809e-007
-	-	ARMA(3,3)	3.34121e-007	ARMA(3,1)	3.64664e-007
-	-	ARMA(4,2)	3.34038e-007	ARMA(3,3)	3.65022e-007
-	-	-	-	ARMA(4,4)	3.64997e-007

USDCHF

Open		*High*		*Low*	
Model	*FPE*	*Model*	*FPE*	*Model*	*FPE*
ARMA(2,2)	2.34717e-006	**AR(1)**	2.03942e-006	**AR(1)**	2.02144e-006
ARMA(2,3)	2.34699e-006	ARMA(1,2)	2.04086e-006	ARMA(1,2)	2.02408e-006
-	-	ARMA(2,1)	2.04208e-006	ARMA(3,4)	2.02598e-006

USDJPY

Open		*High*		*Low*	
Model	*FPE*	*Model*	*FPE*	*Model*	*FPE*
ARMA(1,1)	1.91621e-006	**AR(1)**	1.62652e-006	**AR(1)**	1.75178e-006
ARMA(2,1)	1.91506e-006	ARMA(1,2)	1.62734e-006	ARMA(1,2)	1.75304e-006
-ARMA(2,2)	1.91554e-006	ARMA(2,3)	1.67436e-006	-	-
-	-	ARMA(2,2)	1.62788e-006	-	-
-	-	ARMA(2,3)	1.62819e-006	-	-
-	-	ARMA(2,4)	1.62968e-006	-	-
-	-	ARMA(3,1)	1.62841e-006	-	-
-	-	ARMA(3,4)	1.62993e-006	-	-

12.4 Autocorrelation plots-Residuals

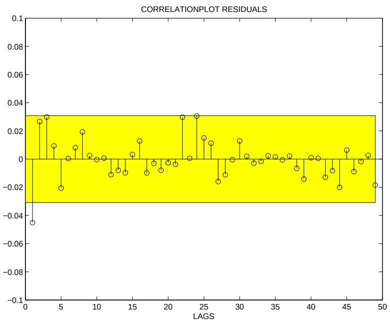

Figure 17: EURGBP-Open

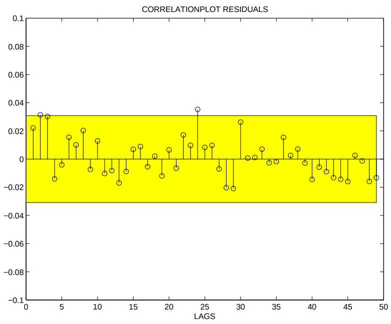

Figure 18: EURGBP-High

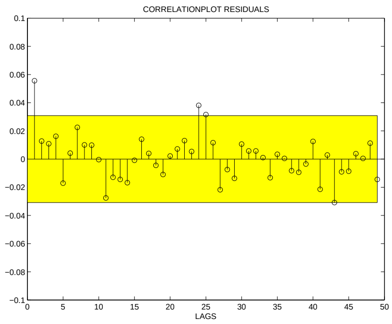

Figure 19: EURGBP-Low

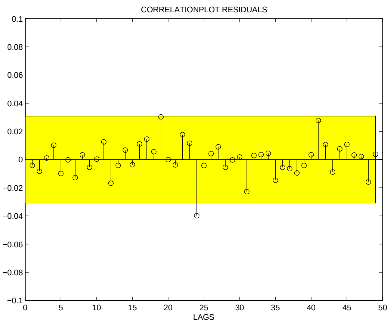

Figure 20: EURCHF-Open

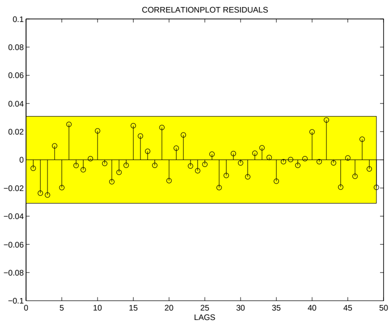

Figure 21: EURCHF-High

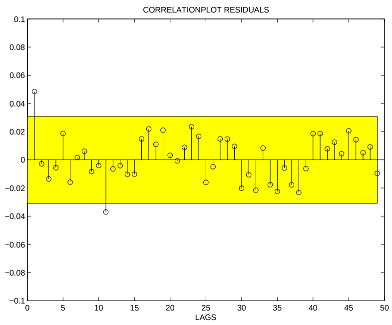

Figure 22: EURCHF-Low

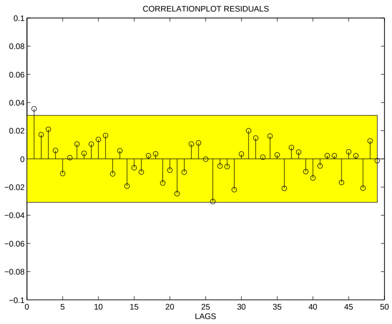

Figure 23: EURUSD-Open

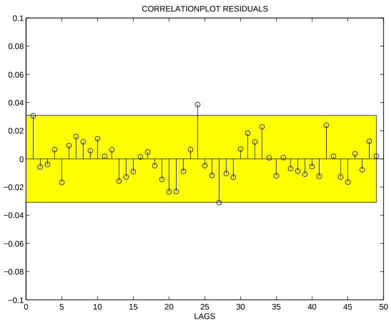

Figure 24: EURUSD-High

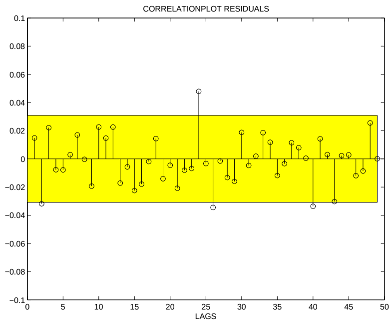

Figure 25: EURUSD-Low

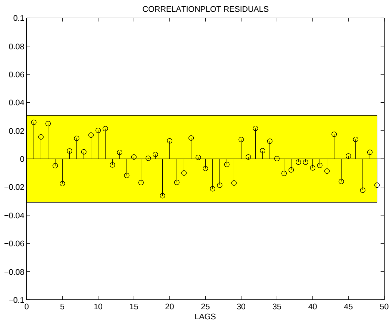

Figure 26: USDCHF-Open

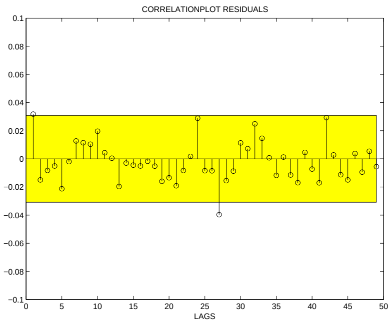

Figure 27: USDCHF-High

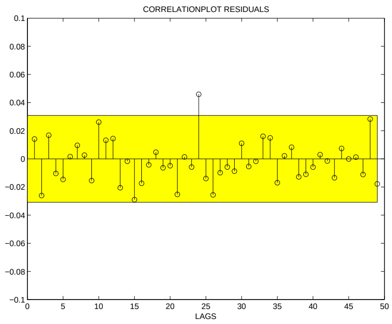

Figure 28: USDCHF-Low

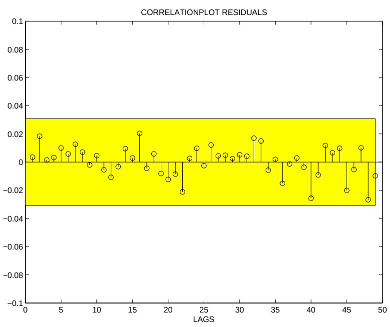

Figure 29: USDJPY-Open

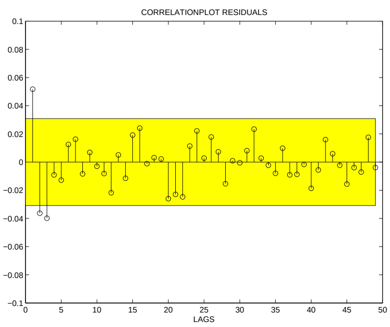

Figure 30: USDJPY-High

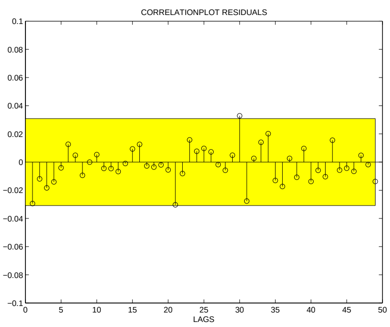

Figure 31: USDJPY-Low

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