JÖNKÖPING INTERNATIONAL BUSINESS SCHOOL
JÖNKÖPING UNIVERSITY

The Foreign Exchange Market

An Algorithmic Approach to Efficiency Testing

Master's Thesis in Economics

Author: Tobias Tysk

Tutor: Andreas Stephan

Jönköping May 17, 2013

Master's Thesis in Economics with Subfield Finance

Title:	The Foreign Exchange Market: An Algorithmic Approach to Efficiency Testing
Author:	Tobias Tysk
Tutor:	Andreas Stephan
Date:	May 17, 2013
Subject terms:	Efficient Market Hypothesis, Algorithmic Trading, Foreign Exchange Market, High Risk Investment.

Abstract

The goal of any risk averse trader is to generate relatively large profits with low amount of risk. The foreign exchange market is the largest market for financial investments. The improving technology is waiting to get incorporated into the trading strategies and take over the trading process from humans. Using a strategy and manipulating the technology to not have an emotion for a position and only trust the facts suggest an improved way of trading. The research at hand have generated results that provide evidence against the efficient market hypothesis, but more research is needed, while at the same time give an opportunity for the average trader to improve the portfolio.

Table of Contents

Figures

Tables

Appendix

1 Introduction

The stock market today is very diversified; there are thousands of different investment opportunities. The interesting phenomenon, however, is that by using a steady trading strategy there is a possibility to realize profits. In accordance to multiple studies, the only way to realize these profits is by taking on loads and loads of risk. According to Chaboud, Hjalmarsson, Vega, and Chiquoine (2011) there is no gain of risk by using algorithmic trading on the foreign exchange market. This is very peculiar since the price changes in the foreign exchange market (ticks) appear much more frequent than on the stock exchange. Due to the frequent price changes there should be more opportunities to realize profits if it is possible to analyze the prices and be able to predict future price-movements. The reason why this topic is still interesting is that Chaboud et al. (2011) focus on an arbitrage strategy, which, as discussed later, is almost impossible in today's foreign exchange market.

Throughout this paper lies a theme of profit maximization through a structural agenda. The empirical research of this paper will consist of creating an algorithm that follow a specific pattern that produces sell/buy signals through technical analysis of the past prices and the order book.

The content of this topic is going to comprise several areas such as the efficient market hypothesis and its counterproofs, the rise of computer trading, and algorithmic trading. An algorithm will be programmed in order to realize abnormal profits applying models that efficiently analyze past prices (in a mean reverting fashion).

The result, if positive, of this thesis will have impact on the market in two ways. The efficient market hypothesis will be shown to have flaws, which are indications of inefficient prices that could generate abnormal profits for traders using the same strategy/strategies. The second impact would affect the use of algorithms to trade instead of paying huge amounts to people tracking the market manually, especially for individual traders. A positive result of this research will give individual traders the information that trading forex with robots could generate extra income. There is also the possibility for firms and institutions to elaborate on the models to make use of this research.

The structure of this thesis is traditional. It starts with the introduction in this first section, section two presents the theoretical background for the study. The section on theory brings forth any important theory that may have impact on the testing process. Section three evaluates different strategies that will be used when testing the efficient market hypothesis including the functionality of algorithmic trading. Section four presents the results of the testing and section five analyzes the results. The sixth section sums up the thesis by presenting a conclusion and section seven presents a discussion of the research and suggests further research.

1.1 Background

The different topics that will be discussed in the theoretical section will be (including those mentioned above) behavioral trading, value at risk, various trading strategies and their evaluation.

Behavioral trading is a great threat to realizing profits larger than the proxy of a market portfolio. This is mostly due to the emotional attachment to the investment but could also be because of the risk of losing. This is why systematic trading has been very popular during the last decades. Along with the trend of systematic trading, the use of computers to execute transactions automatically have increased substantially (Chen, 2006).

The trader should always be informed about what the actual risk is of committing to a transaction. This is what is called value at risk. This indicator is crucial for a risk-averse investor and their decisions (Dempster, 2002). To reduce risk of the currency taking off to the other direction than was meant the trader can use *stop loss* orders which will automatically close the position if the losses become too great (Osler, 2005).

Trading strategies can take on many forms, everything from a simple moving average to a complicated fractal integrated trading strategy. Due to complexity the fractal trading system will not be covered in this thesis, however, the trading rule that will be used will consist of a few different indicators where a form of moving average is one of the indicators (McDonell, 2008).

The purpose of this thesis is to investigate the opportunities of constructing a trading robot taking most of the topics above into account and through this be able to continuously beat the market. By comparing the results to the market returns and risk the robot, if successful, should generate greater Sharpe ratios than the market portfolio (a proxy will be used such as S&P500, which is diversified and have characteristics of being a theoretical efficient portfolio) (Elton, 2011). The crucial part for this thesis to hold is analysis and usage of available information. Analyzing the current prices and estimating the future prices is a topic of its own, thus the use of past research in this field will be used. Analyzing movements in the foreign exchange market can be done by a candlestick chart and some indicator analyzing past prices (Fischer & Fischer, 2003).

Due to its daily turnover of over $4,000 billion[1] (out of those $4,000 about $1,500 comes from the spot rate transactions), the foreign exchange market is the largest financial market. Its constant growth since at least 1989[2] indicates that it is not going to slow down, especially when considering a growth of 20 % since 2007. This alone is a reason for choosing the foreign exchange market as the market of interest. Adding to the fact that out of the $1,500 billion, which the spot transactions account for, about $500, is traded between the Euro and the US Dollar. Together these two facts give the reason why this paper will focus on the Euro/USD currency pair when trading. (Bank of International Settlements Monetary and Economic Department, 2010)

Looking at historical performance of the S&P 500, which has been seen as a good proxy for the market portfolio, the yearly average return from 1950 has been around 8,5% and from

[1] The numbers from this particular report are the average daily turnover in the month of April if nothing else is stated.

[2] Bank of International Settlements Monetary and Economic Department (1996).

1990 the average has also been 8,5% on average[3]. This means that to beat the market only considering return the average return annually should be above 8,5%. For some ratios in this paper it is mandatory to have a minimal acceptable return. This level will be set at 10% annually to be sure to beat the market. This gives a monthly return of 0,833% and a daily return of 0,038% calculated on 260 days annually on average.

1.2 Delimitations

The forex trading section of financial investments is large and can be very complex depending on how deep and out of the box the trader wants to go. Due to the hypothesis of this thesis the algorithms will not use too advanced indicators such as fractals or quant techniques. This will result in simple algorithms; however a complex algorithm may not provide better results than a simple algorithm. The focus of the paper is to evaluate the possibility for an investor with relatively normal funds of 10 000 USD.

The real-time testing will be done during 0800 GMT+1 through 2100 GMT+1 Monday through Friday during the month of April 2013. Due to environmental reasons the hours have been shortened to thirteen hours a day, the reasons include electricity waste and battery life time of the computer used, however as seen in the analysis this will help to make the algorithm more efficient. Another reason why the time of real time test is shorter is due to the cost of holding a position over night, this will be shown in the analysis.

The data however, has been taken from the Meta Trader Company, whom have a confidential source of the data. The issue is that since the data is confidential there is no way to know if the data comes from Bloomberg or another organization supplying such prices. However, since this is also the data that would have been used if the algorithms were placed on a real account, the problem does not harm the result.

1.3 Problem Definition

As Samuelsson (1965) purposes, the assumption of the efficient market hypothesis is that no indicator can beat the market by technically analyzing the past prices and giving a signal either to sell or buy the specific stock or financial instrument. In other words, it should not be possible to beat the market by analysis, but does this mean that it is possible to beat the market by gambling on the random walk pattern? Questioning Samuelsson and his market efficiency hypothesis has been popular due to many different reasons, one comes from Dow and his theory of price movements over time. As most of these examples are tests on the stock exchange, this research will test the market efficiency on the foreign exchange market.

Manual trading is a time consuming activity since the trader have to watch the market all the time, push buy or sell when the time is right, and exit the position when there is a need for it. Though there are advantages of manual trading, there is an upcoming trend of using robots to trade such that more time can be spent on other activities. An algorithm will be

[3] Own calculations with close prices from finance.yahoo.com

programmed in order to realize the abnormal profits using theories that efficiently analyze past prices.

According to Chordia, Roll and Subrahmanyam (2005) and to Cushing and Madhavan (2000) there exists a possibility to predict short run returns from past order-flow imbalances (arbitrage trading). Their conclusion is backed up by Raj (2000) who investigates the possibility to achieve abnormal profits by using technical analysis on the futures market in the Asia-Pacific region. In addition, the result is backed up by Metghalchi, Chang and Marcucci (2005) as they investigated technical analysis on the Swedish stock market. In a later paper by the same authors, Chordia, Roll and Subrahmanyam (2008) the result was not contradicting but neither conforming. They did pose, however, an alternative theory that during periods of high liquidity there are more efficient prices.

As Gârleanu and Pedersen (2007) explores the liquidity and risk relation to the financial markets they pose an idea that greater liquidity lowers the risk since it is easier to get out of a position. However, as managers use tighter risk management they pose a threat to liquidity, which in turn increases the risk because the aggregate level of liquidity has been worsen.

Research Question:

The ability to make abnormal returns has been discussed in the previous paragraphs, considering the modern technology and how it can be manipulated to perform trades without the usage of humans. This paper will examine the possibility to create a simple algorithm that will outperform the efficient portfolio[4] by operating through contracts for difference (CFD) trading on the foreign exchange market.

1.4 Method

The paper has a clear method, which is an experimental quantitative study where algorithms will be constructed and back tested on historic data. Quantitative experiments are very theoretical (Ryan, Scapens & Theobald, 2002) and use high amount of data. In order to check the result from the back test on real time data the best performing algorithm will be used during a period to test performance and efficiency.

The crucial part for this thesis to hold is analysis and usage of available information. Analyzing the current prices and estimating the future prices is a topic of its own, thus the use of past research in this field will be used. Analyzing movements in the foreign exchange market can be done by a candlestick chart and the so-called Fibonacci retracements (Fischer & Fischer, 2003). The incorporation of the candlestick into the trading robot will be one of the major keys. Using Fibonacci is more of a manual trading indicator since it incorporates many parameters, thus the usage of Fibonacci will not be used extensively. However, the usage of Fibonacci has shown great results, though it demands advanced programming knowledge and time, which is currently a scarce resource.

[4] A proxy of the efficient portfolio such as S&P500 will be used.

1.4.1 Research Design

The research will be done through an ordinary theoretical study where theory will be found through academic journals and books that have had good response in the literature. The models found in the literature will be used to create the algorithm, assuming the authors of the literature used for an indicator tested the functionality and performance. The algorithm will be programmed in the language MQL5, which is a library of commands from the platform, provided Meta Trader 5. The MQL5 has a function that allows the user to choose an already programmed indicator.

The algorithm is then tested on historical data and the result will be presented in the empirical result part of this paper. The analysis will bring up any important finding and then answer the research question.

The advantage of this type is that it uses real data and a process that would be used in real time trading if this would have been done in practice. The disadvantage of this is that the algorithm is not seen as a market participant as the trades are only done on levels and not actually executed together with another market participant. How the algorithm would work in reality would only be known if the algorithm was placed on a real account and not a fictive account.

1.5 Data

Meta-trader is a platform at which prices are connected to a database (which database is only known to the owner of the server) which is the basis of my analysis. Common databases for forex and CFD (contracts for difference) trading are Reuters, EBS (Electronic Broking Services). Back testing the trading robot will be done on the historic prices of Meta-trader (their source is confidential). A reality check of using the robot will be done on live prices such that the robot not only works on back testing, but also in a live trading environment (Douglas, Lovrencic & Pontikis, 2011).

The type of data used in this thesis is going to be the prices of high, low, close, and median for each time frame that is used in the robot. Different indicators need different types of prices. Using different types of prices will give better signals since more data gives more accurate estimations. As Taylor (1987) claims in his study that the best forecasting of exchange rate volatility is made by using open, high, low and closing prices.

2 Theoretical framework

When it comes to forex trading, or any trading for that matter, there is always the issue of constructing a suitable strategy that works in practice. A suitable strategy is something that takes careful testing and consideration before being put together. In this section several strategies will be discussed and combined into a powerful strategy. First a literature review will be presented.

2.1 Literature Review

The field of algorithmic trading is relatively new to research, algorithmic trading started around the mid of 1990's (Hendershott, Jones & Menkveld, 2011), and as with the rest of technological sciences, not even the sky is the limit of where it can lead in terms of investments. There are, however, a few areas that have been looked upon, one of those areas is liquidity. Hendershott et al. (2011) conduct a study on how algorithmic trading (AT) is related to liquidity. They conclude that AT does not actually improve the liquidity as much as AT's are present in the liquid markets. However, they also conclude that AT helps to improve the information in prices due to the quick responses that an AT realizes. This, together with decimalization, creates liquidity.

Cai, Cheung, and Lee (2000) found enough evidence to not contradict the theory of order flow represents the expectations of future prices. Prices do not move due to macro-announcements, more important is the order flow. Meaning that exchange rate movements are more sensitive to order flow than news, they call this independent information. Following is that due to this result, they also conclude that volatility exist both in dependent as well as independent information, but the independent volatility have greater impact.

Evans (2002) and Evans and Lyon (2002) try to prove that information is not the dominant factor in exchange rate movements. Their results show that order flow has a greater impact on price movements. Evans (2002), however, pose a theory that it is only common knowledge that have little impact on prices since it is already accounted for in the short run, but insider information (non-common knowledge as Evans puts it) could be found in the long perspective.

Building on the theme, Ng (2011) proposes that the liquidity risk is lower when the information is of high quality. This suggests that investing in the foreign exchange market is accompanied by low liquidity risk.

Chaboud et al (2011) together with Colliard and Foucault (2009), Biais, Foucault & Moinas (2012), and Lo, Repin, and Steenbarger (2005) find a number of interesting phenomenon's about algorithmic trading and the quality of the market. Due to the ability of the machines to commit trades within milliseconds, the prices are more efficient and the quality of the market improves. This is also called price discovery (Hendershott et al., 2011)

Lo et al. (2005) proposes a problem when the market achieves too high quality. Since the ATs' are highly correlated (Chaboud et al., 2011) the signals that are sent to and from the ATs' will lead to one-sided order book creating low depth and higher risk due to improved liquidity risk. This is assumed to be the reason for the so-called flash crash in 2010

(SEC/CFTF). They conclude their research by stating that algorithmic trading does not improve volatility but instead helps to improve liquidity.

Jones, Kaul, and Lipson (1994) find that short-term volatility is mainly related to the publicly known information. Creating an atmosphere where short-term traders are taking on huge amount of risk in order to create liquidity.

As one could view the order flow of the foreign exchange market as the flow of information, it could be said that the volatility of the market is the same as the change in order flow. Berger, Chaboud, and Hjalmarsson (2009) show that the volatility is strongly related to how frequent the order flow change but also to how the market perceive the new order flow.

There has been a discussion in the past decades about the uncertainty of future price moves and how it should be used to create the optimal portfolio. Sharpe (1966) presents a risk adjusted performance measure called the Sharpe ratio (SR) and claims that the higher the SR the better is the portfolio. The assumptions has been questioned as Sharpe assumes normally distributed errors as well as too generalized for all actors of the market. Sortino and Satchell (2001) present another measure called the Sortino Ratio (SoR) which is a risk adjusted performance measure as well, however the differences have a crucial effect on portfolio optimization. The SoR adjusts risk only using downside volatility, which gives an interpretation of how much investment could lose instead of the total earnings. The less downside deviation the better for a potential gain of the investment return. The analysis of the SoR is the same as the SR as it measures how much excess return the investment has generated per amount of risk, downside risk for SoR, which means that higher values are better than lower when comparing.

Sortino and Meer (1991) tested the theory of downside risk and found that portfolios, which used downside risk to choose investments, performed better than portfolios that used mean-variance to choose investments.

Looking closer at the technical analysis (TA) which is the ground for the thesis at hand, the past research propose that it is possible to generate abnormal returns with TA (Balvers & Wu, 2006). Serban (2010) finds the same conclusion that Balvers and Wu found, except he used a different strategy and examined the foreign exchange market, thus creating more proof for the inefficiency. The question about inefficiency was first brought up by Samuelsson (1965) and later by Fama (1970). They claim that markets should be efficient since news is random. Considering Chiang and Wu (2006) and Serban (2010) the findings by Samuelsson and Fama can be tested again.

Coutts and Cheung (2000) evaluate trading rules on the Hang Seng Index on the Hong Kong stock exchange and find that it is possible to make revenues when trading using technical analysis but the transaction costs eat up the revenue. This provides a curious case when trading on the forex market.

The discussion of the efficient portfolio has been debated for a long period of time. The general conclusion that can be drawn by the discussion is that the efficient portfolio, also called the market portfolio, is purely theoretical. The use of stock market indices could be good proxies instead of the theoretical concept of a market portfolio, such as the S&P500 (Elton, 2011).

2.2 Behavioral Finance

As Fama (1970) explains in his theory of market efficiency, there is a need for rational decision makers in order to create efficient prices. Kahneman and Traversky (1979) find that people are making irrational decisions depending on how they are given the data that leads to market inefficiencies. Behavioral finance is an important aspect of market efficiency since the foundation of market efficiency lies on the assumption that investors are rational.

2.2.1 Utility and Prospect

Every individual have preferences, whether they are clear or complex does not matter, thus there is a possibility to rank certain bundles of goods or investments in an order. This gives an introduction to utility theory, which is the foundation of risk aversion (Barberá, Hammond & Seidl, 1998).

Utility theory has been a widely used[5] theory for examining the behavior of investors on the financial markets, stating that an investment should only be taken if and only if the utility of that investment generated a higher average utility for the investor. This is however hard to evaluate since utility is something intangible and hard to place in context of an investment other than the personal evaluation of the preferences of each individual (Fishburn, 1968).

Arguing an investment according to how much could be lost is something that has been done for a long time, however, according to research (Kahneman & Tversky, 1979) people are much more perceptive when an investment opportunity is presented in how much is to gain from the investment rather than the level of wealth. Their research tested peoples' choice when faced with two investments. The subjects did not know that the investment opportunity was exactly the same but worded in two different ways. The interesting thing here was that the subjects appeared irrational in their answers. Depending on how an investment was introduced, the decision differed.

Extending the prospect theory would be to include the theory of disappointment that Gul (1991) sets forth. Risk aversion is common ground for the utility theory and the prospect theory, also the disappointment aversion theory shares that ground.

The problem found in Kahneman and Tversky (1979) will not appear when an emotionless robot is working on its own without the input of the human behavior. However, is this efficient? This will be discussed in a section below.

2.2.2 Sentiment

Barberis, Shleifer, & Vishny (1998) had noticed a market inefficiency through their years of research. They had found that over- and under reactions to news were common by the ordinary investor, which led to professional investors making huge profits due to their neutrality and expertise in analyzing market movements. The problem of investor sentiment was found especially as investors pay little attention to the statistics of the analysis as compared to the pure facts that was very much used instead.

---

[5] First introduced by Bernoulli in 1738

2.2.3 The Shift

As discussed in Kumiega and Vliet (2012) there has been a shift in the practical usage of behavioral finance. In the past, behavioral finance has evaluated the investor's ability to express the utility of an investment in order to find new investments on the financial market. The new era of trading has changed the use of behavioral finance. The importance of a good trade now lies on the mechanisms used to create the automated trading robot or trading strategy in order to make investments that follow exact instructions. This not only provides less stress on the investor managing the robot, but also it eliminates the human factor that has so many times encapsulated a loss due to wrong judgments and slow trading.

2.3 Random Walk in the Foreign Exchange Market

The theory of a random walk process has been mounted into the literature of statistics since Jules Regnault published the book "Calcul des Chances et Philosophie de la Bourse" in 1863 (Jovanovic & Gall, 2011) and explained in a more reader friendly way by Fama (1965). His proposal was such that the prices in a market are random in the way that past prices have no correlation to the forecasting of future prices. The mathematics of the random walk is simple. When it comes to price movements, the outcome in the next period either is up, down or stays the same. In theory, these movements are random (Shreve, 2004b).

Since Regnaults' book in 1863 there have been many tests of the random walk hypothesis proposed in 1863, the following is most appropriate to the current thesis. Goodhart (1988) found empirics that the exchange market does not follow a random walk continuously, only during short periods at a time. A former notion of this phenomenon is found by Diebold and Mariano (1995) and Gencay (1999) where they test for out-of-sample prediction of future prices. The result is that a simple moving average technique gives better prediction than a random walk, which generates a signal about technical analysis outperforming pure fundamentals.

Evans (2002) confirms Gencay when he evaluates in part the relation between the assumptions of path dependency and a random walk. Conclusions are drawn to explaining the exchange market as a path dependent movement in prices, as a result technical analysis should generate greater forecasts than fundamental analysis.

Olsen (2005) claims that the movements in the exchange rate are path dependent due to dependence between current and future prices. Jegadeesh (1990) found strong autocorrelation in past prices in his research of the stock prices from 1934-1987. This creates some obstacles to the random walk hypothesis and instead points towards a possibility of predictive power of a technical analysis.

2.3.1 Mean Reverting Process

Found in Kestner (2003) is a theory of mean reversion in price movements, meaning that prices are only oscillating around a long-term mean value. If this was the case, the markets would definitely not be efficient since an investor would just have to wait until the price dropped a few points below the mean and then buy and hold until the price rose a few points above the mean and then go short. Obviously this is not the case in today's stock or exchange market, however, even though the theory of mean reversion does not work it is possible that the point of reversion is moving over time. A very common strategy is the Moving Average (MA) where the trader expects the prices to rise when the new price cuts the MA from below and expects the prices to drop when the new prices cuts the MA from above. How well this strategy works in practice is ambiguous.

Serban (2010) works with this theory of mean reversion and builds upon the past research from Engel and Hamilton (1990) and Okunev and White (2003) that the foreign exchange market is showing signs of mean reversion in the long-run whilst the theory of momentum in price swing are more present in the short-run.

Several researches have concluded that stock prices have followed the mean reversion theory instead of random walk theory during periods of the last century (Jegadeesh, 1990; Kim, Nelson & Startz, 1991; Lo, 1998; Lo & MacKinlay, 1988) however, there are not many research papers investigating the foreign exchange market.

2.3.2 Momentum

What exactly drives the prices has been determined to be the news, either incorporated in the past and current prices but also the order book, and as discussed by Malkiel (2003) the flow is random and thus unpredictable. Through research there have been some strategies that have been shown to work for periods of time and show signs of recurring now and then in the financial markets. One of those strategies is the theory of momentum. Momentum is a concept of trend, but it can be used to evaluate trend in not only prices, but also other types of series such as the indicators that will be discussed later (Kestner 2003).

2.4 Market Efficiency

The Efficient Market Hypothesis (EMH) was introduced by Samuelsson (1965) but was recognized when Eugene Fama (1970) published the review of Samuelsson together with a proof of the hypothesis.

The EMH consists of three levels: tests for return predictability, event studies, and tests for private information. The hypothesis is evaluating the amount and type of information that is present in the current prices. Assumptions of the EMH are strict and somewhat irrational but accepted. The assumptions are the following: all agents interpret new information the same way and act rational upon this new information and at the same time not gambling. The EMH consists of the two main types of analyzing market movements, technical and fundamental analysis. Technical, as the name suggests, is a method in which the analyst uses econometric manipulation of data to find patterns in price or order flow movements. Fundamental analysis consists of macroeconomic theories where changes in a specific variable produce a certain signal that should affect the stock/market in a specific way. Fundamental analysis, thus, considers the broader picture of the market and concludes what should happen according to interest rates, inflation, and so forth.

According to Malkeil (2003) neither technical nor fundamental analysis is good enough to disprove the EMH. This is due to the following logical proof of the EMH. As the EMH is built upon the theory of the random walk, which on its own assumes prices to reflect all known information, the news of tomorrow will only affect tomorrow's prices. This mean that tomorrows prices have no other relation to today's prices other than the starting value of tomorrow is close the closing price of today. As of now we have a price movement only affected by future news. This means that the price today is an estimated interpretation of all the known information. At this point it would be enough to play on future news. However, because news flow is unpredictable, so is the future price change. This means that beating the market is only possible by placing bets, which is going against one of the assumptions.

Tests for return predictability is more commonly named weak-form efficiency and it states that an agent should not be able to forecast future returns with the use of historical prices alone. It is, however, important to point out that not only should the forecasts generate profitable returns but also the returns should give a higher return-to-risk ratio than a portfolio consisting of all possible investments (Fama, 1970)(Cuthbertson & Nitzsche, 1996). This type of efficiency is easily tested by using technical analysis.

As the name event studies suggests, this type of efficiency focus on the information flow to the market. This is also called semi-strong form of efficiency. This type of efficiency evaluates whether or not it is possible to beat the market portfolio when trading on publicly known information (Fama, 1970).

The last form of efficiency is called strong form efficiency, Fama calls it tests for private information, and it is exactly what the name says. If this form of efficiency is found to hold then it is not possible to gain above-average returns without above-average risk even when trading on privately known information. Privately known information is considered information that has not yet found its way to the market agents (Fama, 1970).

Through the years there has been critique filed towards the EMH, especially by Malkeil (2003).

Kestner (2003) pose an interesting thought. It goes in hand with the theory of Popper falsification (Ryan et al., 2002). Disproving the EMH is only possible if time after time finding a strategy that can predict future movements. If an agent finds himself in a position where he has generated large profits he cannot claim to have proven the EMH to be false. At this point he can only say that he has found a way, at one point in time, to generate high profits. If it can be done repeatedly in different markets, then one can start to accept the alternative hypothesis of EMH that markets are predictable.

2.4.1 Disposition

Odean (1998) tests the disposition effect among investors and found that selling winners and holding on to losers is a common mistake in the market at the time. This is not only very inefficient for the investor, but also creates arbitrage opportunities since irrational behavior is present in the market. Odean also presents the result that disposition effect is less present during tax selling behavior in December.

2.4.2 Dow Theory

The first editor of the Wall Street Journal Charles H. Dow wrote many papers about the stock market and a compilation of these editorials could be summarized by a theory named in his own honor, the Dow Theory. The theory is a set of six pillars where each pillar contributes to a system that could be used to test the efficiency of the market (Brown, Goetzmann & Kumar, 1998).

The six pillars are the following (Brown et al., 1998):

- Market moves in three ways.
- Trends have three phases.
- News is discounted.
- Averages must confirm with each other.
- Volume confirms trends.
- Trends persist until there is a clear signal.

The first pillar, about the market, states that there are three terms in which the markets move. The main movement is a long trend that could last for longer than a year. The medium swing is the intermediary trend that could last from a week to more than two month. The short swing is the shortest trend, which could last for an hour to about a month. These trends could occur simultaneous in opposite directions (Brown et al., 1998).

The second pillar states that trends follow a certain pattern including three phases. Phase 1 is called the accumulation phase where informed traders absorbs shares. Phase 2 is the rally of the prices where the informed traders profits from their previous trades. Phase 3 occurs when the rally is over and the informed traders exit their positions and collect their profits (Brown et al., 1998).

Pillar number three is an agreement with the EMH as it states that prices already include information as the news is presented (Brown et al., 1998).

Pillar number four says that industries moves together. If one industry shows positive signals, then any industry that has a relation to this industry should show positive signs as well. Dow had observed that averages of industries related to each other move together (Brown et al., 1998).

The fifth pillar incorporates the amount traded on the exchange together with the trend. If the trend is not supported by the volume then the market does not agree with current price movements, which will lead to turn points shortly after the supposed trend (Brown et al., 1998).

The last pillar of the Dow Theory states when to exit the market. According to Dow, the present trend will not stop until there is a clear-cut sign that signals a stop or a reversal (Brown et al., 1998).

2.5 Technical vs. Fundamental Analysis

There have been numerous debates about the importance of technical and fundamental analysis. A survey was made by Lui and Mole (1998) which consisted of answers from foreign exchange dealers in Hong Kong as well as large banks[6], the result showed that there is almost no difference between technical and fundamental analysis when determining trends while technical analysis is better at discovering turning points in the time series. One must

[6] The survey was qualitative and the answers are positive statements, however posed theory is not tested within the survey.

remember that this survey was done over a decade ago and only asked one part of the market, namely Hong Kong. Their result do however pose an interesting factor in deciding whether fundamentals or technical analysis generate greater signals. The findings postulate the question of time frame trading. In the short-run the technical analysis is praised while in the long run the fundamental analysis is found to be most reliable. The preference of switching was found around monthly trading.

2.5.1 Fundamental Analysis

2.5.1.1 Arbitrage Analysis

The work of Chaboud et al. (2011) is mainly based on the theory of arbitrage trading. An arbitrage opportunity is defined as something that would generate positive payoffs while inducing no risk Cuthbertsson & Nitzsche (1996). According to the EMH, arbitrage opportunities should not exist in an efficient market since arbitrage opportunities are proofs for market imperfection.

Chaboud et al. (2011) evaluates the strategy of arbitrage trading in their research, as they form a triangular model evaluating three large currency pairs. Checking them for inequalities and then placing orders when equalities do not hold. They take use of a robot to be able to place orders within milliseconds such that no opportunities go away. They find that as the use of ATs increase in general from 2005 and onwards the arbitrage opportunities have decreased significantly. The shrinking of bid/ask spreads, together with decimalization, has also affected the frequency of arbitrage opportunities.

2.5.1.2 Parities

There are a number of parities that analyze current exchange rates and evaluate whether they are over or under priced. One of the most known is the covered-interest parity (CIP). CIP is an evaluation of current and forward prices and incorporates the interest rate.

$$\frac{F}{S} = \frac{1+r}{1+r^*} \qquad (1)$$

The CIP is evaluated from the function above which states that the forward rate, F, divided by the spot price, S, should have the same ratio as the interest rate in the domestic country, r, divided by the interest rate in the foreign country, r*. If this does not hold, then an arbitrage opportunity exists (Cuthbertson & Nitzsche, 1996).

There is also the uncovered interest parity (UIP) which is very similar to CIP, but instead of working with the forward rate, F, an expected exchange rate, s_{t+1}^e, is used (Cuthbertson & Nitzsche, 1996). The difference here is that s_{t+1}^e is an expected value, which could be argued to be biased, and gives false signals.

The difference between CIP and UIP is that CIP assumes exchange risk to be covered as the investor is able to trade on forward contracts as where the UIP does not assume coverage of exchange risk since the s_{t+1}^e is non-tradable due to its nature (Cuthbertson & Nitzsche, 1996)

Thus, UIP is much more reliant on the analyst's ability to account for different scenarios and evaluate current data such as inflation, interest rate, and unemployment, etc. There are many factors that could be used to analyze future rates, the problem is that there is not one set of factors that could always be used. Sometimes one set of factors are important, while the next period demands another set of factors. Knowing which factors that should be used is unknown, thus the problem of bias (Cuthbertson & Nitzsche, 1996).

2.5.2 Technical analysis

Technical analysis, also called quantitative trading, evaluates the past prices together with the order flow. The evaluation should give some kind of hint of where the market is heading next. The difficult part of technical analysis is to find an actual pattern that could give appropriate signals. There are a lot of different quantitative strategies that founders claim to be very successful. However, due to the ever-changing market conditions there is no strategy that could work forever. There is a need for change, at least an update to accommodate for new technology and news regarding trading.

One basic assumption of technical analysis is that history repeats itself, a reason why fractals are popular in technical analysis, and being able to recognize when repetition occurs will definitely be of advantage (Douglas et al., 2011).

The price movements can be visually shown in a chart. The chart can be visualized in many different ways such as a line chart with current price or a bar chart or a candlestick chart. The latter two shows the open, close, high and low prices for each new bar. This research will use candlestick charts, as it appears easier to understand than the others with the same amount of information (Fischer &Fischer, 2003).

Metghalchi et al. (2005) tests the usefulness of a moving average as a strategy of technical analysis and find that it does have power. Their study suggests a market imperfection as their result indicate prediction abilities by a simple moving average.

2.6 Performance Analysis

One very important distinction that should be noted is that the standard deviation measures the uncertainty of, in this case, value changes and not the risk changes. Risk is something that is bound together with a value and the future (Sortino & Satchell, 2001).

2.6.1 Sharpe Ratio

The Sharpe Ratio (SR) was introduced by William Sharpe in 1966 (Sharpe 1966), the measure was introduced already in 1952 by Roy (1952) however his proposal used a disaster level instead of the risk free rate return. Roy measures the minimal accepted return instead of measuring the excess return. It was then called reward-to-variability ratio but as the measure became popular academics later called it the SR. The following is the SR:

$$SR = \frac{\overline{R_i} - R_f}{\sigma_i} \qquad (2)$$

The Sharpe ratio is just in the sense that leverage do not affect the outcome, it only looks on how much the actual return is compared to the amount of risk taken by positioning.

According to portfolio theory there should not be any investment opportunity with a larger Sharpe ratio than the market portfolio since then the market portfolio would not consists of all investment opportunities. This comes from the theory of individual and market risk where diversification takes place. This means that producing higher Sharpe ratios by algorithmic trading shows evidence that it is possible to beat the market (Elton, 2011).

2.6.2 Downside Risk

One important deviation from the SR is the downside risk theory. The theory indicates that an investment is only as good as the worst return and how often the investment underperforms. Downside risk measures the deviation when the return is lower than a minimum acceptable return (MAR). From these values the standard deviation is calculated and thus gives a value different from the regular uncertainty measure.

There are two important measures of downside risk, average and magnitude. The average downside risk value is information of how much the average return below acceptable rates is and the magnitude of the downside risk is the worst-case scenario (Sortino & Satchell, 2001).

2.6.3 Sortino Ratio

The Sortino Ratio (SoR) is an elaboration of the SR and is very useful for investors who want to evaluate the downside risk of an investment. The downside risk is the risk associated with the returns which fall short of an acceptable return level and in turn only show how an investment has been performing in the past, considering this satisfactory level of return. The formula for the SoR is the following:

$$SoR = \frac{\overline{R_i} - SLR_i}{DR_i} \tag{3}$$

R_i is the realized return for a specific period, SLR_i is an abbreviation for the satisfactory level of return for the period while DR_i is the downside risk. The downside risk is calculated as the usual standard deviation, however the downside risk only use the periods where the return fall short of the MAR which is the same thing as SLR. This value, thus, evaluates the chance of a decline in the price compared to the SR, which evaluates the return per risk (Sortino & Satchell, 2001).

2.6.4 Value-at-Risk

Value at Risk (VaR) is a good indicator of how risky it is to take a certain investment. It has been around as a statistical measure for a very long time but has been very much used since the crash in 1987 (Jorion, 2007). There are many different ways of calculating the VaR with the easiest way is to sort each return in a histogram and then choosing the percentage level satisfying the study and finding the corresponding return to that level. The usual percentage is around 5 % but as with all statistics the 1 % level is also interesting.

VaR has been popular due to the result of the calculations. It quantifies the risk of an investment in terms of how much value the investment may lose if the market would turn in the wrong direction. However, as with most statistical calculations, the VaR uses historical data. This means that if the market conditions stay approximately the same, then VaR is a good measure but if there is a significant change in information flow or occurrences that could impact the stock or currency then VaR could be misleading (Ruppert, 2004).

VaR measures the riskiness of a current position based on historical standard deviations. The only assumption that VaR have is that the sample needs to be normally distributed (Alexander, 2008a).

VaR works in the following way: the profit of a trade is divided by the amount invested. The returns are then ordered from largest to smallest. Then the 95th percentile is the value at risk for a new trade (Ruppert, 2004).

2.6.5 Statistical measurements

When evaluating and analyzing data it is important to know how the data is built up. There are three terms that needs to be clarified in order to be able to analyze the data of this thesis. The normal distribution, also called the Gaussian distribution, has a large role in this analysis. The VaR is assuming this condition, even though it is fairly theoretical. The studies of Laplace have shown that as the size of the sample increase, the sample converge to a normal distribution. The rule of thumb usually states larger than 30 observations before the central limit theory (CLT) is said to apply (Jorion, 2007)(Shreve, 2004a). However, when using financial time series data, CLT does not apply no matter how large the sample becomes (Esch, 2010).

The second term is skewness. Skewness defines how the distribution is shaped, if it tilts towards one or the other side. A positively skewed sample indicates a long tail on the right side, which means that the returns (in this case) are more often positive than negative. The normal distribution has a skewness of zero (Jorion, 2007)

The last important term in the analysis is the kurtosis. Kurtosis is a value estimating how flat the sample distribution is. Large kurtosis values indicates that the histogram have fat tails meaning that there are more observations in the tails than if the data would have been normal. The normal distribution has a kurtosis of three (Jorion, 2007).

A non-normal distribution indicates that the returns vary considerably between years, which mean that the volatility is not constant. A way to still work with such data is to use a GARCH (Generalized Auto-Regressive Conditional Heteroscedasticity) model. As Esch (2010) investigate the normality in the data set of financial returns and finds that the norm is that data does not follow a normal distribution, which is why a GARCH model is used instead to analyze the data. As this thesis is testing already known strategies, there is no need to predict future volatility. However, if a new strategy was to be found, then evaluating the future volatility is necessary.

2.7 Manual vs. Automatic Trading

There are a couple of reasons why automated trading bots have infiltrated the market the past decade. One significant reduction in execution costs have occurred since automated trading started. It is very expensive for a company or a personal investor to go to a trading floor each day and make manual orders instead of having a computer do it automatically. The other reason why automated trading is popular is because of the analytical tools that can be applied to the strategy very fast and incorporated in the decisions directly. If a manual trader would have done so it would have taken more time (Venkataraman, 2001).

2.8 Trading Forex

Tinghino (2008) writes in his book about the procedure of trading forex. The market does not work exactly as the other financial markets as there is no external costs other than the amount of the trade times the value of each lot. This means that the price per lot that is shown, is also the price you pay. Conversely in the stock market where there exists courtage per trade together with a percentage if the trade is large enough. The cost of trading forex is thus included in the lot price. Usually the brokers charge the trader by pips (percentage in point). Today the usual pip spread is about two, which mean that if the lot size is one and the value per lot is 100 000 USD then the cost of each lot is 2 USD since each tick is a hundredth of a cent (Douglas et al., 2011).

2.8.1 Leverage

The use of leverage in forex markets is vast. Brokers offer a leverage ratio of up to 1:500. In the CFD market, the use of leverage is not the same as in other market where leverage actually adds to the account balance. The leverage in the CFD is used to calculate the margin (discussed later) which means that there is no demand for an actual bank loan or such. There is of course a risk in using leverage. The larger the leverage the larger the trades can be. This also means that the equity of the account (account balance - current return of open positions) change quicker. A long position in a downtrend could, thus, be devastated and automatically closed if the margins become too small. However, leverage is needed for the average investor in the forex market today due to the construction of the market itself (Douglas et al., 2011).

Leverage is not always good. The so-called leverage effect could be very harmful for the investor if the market runs in the wrong direction than the investor thought. Leverage, in theory, is a tool to multiply the return no matter if they are negative or positive. For example, an investment funded by 50% leverage only needs to increase by 20% in order for the investor to have gained 40% of equity. However, the same result works for the losses. An investment funded by 50% of leverage and drops 20% have caused the investor to lose 40% of equity.

2.8.2 Margin

The interesting phenomenon when it comes to leverage on a forex trading account is that the leverage level is constant, thus it do not change if the account balance change. The leverage is only used when placing orders and calculating the margin of the account. The margin is calculated the following way:

$$Margin = \frac{Standard\ Lot * Lots}{Leverage} * Currency\ Quote \tag{4a}$$

The currency quote is one if the account is denominated in the same currency as the position is long. Meaning that if the position is long USD and denominated in USD then the currency quote is one, if the position is short USD and denominated in USD then the currency quote is the price that was used when placing the order. The margin is a value that shows how much equity is needed to cover current and pending orders (Douglas et al., 2011).

The margin is used to calculate a ratio called margin level. The margin level is a ratio between equity and margin (see equation 4b). Brokers have a restriction on this ratio, thus it is important to check this ratio. The restriction varies from broker to broker but there are brokers who have the restriction of 50%, which means that if the current position is long USD with lot size 1 and leverage 500, the margin is 200 USD. This means that equity must be larger than 400 USD, otherwise the position will be closed by the broker. The lowest margin level of a new position is larger than the margin call. The actual level varies as well, but there are brokers who have a 50% margin call which also have the margin level of a new position at around 110% leading to a minimum equity level at 440 USD[7].

$$Margin\ Level = \frac{Account\ Equity}{Margin} \tag{4b}$$

2.8.3 Trading Through CFD

Trading forex can be done in many different ways, one of the most popular these days is the contracts for difference (CFD) technique. This type of trading allows the trader to make trades dependent on a so-called margin instead of trading with actual value. The profit calculations are made exactly the same such that profit is the sell price less the buy price times the size of the order, however, the value of the amounts of stock or currency do not leave the traders account until the position is closed. If the trade was profitable the value of the account increases, otherwise it decreases. As the size of a currency trade is very large, the option of trading through CFD is widely used (Brown, Dark & Davis, 2010). Trading through CFDs, the VaR should be the *stop loss* level in profit terms. If the *stop loss* is set to 250 points with a lot size of one for example, then the value that is at risk is 250 USD.

[7] Own calculations.

3 Research Method

Research in the strategy field of trading is not young but ever changing. There are not many research papers that explain the theory of an indicator, just if it works or not. The theory used in the following section is mostly found in books, with a few inputs from research papers on the performance of that indicator.

3.1 Momentum and Trend Analysis

Markets have shown plenty of signs of momentum. Momentum in the market prices is shown by fairly long trends giving the investor a chance to gain large profits. As with all momentums and trends, the second value that is looked upon should not be too far back in time since then unnecessary information is contained in the prices which could result in a mistake in the analysis (Kestner, 2003).

There has been extensive work in this area when it comes to examining the equity market and stocks in particular, however, Chiang and Jang (1995) found that the same patterns have been akin in the foreign exchange market as well. This creates an ambiguity in the research field and thus the need for new research is prompted.

Trend is a very popular way of analyzing the market. The shorter the time frame that is used, the greater volatility/ uncertainty is present in the trends. Douglas et al. (2011) explains an uptrend as a series of bars where the high's and low's continue to get higher and a down trend where high's and low's continue to get lower and lower. Each trend ends when the proceeding high and low does not conform to the definition of a trend.

3.1.1 Moving Average

Kestner (2003) discusses the strategy of moving average (MA). The MA is a momentum strategy since it evaluates two values from two points in time. In an MA strategy these two values could as in the first case, below, be the current price and an average of past prices. The simple MA is easily calculated by the following formula:

$$MA = \frac{1}{N} \cdot \sum_{i=0} Price_{t-i}\,, i\ is\ the\ number\ of\ periods\ back\ in\ time \qquad (5)$$

There are two pure moving average models, one examines price and a moving average while the other examines two moving averages and create signals when they cross.

Case 1: $MA = Current\ price - Average\ price$

The interesting part here is not whether the MA is positive or negative. What is wanted is when the MA turns negative or positive, when the current price and average price cuts each other, since this is when a position should be taken.

Case 2: $MA = Average\ price\ x\ periods - Average\ price\ y\ periods$

The same principle works here, however, if the gap from current prices is too far, then the profits become more volatile which in turn usually generates negative profits. (Kestner, 2003)

Even further developing of the second case can be made and extending the number of MA's to three. Using a fast MA, medium MA and a slow MA can result in good trading signals as well. It does, however, provide periods where no market activity is made (Douglas et al., 2011).

Short signal - the fast MA crosses the medium MA below the slow MA. Closing the position should occur when the fast MA crosses the medium MA below the slow MA.

Long signal - the medium MA crosses the slow MA below the fast MA. Closing the long position should occur when situation is no longer valid.

3.1.2 Exponential Moving Average

$$EMA = \alpha \cdot close_t + (1 - \alpha) \cdot x_{t-1} \tag{6}$$

$$\alpha = \frac{2}{1 + bars} \tag{7}$$

What is meant in the EMA formula is that new information has greater impact than in the regular MA. The α in the function is the smoothing factor and the larger it is, the faster the EMA responds to new information (Gross & Ray, 1965).

A more advanced use of the EMA is to use the triple EMA (TEMA). It is more efficient than the EMA when looking for long lasting trends. However, it does perform poorly on short-term fluctuation data (Gross & Ray, 1965). It is calculated as follows:

$$TEMA = (3 * EMA) - (3 * EMA\ of\ EMA) + (EMA\ of\ EMA\ of\ EMA) \tag{8}$$

3.1.3 Oscillators

Oscillators are mathematical tools that evaluate reversals in the market. If used properly and carefully, it could be very powerful.

3.1.3.1 Awesome Oscillator

The awesome oscillator (AO) is using less statistics than other types of oscillators. Instead it looks on chart-patterns and evaluates the movements in order to form signals of buy or sell. It was introduced by Bill Williams and is explained in his book "New Trading Dimensions" from 1998, Williams (1998).

Williams (1998) explains his indicator well and shows that the AO have three buy signals and three sell accompanied with the respective buy signal. He calls them Saucer, twin peaks, and cross the zero line. See appendix 2 for a graphical interpretation. Williams also states that it takes at least three bars to create a signal.

The overall information that the AO gives comes from a simple formula:

$$AO = 5\ bar\ MA(meadian\ price) - 34\ bar\ MA(meadian\ price) \tag{9}$$

The histogram below the price chart in figure 5 (appendix 2) shows the AO value.

The Saucer evaluates when there is a turn from green to red bars in the histogram. Green to red gives a sell signal and red to green gives a buy signal. One must be careful to evaluate the market force in order to know whether or not the color shift will generate price cascades or not. As seen in the graph the sell signal in the beginning give a price cascade, whereas the third color shift results in a stable price until the next color shift and then a price cascade occur. The buy saucer can only appear above the zero line while the sell saucer only appears below the zero line (Williams, 1998).

Twin Peaks is a chart pattern that creates two peaks with the first peak being further from the zero line than the second peak. The buy signal is only produced below the zero line and the position should be place directly when the bar color shift from red to green. The opposite is used for the sell signal (Williams, 1998).

Crossing Zero is a fairly volatile situation in the histogram and should be watched carefully. As seen in the graph, and also in more situations for the twin peaks pattern, the last peak is usually followed by a crossing zero pattern that creates large profits if the position is taken from the twin peak signal. The crossing zero pattern gives a buy signal when the bars are green at least 2 bars before the crossing and it gives a sell signal if at least the preceding two bars are red (Williams, 1998).

3.2 Statistical Analysis

Statistical analysis in this paper is considering the issue of volatility and how it affects the trading strategy. There are plenty of ways to measure volatility, and there are probably as many ways to include volatility in the trading strategy. Below are two indicators that will be used to incorporate volatility measurements into the strategy and take advantage of the volatility.

3.2.1 Bollinger Bands

Bollinger band evaluates the volatility of the recent price changes; depending on how many periods the trader want to have in memory the amount of signals will vary. The use of bollinger bands is especially effective to examine the market pressure. A report on the method from Forbes, Devcic (2007), states that in the majority of the cases where the price change cuts the bollinger band the market bounce back. See appendix 2 for a graphical interpretation.

Bollinger band is, as the oscillators, an indicator that shows the state of the market such that it is overbought or oversold. The upper line shows the overbought scenario and if prices move past that line, the markets should reverse and go back down again. Conversely, if prices move past the lower line the market should reverse back up (Devcic, 2007).

The reason why this is a statistical indicator lies in the mathematics behind the upper and lower lines. The middle line is an EMA, but the upper and lower line shows the volatility with two standard deviations from the EMA, which makes them continuously adjust to new prices. The number of standard deviations (SD) can be changed to create even stronger signals, however, the larger number of SD's the less signals will be produced.

3.2.2 Parabolic SAR

One of the more advance indicators is the parabolic SAR. Parabolic SAR was first introduced by Wells Wilder in his aforementioned book. As with the ATR, parabolic SAR has stayed popular even though it was developed before the computers (Wilder, 1978)

SAR stands for "stop and reverse" which creates an environment for the robot to never be outside the market. Parabolic SAR works best in volatile markets with many different trends, otherwise there will be many signals to follow which may not generate positive returns when accounting for transaction costs. One of the most intriguing things about the parabolic SAR is that it does not only provide a direction for the trend, it also provides a trailing *stop loss*, see section 3.3.1.1, which is very useful in money management (Wilder, 1978).

Wilder (1978) explains the indicator well in his book and a short summary of that is shown below. There are a few concepts that need to be sorted out. The SAR of one period is similar to an autoregressive model where the current value consists of a portion of an older value. The SAR is calculated as below:

$$Uptrend\ SAR_i = min \begin{cases} SAR_{i-1} + AF_{i-1}(EP_{i-1} - SAR_{i-1}) \\ SAR_{i-1} \\ SAR_{i-2} \end{cases} \tag{10}$$

$$Downtrend\ SAR_i = max \begin{cases} SAR_{i-1} + AF_{i-1}(SAR_{i-1} - EP_{i-1}) \\ SAR_{i-1} \\ SAR_{i-2} \end{cases} \tag{11}$$

SAR	"Stop and Reverse" value	Calculated from previous SARs
AF	Acceleration factor	Starting at 0.02. Each time the EP change, 0.02 is added.
EP	Extreme point	Uptrend: highest high of the trend. Downtrend: lowest low of the trend.

Table 1 - Parabolic SAR Calculation abbreviations

In an uptrend the current SAR value cannot be above the previous two low values and in a downtrend the current SAR value cannot be lower than the previous two high values (Wilder, 1978).

What is the meaning of the SAR value? The SAR value is the trailing stop of the position and as the market trend is reversed and prices move towards the SAR, the indicator signals the position should be reversed. This is also the reason why the parabolic SAR is best used in a trendy market. If prices move in a small range then the SAR will not react fast enough to give profitable signals (Wilder, 1978). See figure 3 in appendix 2 for a graphical interpretation.

The table above mentions that AF is increased by 0.02 (step) each time the EP change. The number 0.02 was used by Wilder in his book. However, using a smaller number will create a less sensitive indicator while a larger number would increase the sensitivity of the indicator. Wilder also mentions that there should exist a max number for the AF. His proposal was 0.2. Exactly why the number 0.2 is used is not declared, however the use of a smaller number will create a less sensitive indicator while a larger number will generate more sensitivity to reversals. The maximum number only affects the indicator when there are longer trends while the step affects each value of the SAR (Wilder, 1978).

3.3 Risk / Money Management

There is an important question about volatility that is crucial for every risk-manager in any market. In the following paragraphs the implementation of risk-management will be analyzed.

3.3.1 Stop Loss

The *stop loss* technique is a very commonly known technique for reducing the value at risk, thus managing risk in an easy way. However there has been some critique to the proposed technique by Olsen (2005). He has found a relation between the price cascades that occurs in the exchange rate market. A price cascade is a very severe threat to profit if it happens in the wrong direction. This is one reason why a *stop loss* order is a good way to defend the equity from falling. Nevertheless, as Olsen claims, *stop loss* orders cluster around a specific value and when that value is hit there is a fast fall/rise in prices.

Kestner (2003) proposes an ideal *stop loss* by using a range formula that examines how large a bar is and the average bar size for some periods, the formula is called average true range (ATR). He claims that a double ATR of the last 20 bars negative the initial value should be the targeted *stop loss*.

3.3.1.1 Trailing Stop

Trailing stop is a technique developed within the field of risk management that will work in the following way, as the price moves in the presumed direction the *stop loss* will automatically move in the same direction with an exact exit position of the preset percentage. Once the price trend changes the trailing stop will keep the lowest percentage loss and not move back (Yin, Zhang & Zhuang, 2010).

As discussed in Yin et al. (2010) there is a relation between the optimal trailing stop, the amount of risk and the corresponding expected return. According to their research, the optimal trailing stop for a position expecting to generate a 40 % return, for example, is in-between 15-30 % of the value of the position depending on the volatility of the position. There is also a clear relation between volatility and expected return such that higher volatility demands a higher percentage of trailing stop.

3.3.2 Take Profit

Take profit is a widely used technique for accepting certain profit and close the position automatically. As discussed under the topic of *stop loss* orders, Olsen (2005) also tested *take profit* orders as a reason to price cascades. The results was that *take profit* orders also contribute to price cascades, however the lasting of the cascade was greater on *stop loss* orders than *take profit* orders.

4 Empirical Results

The following section will only present the actual finding and the calculations that go together with the result. A thorough analysis of the result will be done in section 5.

4.1 Outcomes

There are many different types of analyzing a performance by an algorithmic trader, a few of them which are found to be more useful when it comes to perfection and comparison to the efficient portfolio is presented below. See appendix 3 for tables on further result data. The algorithms are explained below to give an insight of what have generated the following results.

Do to complexity of too many signals at once there have been a few algorithms produced in order to test the market efficiency. The signals are more stable when there are only a few outgoing signals. Below are explanations of how the algorithms work.

Many of these indicators may work when trading manually, while only a few actually work when trading algorithmically. The algorithms below have shown the best results.

4.1.1 Algorithms

Any algorithm will start with a deposit of 10 000 USD. The lot size may differ from algorithm to algorithm, however if the lot size is set to a constant it will be set to 1.

AO and EMA

AO and EMA (TyskAOEMA) is a simplification of the TyskAOTEMA that only uses a simple EMA instead of a triple EMA. The money management is the same as with the TyskAOTEMA but the lot size in this robot is not constant. It changes depending on how the last trade(s) has turned out to be. If there is a loss, the next trade will use less lots and will do so until a profit is made.

This algorithm showed best performance on the minute data (M1), thus the result for this time frame only will be shown and analyzed below.

AO and TEMA

The AO and TEMA algorithm (TyskAOTEMA) make use of the AO and the TEMA with a *stop loss*, a maximum value *stop loss*, a *take profit*, a maximum value *take profit*. This robot will continuously place an order with the lot size of 1. It operates on the 20 minute time frame (M20).

Bollinger Band

The Bollinger Band algorithm (TyskBB) evaluates past and current prices. The past prices are used to calculate the standard deviation (StdDev). Then the algorithm evaluates the current price and compares it to the StdDev. If prices have cut the two StdDev line a signal is created.

The money management used in this algorithm is a combination of several types. There exists a normal *stop loss* and a trailing *stop loss*. Then there is also a maximum value *stop loss* that exits any position with greater loss than this value. For the profit side of this algorithm there are the normal *take profit*, a trailing *take profit* and also a maximum value *take profit*.

TyskBB does not work well on all time frames but produce profits on most at least. The best time frame after thorough analysis was the hourly (H1). The lot size of this robot is set as a constant to 1 lot.

Parabolic SAR

The fourth and final algorithm is based on the parabolic stop-and-reverse indicator, both as the buy/sell signal generator as well as a trailing stop function. The algorithm has shown best result on the 12 hour timeframe H12.

4.1.2 Return

Deposit 10,000,00	Leverage 1:500	2007-01-01 --> 2012-12-31		
	TyskAOTEMA	TyskAOEMA	TyskBB	TyskPSAR
Return	518,19%	459,30%	512,99%	353,68%
Net Profit	$ 51 823,20	$ 45 930,24	$ 51 298,80	$ 35 368,40
Gross Profit	$ 467 993,80	$ 446 792,72	$ 115 746,90	$ 164 440,30
Gross Loss	$ -416 171,00	$-400 862,48	$ -64 448,10	$ -128 961,90
Profit Factor	1,12	1,11	1,8	1,27
Number of Trades	1 597	1 430	158	185
Profitable Trades	589 (36,88%)	834 (58,32%)	83 (52,53%)	64 (35,59%)
Expected Profit per Trade (Value)	$ 32,45	$ 32,12	$ 324,68	$ 191,18
Average Profit	$ 794,56	$ 535,72	$ 1 394,54	$ 2569,38
Maximum Consecutive Wins	8 ($ 3 569,3)	21 ($ 15 397,14)	7 ($ 4211,7)	5 ($ 9 388,7)
Maximum Consecutive Losses	14 ($ -5 784,20)	13 ($ -588,73)	7 ($ -6 248,90)	7 ($- 7 791,2)
Absolute Drawdown	$ -620,50	$ -4 823,00	$ -2 039,30	$ -4040,2
Maximum Drawdown	$ -24 966,50 (-52,87%)	$ -21 880,88 (-31,57%)	$ -6 947,4 (-10,36%)	$ -17 301,9 (-59,73%)
Sharpe Ratio (S&P500= -0,00) (EURUSD=-0,03)	0,29	0,22	0,32	0,17
Sortino Ratio (S&P500= -0,05) (EURUSD= -0,25)	0,42	0,39	0,46	0,35

Table 2 - Algorithmic Performance 2007- 2012

The reference to the index below is the S&P500 and the currency is the currency pair EURUSD. The period of analysis is between 2007 and 2012.

The index have shown to be volatile during the test period with the global economic crisis starting in 2008 and have during the period risen with a total percentage of 0,1% with the worst year of 2008 leading to a 38,5% drop. The other years have given greater returns with the best return occurring in 2009 with 23,45%.

4.1.3 Sharpe Ratio

The TyskAOTEMA performed very well as there is only one year that gives lower ratios than the S&P500. The ratio of 0,29 while the overall ratio for the index is -0,11 show that the market has been challenged. Yearly the ratios varied but in general the ratio has been higher compared to the index.

TyskAOEMA also gave good results with a ratio of 0,22 overall but the yearly ratio have varied a lot. Two out of six years the algorithm underperformed the market with the lowest value of -0,37 in 2007 and the highest value of 0,45 in 2010.

TyskBB gave the largest ratio overall with a value of 0,32. Yearly the algorithm was consistent giving positive ratios except the last year when generating a -0,16 ratio. The best years was found in 2010-2011 with ratios above 0,5.

The TyskPSAR gave large profits and losses. The overall Sharpe ratio ended at 0,17. The yearly ratio varied between -0,16 to 0,39.

4.1.4 Sortino Ratio

The SoR does not contradict the result from the Sharpe ratio as expected. Starting with TyskAOTEMA which generated a good results of a 0,42 overall. Yearly ratios vary some with the lowest at -0,51 in 2009 and the highest at 2,79 in 2010.

The TyskAOEMA algorithm also outperformed the index overall with a ratio of 0,39 but on a yearly basis the values varied. Twice did the SoR underperform the index which was 2007 with a value of -0,66 and in 2012 with a value of -0,1.

TyskBB, which made the least trades during the period, showed some good SoR. The overall was 0,46 compared to the index of -0,05. The yearly ratios outperform the index four out of six years. The lowest value was -0,6 in 2012 while the largest was 6,01 in 2011.

The TyskPSAR had an overall SoR of 0,35 which was a better value than the stock index and the currency rate. The yearly rate has varied between -0,29 and 0,61. Only once was the SoR below zero.

4.1.5 Statistics

	Statistical Calculations			
	TyskAOTEMA	TyskAOEMA	TyskBB	TyskPSAR
Correlation				
S&P500	0,15	0,03	-0,22	-0,18
EURUSD	0,27	-0,02	0,05	-0,25
Downrisk	-21,27%	-21,91%	-19,01%	-31,57%
Value at Risk	-7,04%	-6,00%	-13,37%	-18,92%
Kurtosis	3,53	18,36	-0,41	7,26
Skewness	1,8	2,82	0,6	2,36

Table 3 - Statistical Measures.[8]

4.2 Real Time Test

Return	1,90%	Net Profit	$ 190
Profit factor	1,07	Trades	18
Profitable trades	9 (50%)	Maximum Drawdown	$ - 2 141,00 (-17,62%)
Expected Profit	$ 10,56	Consecutive losses	6 ($ - 983)
Average profit	$ 331,89	Consecutive wins	5 ($ 2 148)

Table 4 - Real Time Test Outcome.

The t-statistic for the return during April being different from the average return of 3,08 % is -1,528 which is lower, in absolute terms, than the critical value of 2,11 at the 5% level with 17 degrees of freedom meaning that the return in April is not statistically different from the mean return during the back test (Gujarati & Porter, 2009)

[8] Own calculations

5 Analysis

5.1 Indicators

In this research only a few indicators/strategies have been used and there are more known indicators that have not been used. Some examples include the Fibonacci retracement, the stochastic oscillator and the moving average convergence divergence (MACD). The strategies were looked upon before exclusion and were found to not fit into the criteria for this study.

The strategies that have been used in the study was easy to understand and powerful in previous research but had not been tested thoroughly on CFD trading or the foreign exchange market.

5.2 Return

First of all, it is important to once again make clear that the leverage of these algorithms is 500:1 meaning that instead of having a hypothetical account balance of 10 000 USD with a maximum lot size of about 0,01 the hypothetical account balance will be 5 000 000 USD with a maximum lot size of around 5. As there is no need for an actual loan, the leverage could be set constant knowing that the larger the leverage the larger the potential loss will become. This is because a 50 % margin call with leverage 500:1 will need a position to drop many times more in order for the broker to close the position automatically. The automatic close of a position is a safety net as well since it will dampen the actual loss. If the leverage is too large there might be negative numbers on the account balance unless the broker has a non-negativity restriction as most do.

The results of the algorithms overall impressed. The TyskAOTEMA showed great performance by producing over 50 000 USD over 6 years, so did the TyskBB. Looking at the SR there are some differences but the overall ratios show good indication for a complement to the pile of disproof of the EMH. The question is whether or not the results are trustworthy. On average, the TyskAOTEMA generated 80% per year with a drawdown larger than the initial deposit at a few occasions. In the long run this may work if the robot is placed at the right time such that the largest drawdown does not take the account balance down to zero.

This drawdown is only important due to the high leverage. If the starting equity would have been 1 000 000 USD instead of 10 000 USD with a leverage of 1 instead of 500 the drawdown would have been much less interesting. Because a 20 000 USD drawdown from 1 000 000 USD is 2 % which is irrelevant comparing the drawdown of 20 000 USD from 40 000 USD which is 50% and highly relevant for the continuation of trading. In this sense the leverage creates the risk but also the possibility to achieve abnormal returns. Considering this alone, the TyskBB have shown great results with the lowest amount of drawdown. There are two reasons why the TyskBB have the lowest drawdown. The first reason is because the strategy analyzes the prices better, and the time frame is larger compared to the other strategies. This creates a more stable process.

The risk of trading on the foreign exchange market is very large, especially trading CFD's. However, by using *stop losses* and technical analysis the risk is reduced. In addition, it would be more risky if there was a chance of not being able to exit the market as the position lost or gained value. This is in line with Gârleanu and Pedersen (2007) and their study on the liquidity and risk relationship. As Douglas, Lovrencic and Pontikis (2011) explain in their handbook to forex trading there is more risk when using higher leverage since the tradable volume increases and it is logical for risk to increase in that situation. However, taking advantage to trade in high liquidity environments as the foreign exchange market makes the risk decrease a little. The important factor is a working strategy. There should be strong signals and good money management. All the algorithms prove that it is possible to make abnormal profits also confirmed by Raj (2000), but only some show that it can be done with a good control of the risk in the manner as Gârleanu and Pedersen (2007) suggests.

An important aspect of being able to beat the market continuously is to evaluate the option to configure the settings of the algorithms as time goes by. This could be done if the algorithm is learning as more data is added to the memory; however, the purpose of the thesis was to evaluate the possibility to program an algorithm to beat the market. As four different algorithms with different indicators have shown to be performing well, there is an indication that a proof against the EMH is not far away but since the result is not always outperforming the market there is doubt that the proof holds.

As the SR and SoR vary a lot during the years and do not always end up as the better investment there is too much volatility within the data to have a single strategy to constantly outperform the market. However, one question that should be asked is if it is reasonable to try to beat a theoretical portfolio or if it is enough to beat an index instead. Evaluating the difference in SR and SoR when the index is higher and vice versa, there is a significant difference between the SR's when the index is higher and vice versa. When the index is higher the average difference is 0,36 while if the index is lower the difference is 0,51. The 0,16 difference between the two scenarios shows that the strategies are better at risk adjusting to the current market situations than the index. Comparing the same numbers for the SoR the averages are 0,45 and 1,29 respectively which highlights the result even more. As the SR and SoR are higher the majority of the time they are the better investments but not good enough to disproof the EMH.

The monthly SoR is a good indication of what to expect when using a certain strategy, especially for risk averse traders. Having low downside risk together with a high SR is preferable. Comparing the SoR of the strategies and the index there is an indication that the downside risk is low compared to the return generated. If time was not a scarce resource, the TyskBB would have been the best strategy among the four but at the same time it is good to notice that even though the TyskAOTEMA traded ten times more the ratio was about the same anyway.

5.3 Statistics

Have the results been able to suggest the EMH to be false? The answer is ambiguous. The suggestion of the EMH to be false comes from the ability to make large profits. The risk-adjusted measures suggests that the return per risk ratio is higher than the market portfolio which indicates an investment opportunity that is better than the efficient portfolio and according to Elton (2011) this should not be possible. However, looking at the smaller parts of the results such as the monthly data at a yearly basis, the result suggests that there are years when the return is greater according to SR and SoR. However, there are also years when the ratios are lower. This indicates that the possibility to constantly beat the market is not possible, at least not with the current strategy.

The index has performed badly during the test period with the global crisis and all. Looking at all years other than the financial crisis, it is obvious that both SR and SoR have performed well. The majority of years have showed that it is possible to outperform the market.

Table 2 declares three important points. The correlation between the strategies and the indices are low. This would have been positive if the strategies had a constant positive return regardless of the performance of the index, while the reality shows that they do not follow any similar pattern. The second point is the down risk percentage. This value is an indication of the worst-case scenario in one month. All but the parabolic SAR laid around -20%, which is a large loss in one month. However, important to remember is that the amount invested is constant while the balance increases. This means that if the strategy would have continued in the same direction for some years, the losses would have been smaller percentage wise. The losses get smaller as the account balance increase. This is true for all strategies except the TyskAOEMA since this strategy increase the investment as the balance increase. These strategies have the highest potential to make profits while at the same time it is the riskiest as the investment increases. The parabolic SAR has a magnitude of -31%, which is the highest. However, comparing the potential loss in a month to the TyskAOEMA there is more risk in the latter.

The Third point is the value at risk. The returns of the tests have shown to be non-normal. This is however in line with the research of Esch (2010) where it is described that financial data usually do not follow a normal distribution. This is not a major problem as the purpose of the VaR in this thesis is to estimate the previous VaR and not predict the future. Alexander (2008b) writes about the non-normality of the return data. If there exists non-normality the data follow a so-called leptokurtic distribution, the implications is that the VaR will be overestimated. The data in this paper have larger kurtosis values which means that it is not normal but instead follow a leptokurtic distribution, thus the analysis can be done by following the findings of Alexander (2008b). As the kurtosis value gets larger, the overestimating increases as well.

The VaR for the strategies may be biased as the returns do not correspond to normal distributions. However, as each algorithm consists of a *stop loss* there is a low probability to generate larger losses than the *stop loss* per trade, which is a safety net. Comparing the VaR with the *stop loss* of each strategy one can see that in the TyskAOTEMA the VaR is slightly greater than the *stop loss*. The interesting thing here is that the largest loss is greater than the *stop loss* in absolute terms. This indicates either illiquidity or technical disruptions. The TyskBB actually have a VaR greater than the *stop loss* in absolute terms, resulting in a dangerous process. The largest loss is almost twice as large. This is an indication of poor performance and could be a result of imperfect data as discussed in 1.2.

The TyskAOEMA had a VaR of -6% per lot. This is about the same as the *stop loss*, which is a good sign. The *stop loss* is set in points, meaning that it is not affected by the volume invested. The TyskPSAR had the highest VaR, which is to be suspected as the volatility of the returns is high. This is conforming to the down risk as well. As the AOTEMA, AOEMA and the PSAR have kurtosis values of over three they are considered to follow leptokurtic distribution leading to an overestimated VaR. Doing a Jeraque-Bera test on these data sets it is clear that they are not normally distributed as the p-value is 0.

5.4 Algorithmic Efficiency

This section will focus on how the algorithm performs compared to amount of trades, the number of win trades /loss trades and if there is a possibility to improve or if there is a need for some loss trades in order to create better payoffs. Evaluating the robot itself is important to do continuously since market conditions change. This is one argument in favor of the EMH since it says that one strategy cannot continuously beat the market and if the strategy is altered from time to time, then that could be seen as a change of strategy thus not a disproof of the EMH.

5.4.1 Algorithm Performance

The criteria for selecting the best algorithm for a real time test compounds of two variables, the SoR and amount of trades. TyskAOTEMA and TyskBB have the highest SoR. Since TyskBB only traded 158 times during six years makes this choice easy. TyskAOTEMA will be tested on the real time data during the month of April. This is according to Sortino and Meer (1991) since SoR uses downside risk in the calculation.

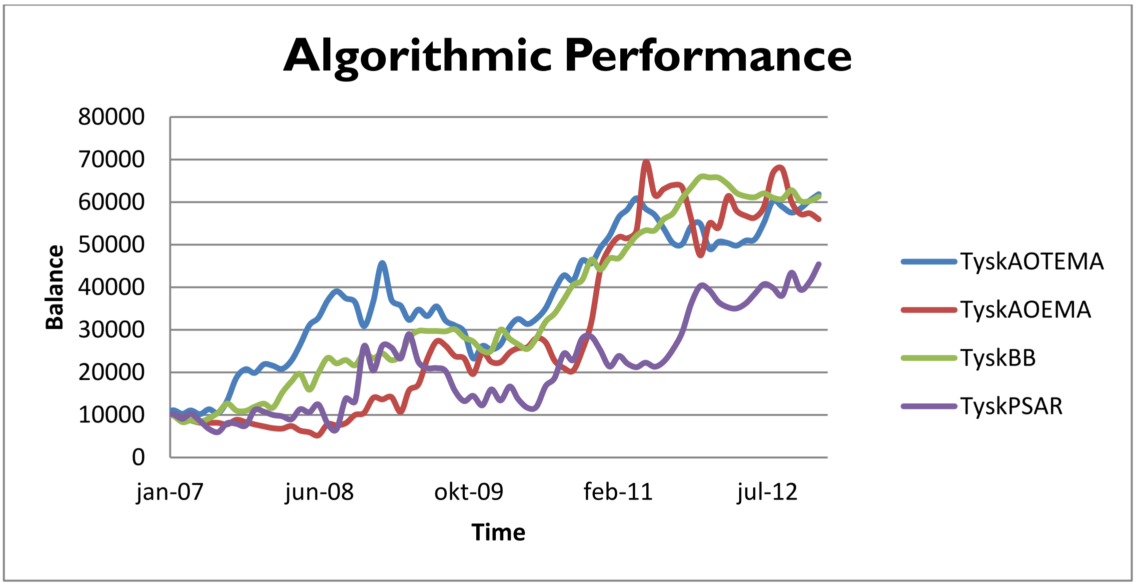

Figure 1 - Algorithm Account Performance from Back Testing. [9]

[9] Calculations in excel from the results of the back testing.

5.4.1.1 TyskAOTEMA

Evaluating the performance of TyskAOTEMA should clarify why this algorithm was selected for the real time test. Starting with the amount of trades, which was 1597 in total during the whole test period. 590 of these trades generated a positive return leading to a 36,94% profitable trade percentage. The percentage is low, however comparing the average return per trade it is clear that most of the losses are smaller on average than the profits, which gives a positive indication for functionality. The gross profit exceeded the losses resulting in a positive profit factor. The profit factor ended up at 1,12 overall. A profit factor above 1 is good but larger numbers is preferable.

The average profit of all trades was 32,45 USD while the average profit trade was 793,21 USD. This is one reason why the profit factor is low. Large profits and large losses give a small average and high volatility.

Performing well includes being able to make consecutive profit trades and few consecutive loss trades. The algorithm made eight trades in a row at the most with a profit while fourteen loss trades in a row at the most. The maximum drawdown which is the amount that has been lost from a previous high was -24 966,5 USD. This could have been devastating if this drop would have occurred at the start of 2007 when the balance was only 10 000 USD. This creates a large risk of using this algorithm. The minimum amount that would have been needed for this algorithm to be able to start at any time during this period would have been when the minimum amount would have been large enough to place a new trade after coming out from the drop of -24 966,5 USD. The margin level of the account needs to be larger than 110% to place an order and the leverage is 500. This means that the minimum amount to start at anytime would have been at least 27 200 USD.

5.4.1.2 TyskAOEMA

The TyskAOEMA showed similar result as the TyskAOTEMA, the drawback of the algorithm was that it had a lot of uncertainty in its performance. The SR of this algorithm was only 1,46 which is lower than the TyskAOTEMA but higher than the index. The uncertainty of this algorithm comes from the data that it worked on. The minute data is much more volatile than the 20-minute data since the prices move 20 times more.

The number of trades that TyskAOEMA performed was close to the amount that TyskAOTEMA performed, 1430 to be exact. Out of these 1430 trades, 835 were closed with a profit, which is around 58% of positive trades. The average profit came close to the previous discussed algorithm while the average profitable trade was slightly lower. This was somewhat expected as the only difference between the two algorithms is the moving average technique. The TEMA indicator is much more sensitive to new information which makes it more appropriate for less frequent data, since too fast actions on frequent data could lead to devastating results, which is in accordance to Gross and Ray (1965). Even though the return is less, the profit factor is about the same as the previous algorithm, 1,11. This shows that the losses that this algorithm takes are larger on average than the TyskAOTEMA.

Losses and profits should be handled in a good way, which this algorithm does most of the time. The aggressive reduction in lot size after a loss trade makes this algorithm reluctant to large consecutive losses. The problem however is that the first loss is usually large while the following losses are small. This leads to a consecutive loss count of 13 but the value is -588 USD. There is one drawdown, however, that creates a huge loss of -21 880,88 USD which at the time was a drop of -31,57%. Where the average loss that year was -1 538,68 USD and the overall average loss was -673,2 USD. This shows how volatile the algorithm has performed during the test period, this is mainly due to the lot size that is being used for each trade. The larger the balance the larger the lot size when placing an order after a profitable trade. If that trade gives a loss, the next trade uses a smaller lot size compared to the previous trade but the size is still fairly large. The third trade use a very small lot size of 0,01. Those first two trades could be devastating. In 2011 when the largest drop occurred, the average first loss was -1 912,12 USD and the overall average first loss was -1 135,77 USD. Comparing this to the first loss average for the TyskAOTEMA, which was -407,29 USD. This is much lower and less risky. This is another reason why the TyskAOTEMA has been chosen to do the real time test.

The lowest amount that a trader needs to have as starting balance on an account in order to be sure to not run out of equity during the test period is 24100 USD. This is lower than TyskAOTEMA but the return says that it may be better to put those extra 3000 USD to get higher return.

5.4.1.3 TyskBB

The third algorithm working on the hour time frame should in theory have less volatility as trends are clearer and signals are stronger. This can be seen by this algorithm. Only comparing amount of trades and the net profit it is easily seen that the net profit is about the same, only differing in some few percentage point overall. The amount of trades is ten times more in the TyskAOTEMA. This means that the average profit is ten times larger. The most respectable result of this algorithm is the profit factor. Even though the number of trades are low, the profitable trades give great result and the profit factor ended up at 1,8. This value alone would have made this algorithm the best. Together with the SR and the SoR, this algorithm is a perfect choice for real time test, but the number of trades makes this algorithm distrusted. There might not even be a signal for the month or only one signal. That few signals would not give any trustable results.

Crunching the numbers the highlights lay on the total drawdown for this algorithm. During the whole test period, the total drawdown from a previous top was -6 947,4 USD which is unquestionable the best result out of the four algorithms. One reason why this algorithm has a low drawdown is because it is good at producing short consecutive loss sequences. The loss count had a maximum trend of 7, which is the lowest count by the four, tied with the TyskPSAR algorithm. The average loss shrunk to -856,81 USD while the average profit was 1 398,05 USD. With a profit trade percentage of 52,53% the difference made huge impact on the result. Being able to come back from a loss trade is important for success. The profit count also had a maximum of 7, which is not the best trend, but together with a greater average profit than average loss in absolute terms the average becomes positive.

During the test period the maximum drawdown was at around -7000 USD, this means that in order for an investor to have been able to start at any time during this period the starting equity would have to be greater than 9 200 USD. This is much less than both the

TyskAOTEMA and TyskAOEMA. Then again, the number of trades means that it could take a lot of time before taking a position, and then even longer to exit the position. The cost of having a position overnight is huge in this case. The cost of this for the algorithm became 478 USD. Compared to the TyskAOTEMA and the TyskAOEMA which had 1 284 USD and 864 USD respectively the value is small, but the average cost of holding a position over night tells a different story. TyskBB had a cost of 3,03 USD per trade while TyskAOTEMA and TyskAOEMA had 0,8 USD and 0,6 USD respectively. This makes the TyskBB an expensive algorithm in terms of overnight costs.

5.4.1.4 TyskPSAR

The last of the four algorithms did not perform much less than the others, however there is a lot of volatility in the returns. This is fairly strange as the longer the time frame, the clearer the signals. This result shows that the P-SAR indicator is volatile in nature. The problem with this indicator is that it never stays out of the market, even in periods where the prices move up and down within small intervals. This creates very narrow zones of profitable trades. It may have been due to the setting of the indicator, however another setting was tried and gave worse results. Another time frame was tried but then the account balance was too small to even finish the test. This means that the EHM in its weak form holds for this algorithm since there is only one, or a few, setting(s) that works and the working setting performs mediocre according to the SR and SoR.

Looking at the other values as compared to the other algorithms, the TyskPSAR have shown the worst result of the four algorithms. The worst result of these four algorithms is not bad in any way since it still performed a 366 % return over six years with an SR larger than the market, this is a good result but compared to the other algorithms the result of the TyskPSAR algorithm is the worst. The number of trades is slightly above the TyskBB algorithm with a total of 185 trades and a profitable trade number of 65, which is around 35%. This is the lowest percentage among all algorithms. The importance of a *stop loss* and a *take profit* limit is showing through these results. A *stop loss* following the P-Sar indicator have no *take profit* limit, and as can be seen in appendix 2 figure 3 the buy and sell levels could lie very close to one another, which creates losses. This also means that the losses should not be as large as in the other algorithms. The dilemma here is that the setting of the algorithms makes sure that the trailing *stop loss* moves slowly which can create larger losses, especially with a 1:500 leverage.

Evaluating the numbers that has been the result of the 185 trades and 65 profitable trades it seems to be an indifference between long and short trades, having an equal share of the total trades. This is assumed before since when a downtrend ends a long position is taken while an uptrend ends with a short position. As seen in the profitable trade percentage there is a majority of loss trades. This number is evenly distributed between sell trades and buy trades. The TyskAOEMA had a fairly even distribution with a 58% profitable trades for both sell and buy trades, which creates confidence in the algorithm. The TyskAOTEMA had more buy trades than sell trades with a small percentage, however the buy trades also had a larger profitable trade percentage between the sell and buy trades. Both types had low percentages, but it is good that the type, which occurs the most, produce more profitable trades than the other way around. More buy trades in general together with over 50 % of profitable buy trades give great confidence. Especially in an algorithm that does not trade that much.

Comparing these numbers with the profit factor that was 1,27 for the TyskPSAR there is some instability in the algorithm that creates doubts of future performances. The problem is the high average losses together with the large loss level for both sell and buys trades. This is shown by the large drawdown value of -17 301,9 USD. The TyskBB had a low amount trades as well but kept the drawdown to a minimum at -6 947 USD, which is acceptable and preferable, but low amount of trades together with a high drawdown, creates uncertainty of future returns. The VaR is mainly due to this level of profitable trades together with large drawdowns.

The best algorithm needs to trade a lot in order to get any result during the real time test period. This removes the TyskBB and the TyskPSAR by automation. TyskAOTEMA and TyskAOEMA performed about the same when it comes to drawdown and average profits. The SoR make the decision, which makes the TyskAOTEMA the candidate for a real time test, following the suggestion of Sortino and Meer (1991).

5.4.2 Real Time Test

The real time test restates previous results as the return is in line with the back testing results. The improvement of only trading during thirteen hours per day did not affect as much as wanted during the period. However, the theory should not be disregarded in future research. The worst trade gave a loss of -6,75% which is greater than the value at risk from the back testing. As noted the data followed a leptokurtic distribution resulting in an overestimated VaR. The result overall does not contradict the back testing result, hence the strategy could be used.

5.5 Long Run

The implication of the result is that there is a possibility to gain large returns by using these strategies. This could be devastating for the market liquidity. Looking at the result of Olsen (2005) there would exist cascades if there are too many signals from too many strategies at the same time. This would create a one-sided order book and destroy both liquidity and the depth of the market. This is one reason why there might be a problem to continuously beat the market with the same strategy. As more and more traders realize the strategy the market will get stuffed and if there is a signal the result would be a cascade both at the entrance signal, but also at the exit signal since too many orders will be placed at the same time.

6 Conclusion

The test of the research was done in order to test the efficiency of the market at the weak level since only past prices was used in the test. The research question for this research was if it is possible to outperform the market portfolio by using algorithmic trading and using technical indicators on the foreign exchange market. To evaluate the performance the Sharpe ratio and the Sortino ratio have been used to risk adjust the performance. The result overall said that it is possible to beat the market, but looking closer at the yearly data, the conclusion it ambiguous if the market has been outperformed by the strategies. The strategy with the most potential was the AO together with a triple exponential moving average. Together the indicators gave good signals leading to large profits.

The findings says that it is possible to make abnormal profits in the foreign exchange market by trading using CFD's, but there is a lot of risk using that type of financial instrument. This is mainly due to the leverage settings available to such accounts.

Technical analysis has been proven to be effective on historical data and real time data, giving a good indication of some market inefficiency. However the markets change constantly making it hard to derive a pure strategy for any kind of situation. For the investor there is a backup for this condition called the *stop loss*. The *stop loss* can end a position if the market turns in the wrong direction. The *stop loss* have been used in one way or the other in all strategies tested in this research with good results as it will decrease the value at risk compared to a strategy with no *stop loss*.

One major issue has been the drawdowns, in order to have a successful strategy there is a need for profitable trades. Long trends of large losses are devastating for a trader as could be seen in the performance sheet above. Even though timing is important, a loss trend should not be larger than the original deposit value such that there is a possibility to continue whence the trend ends.

Taking the SR and the SoR as risk adjustment for strategy evaluation showed to be effective. In this particular test, there is no great difference between the two. There is not more than a handful observations where the SoR is outperforming the market while the SR did not or vice versa. This does not mean that they are identical, rather that there is a lot of risk and down risk in this type of trading. The problem when selecting the best strategy did not come from the SoR as there was a clear cut, the problem is found in the strategy itself as there was not many observations which could risk the testing and its strength.

As noted in the end of the analysis, there may be danger towards a mass use of the strategies. If too many traders use the same strategy there would exist a one sided order book, which in turn would create market illiquidity.

7 Discussion

The research presented in this paper used a quantitative empirical test, which is the most appropriate method when testing the efficient market hypothesis. When doing further research within this field there is no need to change the type of study if the focus lies in testing strategies against the EMH. If the focus lies more on the profitability of using algorithmic trading compared to manual trading then a mixture of qualitative and quantitative study is more appropriate to both run the numbers while at the same time ask the current market participants of their perspective.

Further research within the field should take into consideration the use of more complex indicators that could predict the future price moves more accurately, such as implementing the Fibonacci retracements or another type of mathematically complex analyzing indicator. Although the results show that there is a possibility to make abnormal profits, the vast drawdowns should be minimized for a less risky strategy while at the same time leading to greater profits.

What should also be looked upon is the possibility to make abnormal profits while not testing the efficient market hypothesis at its fullest and instead testing the random walk hypothesis. The knowledge of the random walk and that future price movements are unknown could be analyzed from the fact that prices move up and down randomly. By evaluating the average up and down swing, maybe there is a possibility to take advantage of the frequent price swings. The volatility does increase as the time frame gets smaller and testing this pattern on tick data may lead to good results. As this strategy is not testing the EMH through technical analysis directly as there is very little technical about it there was no possibility to test it in this research.

The overall findings are restating past research with some more potential towards a breakthrough in this field. Using more data and complex strategies may lead to more findings but the findings before 2007 may be irrelevant as this type of trading was unavailable at the time.

As one restriction to this thesis was the source of the data, finding better sources (might have to buy the data) is crucial. This will most definitely give more accurate back testing results and could be the key for a successful launch.

A final remark of this research, as algorithmic trading becomes more and more popular among traders there is a chance that the market will become even more efficient compared to the market today. As long as there are different strategies attached to the market there should not be any problems, but if the orders are clustered on one side of the order book substantial problems could and will occur.

List of references

Alexander, C. (2008a). *Market risk analysis*. Chichester: John Wiley & Sons Ltd..

Alexander, C. (2008b). *Market risk analysis. Vol. 4, Value-at-risk models*. Chichester: John Wiley & Sons Ltd..

Balvers, R., & Wu, Y., (2006). Momentum and Mean Reversion across National Equity Markets. *Journal of Empirical Finance*, 13, 24-48.

Bank of International Settlements Monetary and Economic Department (1996). *Central Bank Survey of Foreign Exchange and Derivatives Market Activity 1995* [Report]. Basel: Bank of International Settlements.

Bank of International Settlements Monetary and Economic Department (2010). *Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity in 2010 - Final results* [Report]. Basel: Bank of International Settlements.

Barberá, S., Hammond, P.J., & Seidl, C (1998). *Handbook of utility theory. Vol. 1, Principles*. Dordrecht: Kluwer

Barberis, N., Shleifer, A., & Vishny, R. (1998). A Model of Investor Sentiment. *Journal of Financial Economics,* 49, 307-343

Berger, D., Chaboud, A., & Hjalmarsson, E. (2009). What Drives Volatility Persistence in the Foreign Exchange Market? *Journal of Financial Economics*, 9(2), 192-213.

Biais, B., Foucault, T., & Moinas, S. (2012) Equilibrium High-Frequency Trading. *Paper in progress. SSRN 2024360.*

Brandt, M.W., & Jones, C.S. (2006) Volatility Forecasting With Range-Based EGARCH Models. *Journal of Business & Economic Statistics,* 24(4), 470-486.

Brown, C., Dark, J., & Davis, K. (2010). Exchange Traded Contracts for Difference: Design, Pricing and Effects. *Journal of Futures Markets,* 30(12), 1108-1149.

Brown, S.J., Goetzmann, W.N., & Kumar, A. (1998). The Dow Theory: William Petter Hamilton's Track Record Reconsidered. *Journal of Finance,* 53(4), 1311-1333.

Cai, J., Cheung. Y.L., & Lee, R.S.K. (2001). Once in a Generation Yen Volatility in 1998: Fundamentals, Intervention, and Order-Flow. *Journal of International Money and Finance*, 20, 327-347.

Chaboud, A., Hjalmarsson, E., Vega, C. & Chiquoine B (2011). *Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market* . FRB International Finance Discussion Paper No. 980.

Chiang, T., & Jiang, C., (1995). Foreign Exchange Returns over Short and Long Horizons. *International Review of Economics & Finance,* 4(3), 267-282.

Chordia, T., Roll, R., & Subrahmanyam, A. (2005). Evidence on the Speed of Convergence to Market Efficiency. *Journal of Financial Economics*, 76(2), 271-292.

Chordia, T., Roll, R., & Subrahmanyam, A., (2008). Liquidity and Market Efficiency. *Journal of Financial Economics,* 87(2), 249–268.

Colliard, J., & Foucault, T. (2012). Trading Fees and Efficiency in Limit Order Markets. *The Review of Financial Studies,* 25(11), 3389-3421.

Coutts, A.J., & Cheung, K-C. (2000). Trading Rules and Stock Returns: Some Preliminary Short Run Evidence from the Hang Seng 1985-1997. *Applied Financial Economics,* 10, 579-586.

Cuthbertson K. Nitzsche D. (1996). *Quantitative financial economics: stocks, bonds, and foreign exchange* . New York: John Wiley

Devcic, J. (2007). *Bollinger Band Trading.* Retrieved 2013-02-25 from http://www.forbes.com/2007/05/11/bollinger-intel-yahoo-pf-education-in_jd_0511chartroom_inl_print.html

Diebold, F.X., & Mariano, R.S. (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics*, 13(3), 253–263.

Douglas, A., Lovrencic, L. & Pontikis, P. (2011). *FX Trading: A Guide to Trading Foreign Exchange.*. 2nd ed. Hoboken: John Wiley & Sons

Elton, E.J. (2011). *Modern Portfolio Theory and Investment Analysis*. 8. ed. Hoboken, N.J.: Wiley

Engel, C., & Hamilton, J. (1990). Long Swings in the Dollar: Are They in the Data and Do Markets Know It? *The American Economic Review*, 80(4), 689-713.

Evans, M.D.D. (2002). FX Trading and Exchange Rate Dynamics. *Journal of Finance*, 57(6), 2405- 2447.

Esch, D.N. (2010) Non-Normality Facts and Fallacies. *Journal of Investment Management.* 8 (1), 49-61.

Evans, M.D.D., & Lyons, R.K. (2002). Order Flow and Exchange Rate Dynamics. *Journal of Political Economy*, 110(1), 170-180.

Fama, E.F. (1965). Random Walks in Stock Market Prices. *Financial Analysts Journal*, 21(5), 55-59.

Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance*, 25, 383-417

Fishburn, P.C. (1968). Utility Theory. *Management Science*, 14(5), 335-378.

Fischer, R & Fischer, J (2003). *Candlesticks, Fibonacci, and chart pattern trading tools: a synergistic strategy to enhance profits and reduce risk*. Hoboken: John Wiley & Sons, Inc.

Gârleanu, N., & Pedersen, L. (2007). Liquidity and Risk Management. *American Economic Review*, 97(2), pp. 193-197.

Gencay, R. (1999). Linear, Non-Linear and Essential Foreign Exchange Rate Forecast with Simple Technical Trading Rules. *Journal of International Economics*. 47, 91–107.

Goodhart, C. (1988). The Foreign Exchange Market: A Random Walk with a Dragging Anchor. Economica, 55(220), 437-460.

Gregory-Williams, J., & Williams, B. (2004). *Trading chaos: maximize profits with proven technical techniques*. 2. ed. Hoboken: John Wiley & Sons, Inc.

Gross, D.; & Ray, J.L. (1965). A General Purpose Forecast Simulator. *Management Science,* 11 (6), 119-135.

Gujarati, D.N. & Porter, D.C. (2009). *Basic econometrics*. (5. ed.) Boston: McGrawHill.

Gul, F. (1991). A theory of Disappointment Aversion. *Econometrica,* 59(3), 667-686.

Hendershott, T., Jones, C.M., & Menkveld, A.J. (2011). Does Algorithmic Trading Improve Liquidity? *The Journal of Finance*, 66, 1–33.

Jegadeesh, N. (1990). Evidence of Predictable Behavior of Security Returns. *Journal of Finance,* 45(3), 881-898.

Jones, C.M., Kaul, G., & Lipson, M.L. (1994). Information, Trading, and Volatility. *Journal of Financial Economics*, 36(1), 127-154.

Jorion, P. (2007). *Value at risk: the new benchmark for managing financial risk*. 3. ed. New York: McGraw-Hill.

Jovanovic, F., & Gall, P.L. (2001). Does God Practice a Random Walk? The Financial Physics of a Nineteenth-Century Forerunner, Jules Regnault. *The European Journal of the History of Economic Thought*, 8(3), 332-362.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica,* 47, 263-292

Kestner, L. N. (2003). *Quantitative trading strategies: Harnessing the Power of Quantitative Techniques to Create a Winning Trading Program*. New York: McGraw-Hill

Kim, M.J., Nelson C.R., & Startz, R. (1991). Mean Reversion in Stock Prices? A Reappraisal of the Empirical Evidence. *Review of Economic Studies,* 58, 515-528.

Kumiega, A., & Vliet B.E.V. (2012). Automated Finance: The Assumptions and Behavioral Aspects of Algorithmic Trading. *Journal of Behavioral Finance*, 13, 51-55.

Lo, A. (1991). Long-Term Memory in Stock Market Prices. *Econometrica,* 59(5), 1279-1313.

Lo, A., & MacKinlay, C.A. (1988) Stock Market Prices do not Follow Random Walks: Evidence from a Simple Specification Test. *Review of Financial Studies,* 1(1) 41-66.

Lo, A., Repin, D.V., & Steenbarger, B.N., (2005). Fear and Greed in Financial Markets: A Clinical Study of Day-Traders. *American Economic Review,* 95, 352-359.

Ng, J. (2011). The Effect of Information Quality on Liquidity Risk. *Journal of Accounting and Economics*, 52(2), 126-143.

Malkiel, B.G. (2003). The Efficient Market Hypothesis and Its Critics. *The Journal of Economic Perspectives*, 17(1), 59-82.

Metghalchi, M., Chang, Y-H., & Marcucci, J. (2005). Is the Swedish stock market efficient? Evidence from some simple trading rules. *International Review of Financial Analysis.* 17, 475-490.

Odean, T. (1998) Are Investors Reluctant to Realize Their Losses? *Journal of Finance,* 53, 1775-1798.

Okunev, J., & White, D. (2003). Do Momentum-Based Strategies Still Work in Foreign Currency Markets? *Journal of Financial and Quantitative Analysis*, 38, 425-447.

Osler, C.L. (2005). Stop-Loss Orders and Price Cascades in Currency Markets. *Journal of International Money and Finance*, 24(2), 219-241.

Raj, M. (2000). Disequilibrium in Asia-Pacific Futures Markets: An Intra-Day Investigation. *Journal of financial and strategic decisions.* 13 (2), 97-103

Roy, A.D. (1952). Safety First and the Holding of Assets. *Econometrica.* 20(3), 431–450.

Ruppert, D. (2004). *Statistics and finance: an introduction*. New York: Springer.

Ryan, B., Scapens, R.W. & Theobald, M. (2002). *Research method and methodology in finance and accounting.* 2. ed. London: Thomson

Samuelson, P. (1965). Proof That Properly Anticipated Prices Fluctuate Randomly. *Industrial Management Review*, 6, 41–49.

Serban, A.F. (2010). Combining Mean Reversion and Momentum Trading Strategies in Foreign Exchange Markets. *Journal of Banking & Finance*, 34(11), 2720-2727.

Sharpe, W. F. (1966). Mutual Fund Performance. *Journal of Business*, 39(1), 119–138.

Shreve, S.E. (2004a). *Stochastic calculus for finance. 1, The binomial asset pricing model.* New York: Springer.

Shreve, S.E. (2004b). *Stochastic calculus for finance. 2, Continuous-time models.* New York: Springer.

Soeini, R.A., Niroomand, A., & Parizi A.K. (2012). Using Fibonacci Numbers to Forecast the Stock Market. *International Journal of Management Science and Engineering Management,* 7(4), 268-279

Sortino, F.A. & Meer, R.V.D. (1991). Downside Risk. *Journal of Portfolio Management,* 17(4), 27-31.

Sortino, F.A. & Satchell, S.E. (2001). *Managing Downside Risk in Financial Markets: Theory, Practice and Implementation*. Oxford: Butterworth-Heinemann

Tinghino, M. (2008). *Technical Analysis Tools: Creating a Profitable Trading System*. 1. ed. New York: Bloomberg Press

U.S. CFTC/SEC (2010). *Findings Regarding the Market Events of May 6,* 2010 [Report]. Washington D.C.: U.S. CFTC/SEC.

Venkataraman, K. (2001). Automated versus Floor Trading: An Analysis of Execution Costs on the Paris and New York Exchanges. *Journal of Finance,* 56(4) 1445-1485.

Wilder, W. (1978) *New Concepts in Technical Trading Systems.* Greensboro N.C.: Trend Research.

Williams, B. (1998). *New Trading Dimensions: How to Profit from Chaos in Stocks, Bonds, and Commodities*. New York: Wiley

Yin, G., Zhang, Q., & Zhuang, C. (2010). Recursive Algorithms for Trailing Stop: Stochastic Approximation Approach. *Journal of Optimization Theory and Applications*, 146(1), 209-231.

Appendices

Global foreign exchange market turnover by instrument[1]

Average daily turnover in April, in billions of US dollars

Instrument	1998	2001	2004	2007	2010
Foreign exchange instruments	**1 527**	**1 239**	**1 934**	**3 324**	**3 981**
Spot transactions[2]	568	386	631	1 005	1 490
Outright forwards[2]	128	130	209	362	475
Foreign exchange swaps[2]	734	656	954	1 714	1 765
Currency swaps	10	7	21	31	43
Options and other products[3]	87	60	119	212	207
Memo:					
Turnover at April 2010 exchange rates[4]	*1 705*	*1 505*	*2 040*	*3 370*	*3 981*
Exchange-traded derivatives[5]	*11*	*12*	*26*	*80*	*168*

[1] Adjusted for local and cross-border inter-dealer double-counting (i.e. “net-net” basis). [2] Previously classified as part of the so-called "Traditional FX market". [3] The category "other FX products" covers highly leveraged transactions and/or trades whose notional amount is variable and where a decomposition into individual plain vanilla components was impractical or impossible. [4] Non-US dollar legs of foreign currency transactions were converted into original currency amounts at average exchange rates for April of each survey year and then reconverted into US dollar amounts at average April 2010 exchange rates. [5] Sources: FOW TRADEdata; Futures Industry Association; various futures and options exchanges. Reported monthly data were converted into daily averages of 20.5 days in 1998, 19.5 days in 2001, 20.5 in 2004, 20 in 2007 and 20 in 2010.

Appendix 1 - Turnover Tables Foreign Exchange

Table 5 - Bank of International Settlements Monetary and Economic Department (2010).

Global foreign exchange market turnover by currency pair[1]

Daily averages in April, in billions of US dollars and percentages

	1998		2001		2004		2007		2010	
Currency pair	Amount	%	Amount	%	Amount	%	Amount	%	Amount	%
USD/EUR	.	.	372	30	541	28	892	27	1 101	28
USD/DEM	309	20	.	.	.	.	.	.	.	.
USD/FRF	60	4	.	.	.	.	.	.	.	.
USD/XEU	17	1	.	.	.	.	.	.	.	.
USD/OthEMS	178	12	.	.	.	.	.	.	.	.
USD/JPY	292	19	250	20	328	17	438	13	568	14
USD/Oth	140	9	152	12	251	13	498	15	445	11
USD/GBP	122	8	129	10	259	13	384	12	360	9
USD/AUD	44	3	51	4	107	6	185	6	249	6
USD/CAD	52	3	54	4	77	4	126	4	182	5
USD/CHF	82	5	59	5	83	4	151	5	168	4
EUR/JPY	.	.	36	3	61	3	86	3	111	3
EUR/GBP	.	.	27	2	47	2	69	2	109	3
EUR/Oth	0	0	17	1	35	2	83	2	102	3
USD/HKD[2]	14	1	19	2	19	1	51	2	85	2
EUR/CHF	.	.	13	1	30	2	62	2	72	2
USD/KRW[2]	2	0	8	1	16	1	25	1	58	1
JPY/Oth	9	1	4	0	11	1	43	1	49	1
USD/SEK[3]	3	0	6	0	7	0	57	2	45	1
USD/INR[2]	1	0	3	0	5	0	17	1	36	1
EUR/SEK[3]	.	.	3	0	3	0	24	1	35	1
USD/CNY[2]	0	0	.	.	1	0	9	0	31	1
USD/BRL[2]	3	0	5	0	3	0	5	0	25	1
USD/ZAR[2]	6	0	7	1	6	0	7	0	24	1
JPY/AUD[2]	1	0	1	0	3	0	6	0	24	1
EUR/CAD	.	.	1	0	2	0	7	0	14	0
EUR/AUD	.	.	1	0	4	0	9	0	12	0
JPY/NZD[2]	0	0	0	0	0	0	0	0	4	0
DEM/JPY	30	2	.	.	.	.	.	.	.	.
DEM/GBP	36	2	.	.	.	.	.	.	.	.
DEM/CHF	21	1	.	.	.	.	.	.	.	.
DEM/FRF	10	1	.	.	.	.	.	.	.	.
DEM/XEU	3	0	.	.	.	.	.	.	.	.
DEM/OthEMS	37	2	.	.	.	.	.	.	.	.
DEM/Oth	22	1	.	.	.	.	.	.	.	.
OthEMS[4]	4	0	.	.	.	.	.	.	.	.
Other pairs	30	2	23	2	36	2	90	3	72	2
All currency pairs	1 527	100	1 239	100	1 934	100	3 324	100	3 981	100

[1] Adjusted for local and cross-border inter-dealer double-counting (i.e. "net-net" basis). [2] Included as main currency pair from 2010. For more details on the set of currency pairs covered by the 2010 survey, see the statistical notes in Section IV. [3] Included as main currency pair from 2007. [4] OthEMS/OthEMS: the data cover local home currency trading only.

Table 6 - Bank of International Settlements Monetary and Economic Department (2010).

OTC foreign exchange turnover by instrument, counterparty in April 2010[1]

US dollar against:

Daily averages, in millions of US dollars

	Total	Euro	Yen	Pound sterling
Spot	**1 187 699**	**468 891**	**183 108**	**139 582**
with reporting dealers	421 171	159 180	66 429	47 249
local	145 414	46 591	17 329	16 797
cross-border	275 757	112 589	49 100	30 451
with other financial institutions	598 504	245 922	89 099	76 718
local	242 285	101 494	36 210	29 389
cross-border	356 217	144 429	52 888	47 328
with non-financial customers	168 025	63 789	27 579	15 616
local	67 744	16 085	13 105	4 441
cross-border	100 281	47 704	14 474	11 175

Table 7 - Bank of International Settlements Monetary and Economic Department (2010).

Appendix 2 - Indicators

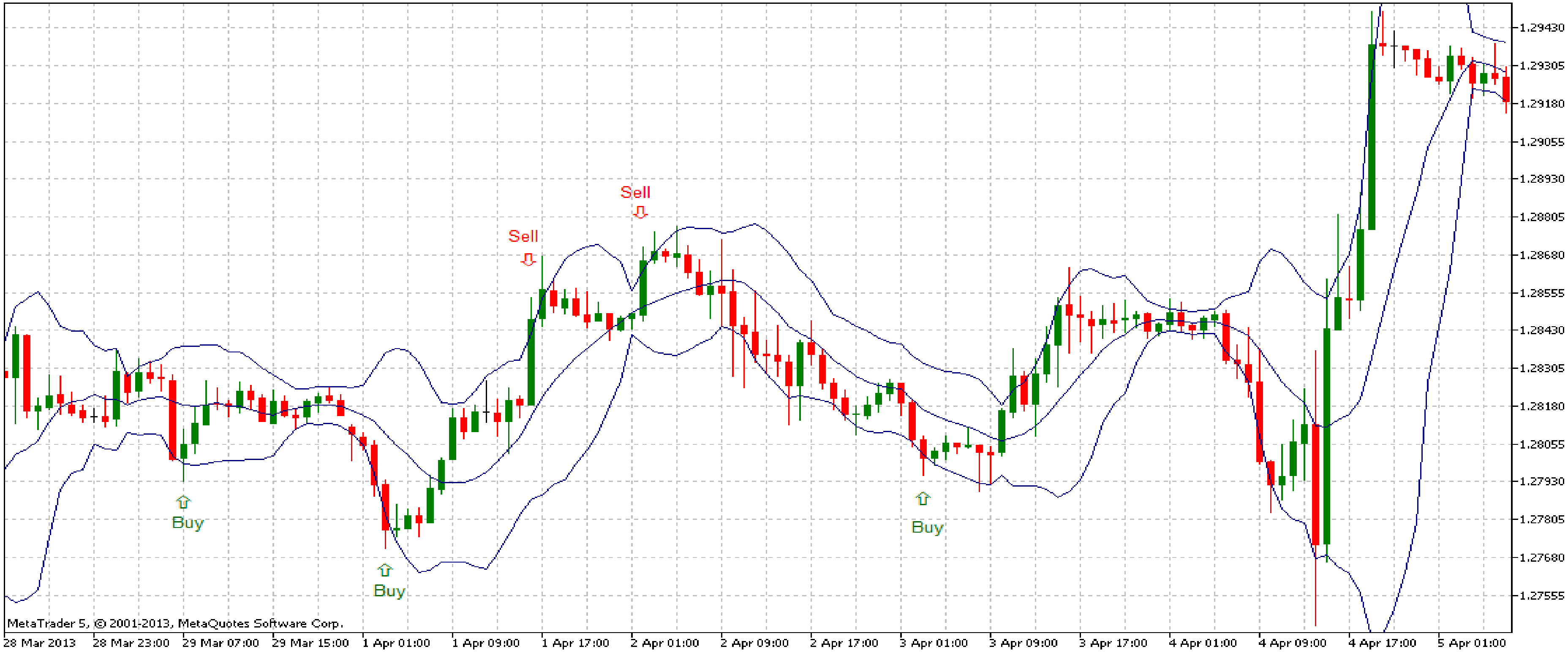

Figure 2 - Bollinger Band

This graph shows the Bollinger Band indicator and how orders are signaled to buy and sell. This graph is only a short time frame from the whole period of testing. As with the previous graph, the green and red bars are the price changes. The blue lines represent the Bollinger Band indicator. The lower and upper line is two standard deviations from the mean line in the middle by calculations on the past 10 bars. The time scale of this graph is from 2013-03-28 -- 2013-04-04. The graph is made through Meta Trader 5.

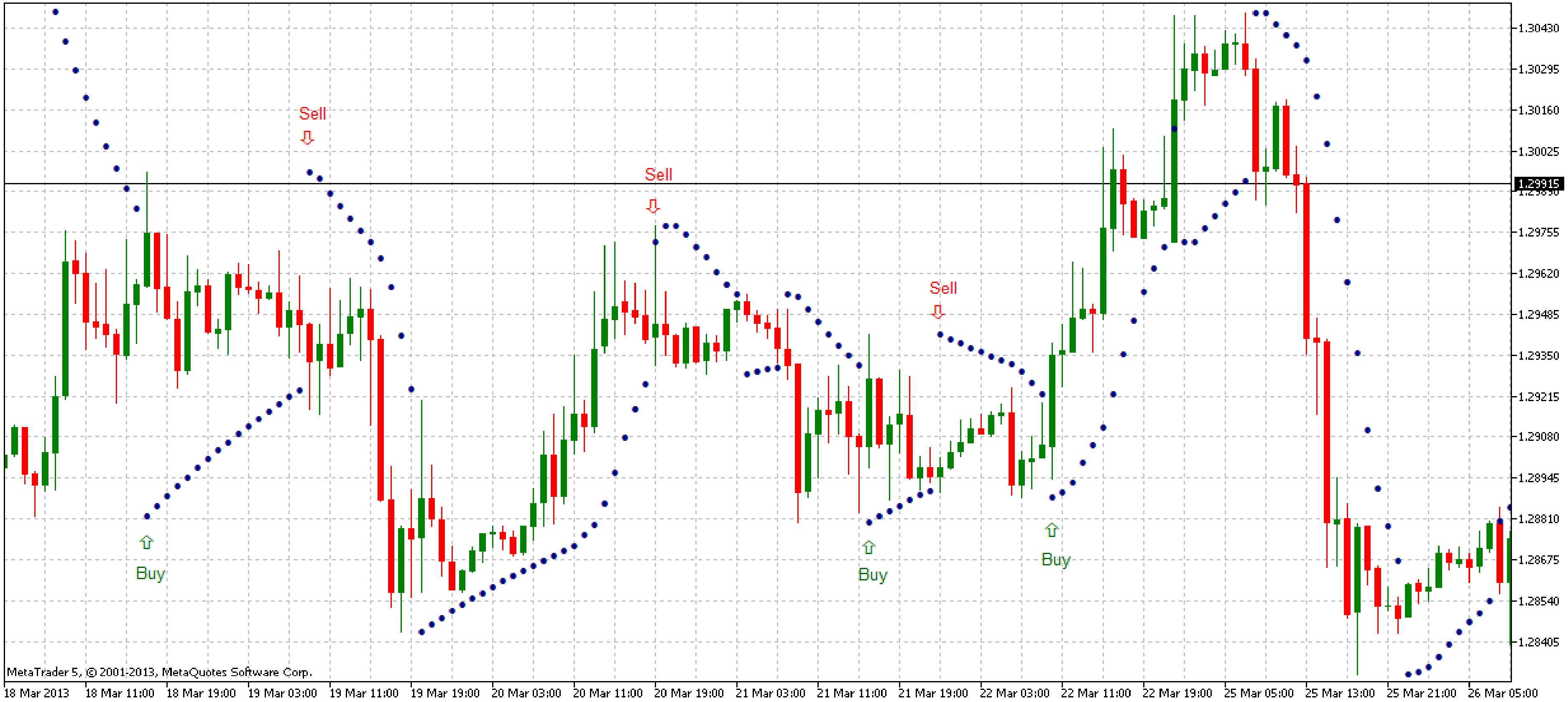

Figure 3 - Parabolic SAR.

This graph shows the Parabolic SAR indicator from 2013-03-18 to 2013-03-26. The green and red bars are the price movements. The blue dots are the respective SAR value calculated from the P-SAR calculations in section 3.2.3. See formula 10 and 11 for the calculations of the SAR value. The graph is made through Meta Trader 5.

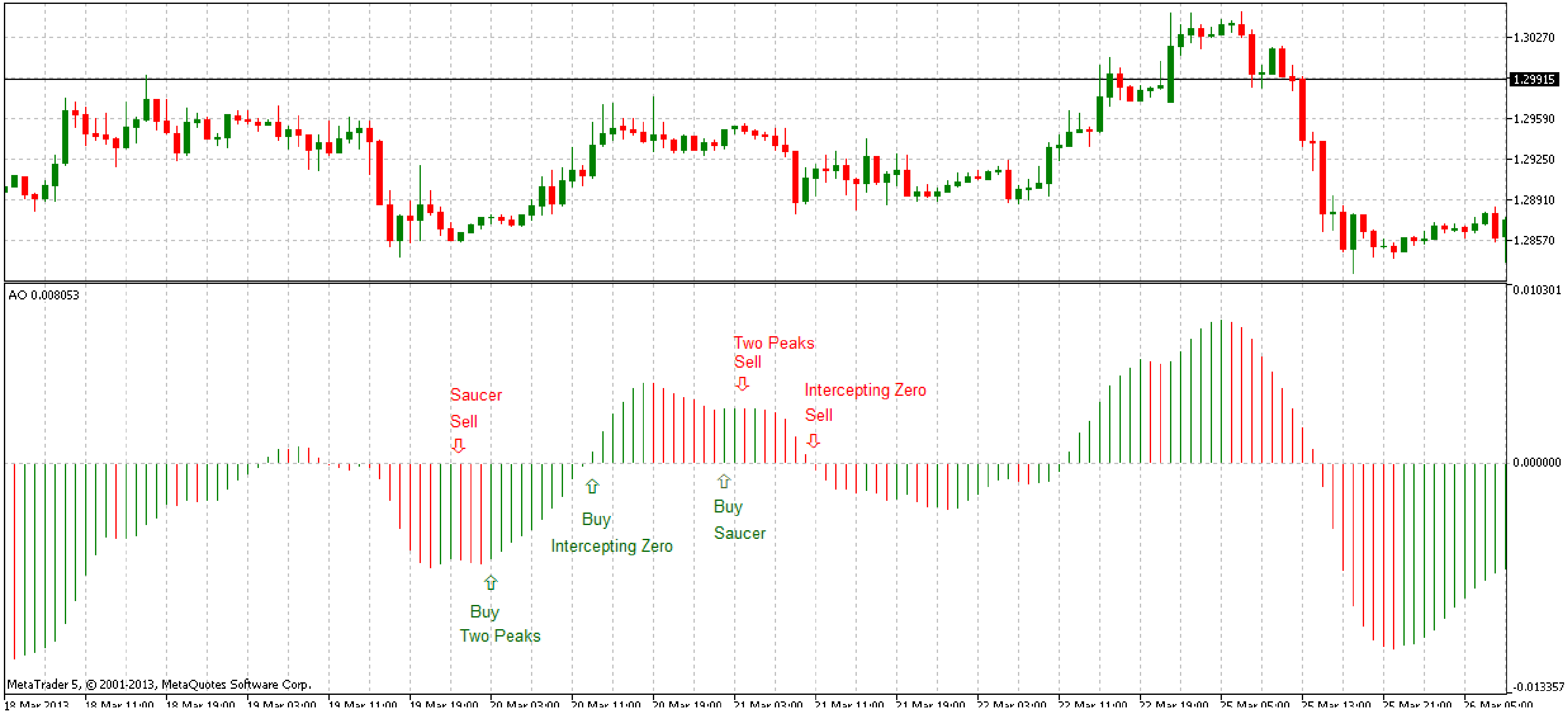

Figure 4 - Awesome Oscillator

The awesome oscillator indicator as described in section 3.1.3.3 show in the lower part a bar sequence of red and green bars. The green bar is a result of the calculations in 3.1.3.3 with a greater value than the value before while the red bars is a lower value than the previous bar. The graph is made through Meta Trader 5.

Appendix 3 - Yearly Performance

Leverage 1:500	2007-01-01 -- >2007-12-31			
	TyskAOTEMA	TyskAOEMA	TyskBB	TyskPSAR
Return	115,44%	-31,26%	16,74%	-0,16%
Net Profit	$ 11 543,60	$ -3 125,68	$ 1 673,5	$ -16,20
Gross Profit	$ 37 987,60	$ 7 152,62	$ 14 136,80	$ 14 568,10
Gross Loss	$ -26 444,00	$ -10 278,30	$ -12 463,30	$ -14 584,30
Profit Factor	1,44	0,7	1,13	1
Number of Trades	115	105	39	35
Profitable Trades	48 (41,38%)	29 (27,62%)	19 (48,72%)	11 (31,43%)
Expected Profit per Trade (Value)	$ 100,38	$ -29,77	$ 42,91	$ -0,46
Average Profit	$ 791,41	$ 246,64	$ 744,04	$ 1 214,01
Maximum Consecutive Wins	5 ($ 5285,30)	3 ($ 1532,30)	7 ($ 4 211,7)	3 ($ 4 536,6)
Maximum Consecutive Losses	6 ($ -2406,00)	13 ($ -588,73)	3 ($ -3478,5)	6 ($ - 3 534,2)
Absolute Drawdown	$ -620,50	$ 3 151,82	$ -2 039,30	$ -4 040,20
Maximum Drawdown	$ -2 809,50 (-23,05%)	$ -3833,7 (-35,89%)	$ -3 934,90 (29,41%)	$ -5145,20 (-46,33%)
Sharpe Ratio (S&P500= 0,03) (EURUSD= 0,33)	0,14	-0,37	0,15	-0,07
Sortino Ratio (S&P500= -0,22) (EURUSD= 0,02)	1,45	-0,66	0,15	0,09

Table 8 - Algorithmic Performance 2007[10]

[10] Own calculations

Leverage 1:500	2008-01-01 -->2008-12-31			
	TyskAOTEMA	TyskAOEMA	TyskBB	TyskPSAR
Return	111,97%	98,29%	109,44%	162,49%
Net Profit	$ 24126,00	$ 6 756,74	$ 12 774,9	$ 16 222,40
Gross Profit	$ 115 821,60	$ 24 133,58	$ 20 694,80	$ 41 383,00
Gross Loss	$ -91 695,60	$ -17 376,84	$ -7 919,90	$ -25 160,60
Profit Factor	1,26	1,39	2,61	1,64
Number of Trades	351	190	23	28
Profitable Trades	138 (39,32%	69 (36,32%)	13 (56,52%)	6 (21,43%)
Expected Profit per Trade (Value)	$ 69,93	$ 35,57	$ 555,43	$ 579,37
Average Profit	$ 839,29	$ 349,76	$ 1 591,91	$ 6 897,17
Maximum Consecutive Wins	8 ($ 3 569,30)	8 ($ 3141,26)	3 ($ 5002,9)	1 ($ 12 962)
Maximum Consecutive Losses	9 ($ -2933,5)	10 ($ -676,17)	3 ($ -3752,8)	7 ($- 6 653,7)
Absolute Drawdown	$ -2 957,00	$ -1 277,42	$ -	$ -3 382,5
Maximum Drawdown	$ -11 923,90 (-29,41%)	$ -2 688,58 (-34,82%)	$ -3 752,80 (-21,96%)	$ -7 549,7 (-53,35%)
Sharpe Ratio (S&P500= -0,59) (EURUSD= -0,12)	0,57	0,38	0,48	0,33
Sortino Ratio (S&P500= -0,63) (EURUSD= -0,27)	1,21	1,02	0,99	1,03

Table 9 - Algorithmic Performance 2008[11]

[11] Own calculations

Leverage 1:500	2009-01-01 -->2009-12-31			
	TyskAOTEMA	TyskAOEMA	TyskBB	***TyskPSAR***
Return	***-44,45%***	64,71%	2,60%	***-39,00%***
Net Profit	***$ -20 298,40***	$ 9921,05	$ 1 569,80	***$ -10 220,40***
Gross Profit	**$ 85 367,10**	$ 55 874,42	$ 17 361,20	***$ 16 495,10***
Gross Loss	***$ -105 665,50***	$ -47 053,37	$ -15 791,4	***$ -26 715,50***
Profit Factor	***0,81***	1,19	1,1	***0,62***
Number of Trades	***359***	244	25	***29***
Profitable Trades	***115 (32,03%)***	121 (49,59%)	8 (32%)	***5 (17,24%)***
Expected Profit per Trade (Value)	***$ -56,54***	$ 36,15	$ 62,79	***$ -352,43***
Average Profit	***$ 742,32***	$ 461,77	$ 2 170,15	***$ 3 299,02***
Maximum Consecutive Wins	***4 ($ 2708,90)***	7 ($ 3510,74)	3 ($ 7885,9)	***1 ($ 6 750,4)***
Maximum Consecutive Losses	***13 ($ -5612,10)***	10 ($ -1701,87)	7 ($ -4513,8)	***7 ($ -7 791,2)***
Absolute Drawdown	***$ -22 945,50***	$ -3 785,34	$ -2 622,00	***$ -13 972,7***
Maximum Drawdown	***$ -22 945,50 (-50,76%%)***	$ -9 336,09 (-32,99%)	$ -6 310,30 (-20,10%)	***$ -16 727,2 (-57,76%)***
Sharpe Ratio (S&P500= 0,29) (EURUSD= 0,06)	***-0,36***	0,29	0,05	***-0,16***
Sortino Ratio (S&P500= 0,25) (EURUSD= -0,17)	***-0,51***	0,55	-0,1	***-0,29***

Table 10 - Algorithmic Performance 2009[12]

[12] Own calculations

Leverage 1:500	2010-01-01 -->2010-12-31			
	TyskAOTEMA	TyskAOEMA	TyskBB	TyskPSAR
Return	93,93%	96,48%	75,89%	57,48%
Net Profit	$ 23 829,40	$ 21 661,20	$ 18 928,80	$ 9 189,40
Gross Profit	$ 93 782,20	$ 82 134,40	$ 27 662,10	$ 33 394,20
Gross Loss	$ -69 952,80	$ -60 473,20	$ -8 733,30	$ -24 204,80
Profit Factor	1,34	1,36	3,17	1,38
Number of Trades	279	254	24	33
Profitable Trades	108 (38,71%)	152 (59,84%)	16 (66,67%)	11 (33,33%)
Expected Profit per Trade (Value)	$ 85,41	$ 85,28	$ 788,70	$ 278,47
Average Profit	$ 868,35	$ 540,36	$ 1 728,88	$ 3035,84
Maximum Consecutive Wins	4 ($ 2518,00)	11 ($ 6853,38)	5 ($ 10693,80)	2 ($ 5839,0)
Maximum Consecutive Losses	10 ($ -4086,00)	11 ($ -1641,2)	3 ($ -2359,7)	5 ($ -4 907,2)
Absolute Drawdown	$ -755,50	$ -3 428,12	$ -990,60	$ -4 327,00
Maximum Drawdown	$ -4 879,9 (-14,2%)	$ -10 390,34 (-34,71%)	$ -3 616,60 (-12,43%)	$ -6 945,80 (-37,33%)
Sharpe Ratio (S&P500= 0,20) (EURUSD= -0,12)	0,86	0,45	0,75	0,28
Sortino Ratio (S&P500= 0,08) (EURUSD= -0,33)	2,79	1,13	1,54	0,5

Table 11 - Algorithmic Performance 2010[13]

[13] Own calculations

Leverage 1:500	2011-01-01 --> 2011-12-31			
	TyskAOTEMA	TyskAOEMA	TyskBB	TyskPSAR
Return	-0,43%	24,54%	49,15%	55,95%
Net Profit	$ -7 253,80	$ 10 308,37	$ 21 686,60	$ 14 084,40
Gross Profit	$ 66 237,00	$ 145 805,81	$ 27 814,70	$ 33 193,00
Gross Loss	$ -73 490,80	$ -135 497,44	$ -6 128,10	$ -19 108,60
Profit Factor	0,9	1,08	4,54	1,74
Number of Trades	318	331	18	29
Profitable Trades	110 (34,59%)	243 (73,41%)	13 (72,22%)	15 (51,72%)
Expected Profit per Trade (Value)	$ -22,81	$ 31,14	$ 1 204,81	$ 485,67
Average Profit	$ 602,15	$ 600,02	$ 2 139,59	$ 2 212,87
Maximum Consecutive Wins	4 ($ 5740,6)	21 ($ 15 397,14)	5 ($ 10 557,4)	5 ($ 9 388,7)
Maximum Consecutive Losses	14 ($ -5784,2)	8 ($ -3 570,01)	1 ($ -2069,7)	3 ($ -3 879,0)
Absolute Drawdown	$-1 243,80	$ -	$ -	$ -3 990,1
Maximum Drawdown	$ -14 077 (-22,69%)	$ -21 880,88 (-31,57%)	$ -2 069,70 (- 3,29%)	$ -4 761,8 (-18,35%)
Sharpe Ratio (S&P500= -0,02) (EURUSD= -0,12)	0,22	0,2	1,38	0,39
Sortino Ratio (S&P500= -0,22) (EURUSD= -0,35)	0,18	0,25	6,01	0,61

Table 12 - Algorithmic Performance 2011[14]

[14] Own calculations

Leverage 1:500	2012-01-01 -->2012-12-31			
	TyskAOTEMA	TyskAOEMA	TyskBB	TyskPSAR
Return	26,20%	1,81%	-6,85%	15,56%
Net Profit	$ 12 835,80	$ 992,72	$ -4 507,40	$ 6 108,80
Gross Profit	$ 53 646,80	$ 131 176,05	$ 7 970,30	$ 25 296,9
Gross Loss	$ -40 811,00	$ -130 183,33	$ -12 477,70	$ -19 188,10
Profit Factor	1,31	1,01	0,64	1,32
Number of Trades	174	305	29	31
Profitable Trades	70 (40,23%)	219 (71,8%)	14 (48,28%)	16 (51,61%)
Expected Profit per Trade (Value)	$ 73,77	$ 3,25	$ -155,43	$ 197,06
Average Profit	$ 766,38	$ 598,98	$ 569,31	$ 1 581,06
Maximum Consecutive Wins	4 ($ 4522,6)	17 ($ 11 936,18)	4 ($ 3187,8)	4 ($ 6 449,8)
Maximum Consecutive Losses	7 ($ -2598)	9 ($ -4 463,79)	6 ($ -4990,5)	4 ($- 4 260,0)
Absolute Drawdown	$ -	$ -3 289,87	$ -5 617,00	$ - 4 393,9
Maximum Drawdown	$ -5 282,4 (-9,53%)	$ -15 162,28 (-21,42%)	$ -5 617,00 (-8,55%)	$ -5 054,9 (-12,66%)
Sharpe Ratio (S&P500= 0,33) (EURUSD=-0,02)	0,16	0,04	-0,16	0,18
Sortino Ratio (S&P500= 0,11) (EURUSD= -0,28)	-0,03	-0,1	-0,6	0,14

Table 13 - Algorithmic Performance 2012[15]

[15] Own calculations

	TyskAOTEMA	M20	Weight
TEMA	100		0,4
AO	5, 34		0,7
SL	800 points trail		
TP	3000 point trail		
	TyskAOEMA	**M1**	
EMA	100		0,7
AO	5, 34		0,4
SL	80 point trail		
TP	30 point trail		
	TyskBB	**H1**	
BB period	10		0,5
EMA period	10		0,5
Deviation	2		
SL	Max 1180		
TP	Max 2515		
	TyskPSAR	**H12**	
PSAR	0,01 - 1		1
SL	0,01 - 1		

Table 14 - Algorithmic Settings