Aalto University
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Automated System Trading, Algorithms and Programming - To Buy or To Sell The Trend?

Economics

Master's thesis

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Abstract

The main purpose of this study is to investigate Bollinger bands profitability and hence market efficiency. This is done by taking into account several different parameters (fees, trading day lag, trend following and reversal strategies, different values for moving average calculation) totaling 5400 outcomes which are combined regarding instruments' asset classes (equity, fx, agriculture, energy, interest rate, and metal).

The data for instruments is collected on Bloomberg using futures' generic contract close prices by selecting the most traded future contract for each month/quarter depending on the instrument for time period 31.12.2009-31.12.2012. I have constructed a user interface in Excel with coding VBA in order to examine Bollinger bands profitability starting from simple text files with close prices and ending to table of results.

The results state, in general, that fx and commodity markets are overall efficient, but excessive returns can be achieved in the stock market by using a strategy based on Bollinger bands.

KEYWORDS

Automated system trading, algorithms, programming, technical analysis, Bollinger bands.

Tiivistelmä

Tämän tutkielman päätavoitteena on tutkia millaisiin tuottoihin Bollinger band -työkalua hyväksikäyttämällä teknisessä analyysissä rahoitusmarkkinoilla voidaan päästä, ja siten myös markkinoiden tehokkuutta. Käytännössä tämä on toteutettu ottamalla huomioon useita eri parametreja (kaupankäyntikulut, kaupankäyntipäivä, trendin mukainen ja vastainen strategia, erilaiset variaatiot liukuvan keskiarvon laskennassa), joiden tuloksena on 5400 lopputulosta. jotka on analysoitu yhdessä muiden saman omaisuusluokan omaavien instrumenttien kanssa (osake, valuutta, energia, korko, metalli)

Data on kerätty Bloombergiltä käyttäen geneeristen futuurikontrahtien päivähintoja ja valiten jokaiselle kuukaudelle/kvartaalille likvidein konrahti instrumentista riippuen aikavälille 31.12.2009-31.12.2012. Analysointi on toteutettu Excelissä käyttäen VBA-koodia, joka alkaa hintatekstitiedostojen avaamisesta ja loppuu tuloksiin.

Yleisesti tulokset indikoivat, että valuutta- ja hyödykemarkkinat ovat tehokkaita, mutta ylituottoja voidaan saavuttaa osakemarkkinoilla Bollinger band –työkalua hyväksikäyttämällä.

AVAINSANAT

Automaattinen kaupankäynti, algoritmit, ohjelmointi, tekninen analyysi, Bollinger bands.

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1. Introduction

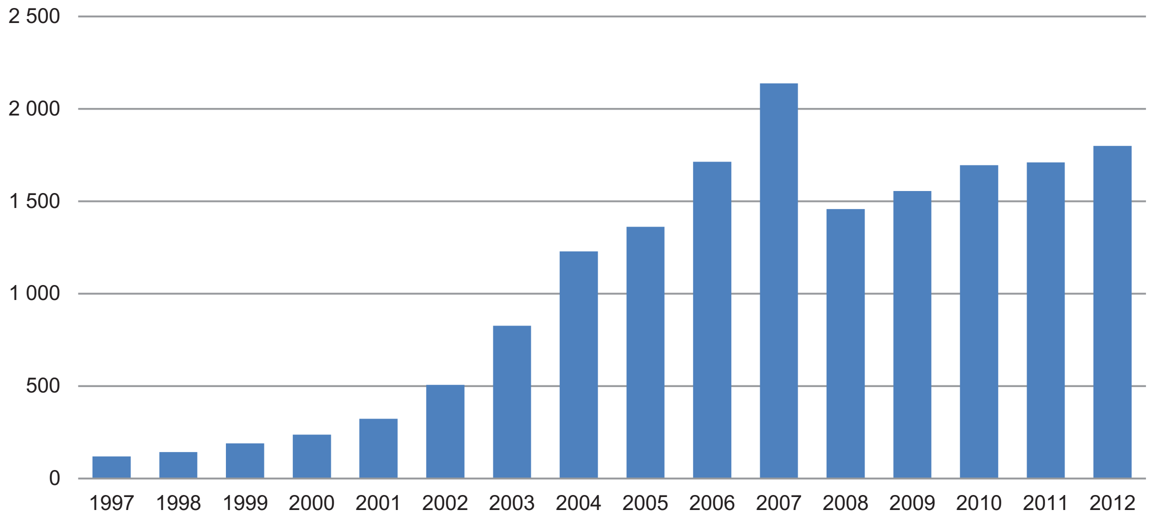
1.1. Background and motivation

Algorithmic trading means the use of electronic platforms for entering trading orders with an algorithm which executes pre-programmed trading instructions whose variables may include timing, price or quantity of the order. Usually trades are executed without any human intervention (T. Lin 2013). Back in 2007 already 30% of the US equities volume was algorithmic (Economist 2007). This equals approximately 20 trillion USD per year. In 2010 as much as 70% of all dollar volume can be attributed to fully automated algorithmic trading (Brogaard 2010). A great portion of algorithmic volume today is high frequency trading. High frequency trading refers to a trading strategy, which is executed by computers to rapidly trade securities in seconds or fractions of a second by exploiting advanced technological tools. The use of high frequency trading (HFT) has increased rapidly in recent years. In 2008, high frequency trading alone accounted 1.6 billion shares per day compared to 3.25 billion in 2009 (Bloomberg Businessweek 2013).

As financial markets have become more technology driven, the educational background wanted by the employers has also consequently changed – especially when we look at the proprietary trading desks, the hedge funds and the major investment banks: a plain B.Sc. degree in finance seems not to be the optimal choice for job seekers. For example, at one of the all-time most successful hedge funds, Renaissance Technologies, almost 70% of employees have a Ph.D. degree with non-financial background: mathematicians, physicists, astrophysicists and statisticians. Generally, advanced quantitative skills and very open mind about the market data are seen by some recruiters a greater asset than an M.B.A. diploma (New York Times 2006). By exploring open positions in the field of quantitative finance today, it's not uncommon at all either that required skill set includes, besides a Ph.D. degree, mastering C++, Java and other coding languages as well.

The overall trend during the past two decades has been towards more quantitative approach in investing and there's seems to be no reversal trend signals in the horizon. Interest rates are record low and 79% of large-cap fund managers are not making any alpha, in other words, beating their benchmark index (in 2011). Hence, it seems reasonable that solutions for portfolio optimization are also being searched from algorithmic trading. Uncorrelated investment solutions and cost efficient index funds do sound tempting when investors are searching yield for their portfolios. It isn't coincidence that world's biggest fund at the moment (end of 2013) is Vanguard Total Stock Market Index Fund with 251 billion USD. An index fund which uses algorithmic trading to track the index in a cost efficient way (Bloomberg 2013). In addition traditional hedge fund assets have gained a lot during past years (Figure 1).

Figure 1 - Hedge Fund AUM, billion USD (HFR 2013)



There are also obvious reasons why especially in broker firms algorithmic trading has become preferred choice during recent years especially among institutional market participants. It helps reducing transaction costs and risk, improves entry speed, increases trade control and reduces bid/ask spread. Also regulatory challenges have pushed consensus towards automated trading (Euromoney 2006). Many broker firms are also discovering possibilities to add pure high frequency trading as one their core business in addition to market making. However, if risks are poorly managed, these business decisions may lead a substantial increase in the overall business risk. This is exactly what happened for example to Long Term Capital Management L.P., 3.6 billion USD bailout in 1998, and Knight Capital Group Inc., software malfunction leaded to a daily loss of 440 million USD (Bloomberg 2012). Consequently proper risk management does play an important role in algorithmic trading.

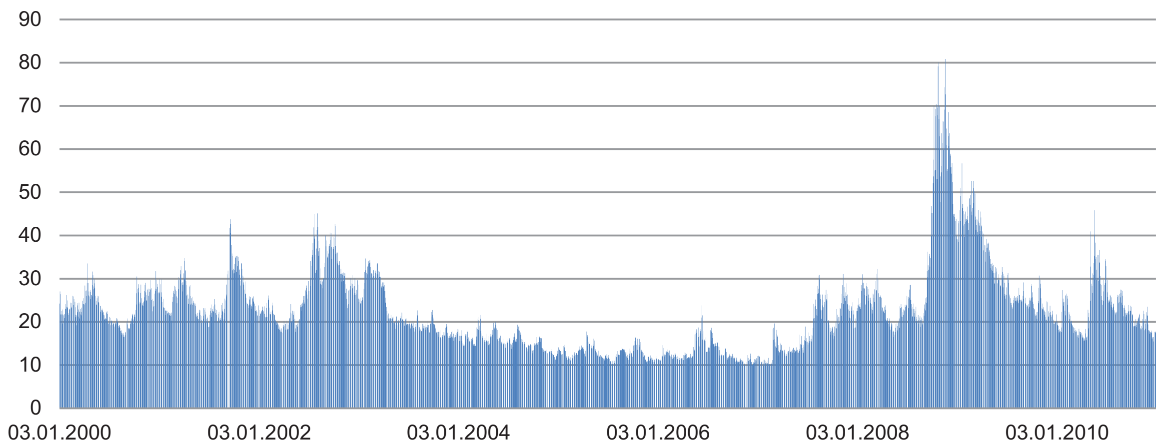
By just scratching the surface of algorithmic trading by previous few examples, it can be easily summed up that algorithmic trading plays a major role in the financial markets and hence it's a field that shouldn't be ignored.

Personally, I've always found markets in general very interesting and fascinating. I'm not meaning especially stock markets, but all the other as well: bonds, commodities, currencies etc. As I'm keen to continue working in financial sector (I started full-time six years ago) and investing as an individual, it is also easier to understand forthcoming challenges and opportunities in the business environment, changes in market regulation, overall market volatility and potential arbitrage situations by studying algorithmic trading, the current tendency. This thesis focuses on testing volatility based trend and trend reversal strategies based on Bollinger bands. Different asset classes are covered including stock market index futures, fx futures and different commodity products - agriculuture, energy, interest rate and metal – totaling 27 different instruments, which we be summarized up as composites based on asset class.

Moreover, I'm not a fan of the idea of stock picking skills and having a "gut feeling" about the markets. In the long run, it's probable that an average investor is not able to select the specific stocks that beat the index when 79% of the professionals are not, as mentioned above. On the other hand, as there are vast amount of portfolio managers in the world, it's more than likely that at least few of them will outperform their benchmark for several years in a row. This is due to pure statistics and probability distribution. To summarize, at least some can be really called stock gurus several years in a row as they are just luckier than the rest. It has been also been shown that, besides stocks, an investor is not statistically likely to select a mutual fund which beat the index in the long run (Malkiel 1973). In addition, one disturbing fact is that there's no proper way to simulate gut feeling by back-testing. Gut feeling as an input can't really be measured in any reasonable way. It has more to do with traders' egos than empirical results.

Preceding opinions, both personal and public, and empirical results have made me solely an investor, who believes only in index funds, and a trader, who believes, if at least something, in statistical edge achieved by analyzing enormous amount of market data. Most of the previous studies regarding trend following strategies, algorithmic trading and its profitability have been focused mainly using moving averages with constant parameters as a buying and/or selling signal. The main problem with these studies, in my opinion, is that they except market to be somewhat constant in the long run and the same parameters to work from year to year – in other words, market fluctuations are being ignored. It's pretty clear that the overall market conditions in equity, fx, interest rate and commodity products were completely different during dot-com bubble (2000-2003) and the last global financial crisis (2007-2008) than in the period between (2003-2006). This can be seen easily by looking, for example, the VIX index (Figure 2), which measures the implied volatility of S&P 500 index options. It represents one measure of the market's expectation of stock market volatility over the next 30 day period. Hence, one of the leading theories in this thesis will be adjusting trading algorithms to the current market conditions measured by volatility.

Figure 2 - VIX Index 2000-2010



1.2. Research question and objectives

This study focuses on trend following and trend reversal strategies by using algorithms to find optimal trading parameters using Bollinger bands (introduced later in the chapter *2.3. Trend Trading Signals and Technical Analysis*).

Firstly, my hypothesis is that volatility is a key driver for profitable trading strategy. This hypothesis naturally includes the assumption that there are market inefficiencies. Secondly, I assume that certain instruments behave in the same way, i.e. have high level of correlation regarding volatility, and hence, they can be combined and analyzed as an asset class composite.

1.3. Structure of the study

After introducing the study in this chapter, in the next chapter I discuss the theoretical framework and go through previous research related to my study. Third chapter discusses the methodology and the fourth chapter introduces the results, before summarizing this thesis in the fifth.

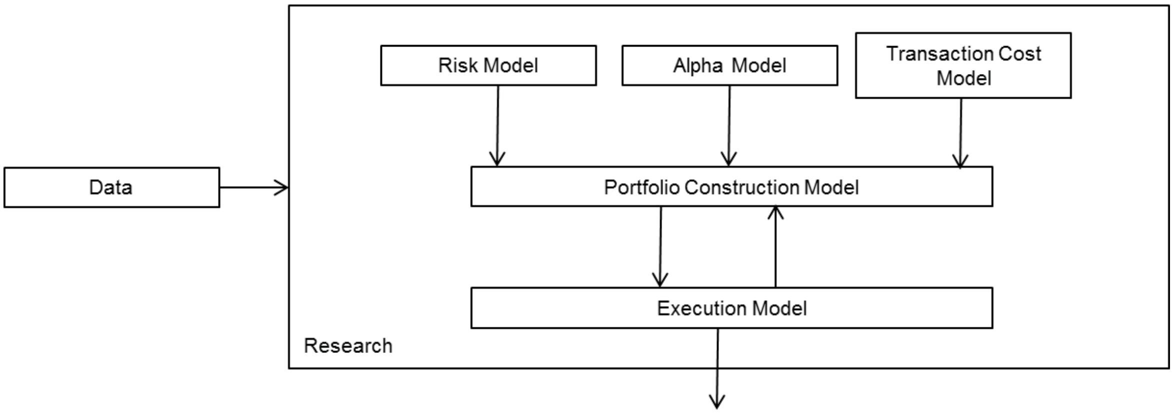
2. Literature review

2.1. Automated System Trading

The concept of automated trading system refers to an idea of computer trading program that automatically submits trades to a given exchange. Depending on trading frequency the speed of data may have a significant influence whether the trading system is profitable or not. Naturally this concerns more high frequency trading, which is not the main focus in thesis as I'll be focusing more on the movements of daily close prices.

Automated system trading consists of many layers all of which must be taken into consideration when building a reliable trading system. First of all, trading system must have a reliable market data feed. This data is analyzed by algorithms to find if there are currently such market conditions, which would have been likely profitable trading opportunities according to back-test (Alpha Model). If the back-test support market conditions then the risk management should be taken into account: does this trade fit to our current portfolio's risk profile and what kind of effect it has on portfolio's total market exposure (Risk Model). Assuming the trade passes this, let's call it "due diligence" process for example, and is executed then the monitoring of the trade starts. Before executing an order, strategy should always also tell when the trade should be exited if the market turns against the trade but also when to close the profitable trade (Transaction Cost Model). (Hanif 2014)

Figure 3 –Trading System Architechture



High frequency trading strategies may go through previous process several thousand times a day - they might hold the instrument only fractions of a second. Consequently, the speed itself is very crucial and it has suggested that any delay from 10 milliseconds to 1 second leads to a statistically significant decrease in performance. (Scholtus et al. 2014)

I'll next cover the basic concepts of algorithmic trading and the special case of high frequency trading. In addition I'll take a look into previous research on the field, the theory of efficient markets and introduce some basic technical analysis tools for estimating trading signals related to trend. Using previous classifications by Hanif (2014) my data and methodology section concentrates mostly on the dynamics of *Alpha Model*.

2.2. Algorithmic Trading

Algorithmic trading originates from proprietary trading desks of investment banking firms (Kendall 2007). In general, it means the computerized executions of financial instruments. Algorithms trade stocks, bonds, currencies and various financial derivatives. Trading via algorithms requires investors to first specify their goals in terms of mathematical instructions. Depending on investors' needs, customized instructions range from simple to highly sophisticated. After instructions are specified, computers implement those trades following the prescribed instructions (Kissel 2014). In general algorithmic trading has become possible due to fully electronic infrastructure in stock trading systems.

Example of simple strategy is trading system used by large brokerage firms that cut large orders into a hundred smaller orders. These trades are slowly entered into the market over some predetermined period of time. More advanced systems are used for example in the field of high frequency trading strategies carried out usually by hedge funds. The term black box trading is used to describe hedge fund strategies, which are complex and mathematically sophisticated algorithms of taking advantage of arbitrage situation across the market (Kendall 2007).

There are also other ways beyond financial market data to use algorithms to help make investment decisions. For example, some hedge funds use Google trends to analyze what kind of words are being searched and are trying to implement these results into profitable trading strategies.

2.2.1. Pros and Cons

Algorithmic trading has several advantages compared to trading carried out by humans. Computer systems have a much shorter reaction time and reach a higher level of reliability. The decisions made by a computer system rely on the underlying strategy with specified set of rules, which lead to a reproducibility of these decisions. Consequently, back-testing and improving the strategy by varying the underlying rules is made possible. Algorithmic trading also ensures objectivity in trading decisions and is not exposed to subjective influences. When trading many different securities at the same time, one computer system may substitute many human traders. So both the observation and the trading of securities of a large universe become possible for companies without employing dozens of traders.

Nevertheless, the automated trading requires constant monitoring. Altogether these effects may result in a better performance of the investment strategy as well as in lower trading costs.

However, it is challenging to automate the whole process from investment decisions to execution. System stability and robustness is the key to avoid mechanical failures. Hence, the less complex the system is the more solid it usually is. On the other hand lack of complexness may lead to further problems as the execution strategy is transparent for other market participants. An execution strategy that is repeating itself is exposed to other market participants and they may observe patterns and take an advantage of the trading system.

Algorithmic trading has been often related to increasing volatility. This has been one of the main topics by the press once in a while. For example, according to Financial Times (2008a, 2008b) algorithmic trades produce snowball effects on volatility. In addition, same kinds of critics are also being presented by Wall Street Journal (2010) and New York Times (2009). However, Chordia, Roll, and Subrahmanyam (2011) show that intraday volatility has actually declined on the NYSE during recent years. It is also shown using an analysis of hourly to daily variance ratios that prices are closer to the efficient market benchmark of a random walk in recent years.

Another aspect for algorithmic trading is its effect on liquidity. These trading strategies may improve liquidity if they act as market makers, but on the other hand if they create extra imbalance the effect may just the opposite. Hendershott, Jones, and Menkveld (2011) show that when algorithmic activity increases, liquidity increases as well. There is other evidence that in the algorithmic trading has leaded to higher levels of volume and hence the overall market quality has actually increased. In addition, for large stocks in particular, algorithmic trading narrows spreads, reduces adverse selection, and reduces trade-related price discovery. The findings indicate that algorithmic trading improves liquidity and enhances the informativeness of quotes. It has also a positive effect on institutional market participants. It helps reducing transaction costs and risk, improves entry speed, increases trade control and reduces bid/ask spread. Also regulatory challenges have pushed consensus towards automated trading (Euromoney 2006).

2.2.2. High frequency trading

Even though high frequency trading is not the main focus in this thesis, it shall be covered, even slightly, due to many studies suggest that HFT firms accounted for 60-73% of all US equity trading volume in 2009. After the global financial crisis the figure has declined, but still was still as high as 50% in 2012 (New York Times 2012).

News arrivals are a driving force behind asset price changes. In the beginning of exchange-based trading a telex and telephone combined with analytical skills were enough for a competitive edge. More recently, a basic internet connection would be enough. Nowadays, trades based on a news feed arrive to the market before any human trader can even take a look at the news. Liquid markets generate hundreds or thousands of ticks every day. Data vendors such as Reuters transmit more than 275 000 prices per day for foreign exchange spot rates alone. Thus, high-frequency data can be a fundamental object of study alone, as traders make decisions by observing high-frequency or tick-by-tick data. For a variety of reasons, high-frequency data are becoming a way for understanding market microstructure. (Gençay et al. 2001)

Hasbrouck and Saar (2010) examine low-latency strategies, which trade in units of milliseconds. They explore submitted, executed, and canceled orders likely part of an HFT program. They argue that low latency HFT activity improves market quality measures such as liquidity and volatility. This is strategy is called quote stuffing, in which strategy spams an exchange with a lot of quotes in a short span of time creating a false illusion that there is interest in a stock when there is none, and canceling such quotes later. An arbitrage opportunity is created if exchanges become overwhelmed with such orders and lag other exchanges, and traders are tricked into submitting orders on the belief that is indeed an interest in a stock. Egginton and Van Ness (2011) investigate this practice and conclude that stocks become more illiquid and volatile during such periods. Generally, due to previous kind of high-frequency strategies the order cancellation rates are in the region of 90%. Madhavan (2012) argues that these strategies are not yet well understood by researchers.

Overall, approximately as many studies find that high frequency trading is harmful to markets as find that it is beneficial. It is therefore difficult to conclude one way or the other whether high frequency trading should be regulated or controlled more from a policy perspective.

2.3. Trend Trading Signals and Technical Analysis

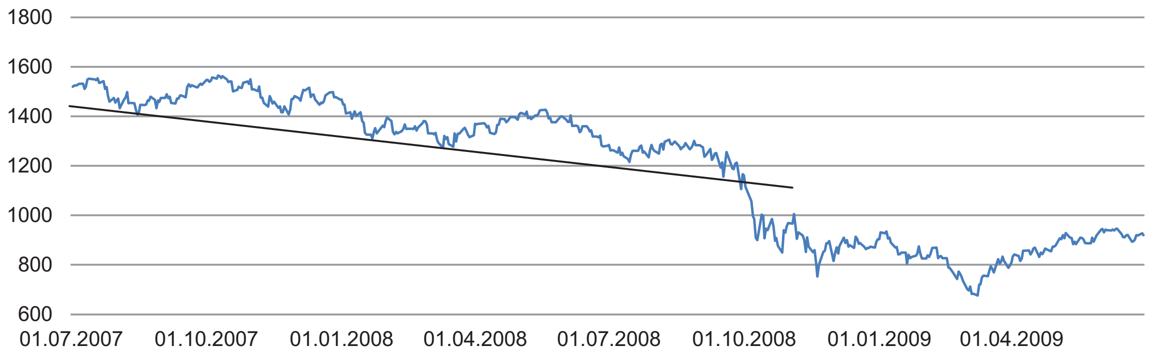
Usually analyzing methods are divided to fundamental and technical. Fundamental analysts attempt to study everything that can affect the security's value, including macroeconomic factors, such as the overall economy and industry conditions, and company-specific factors, such as financial condition and management. Fundamental analysis is considered to be the opposite of technical analysis. Technical analysis refers to a method of evaluating securities by analyzing statistics generated by market activity, such as past prices and volume. Technical analysts do not attempt to measure a security's intrinsic value, but instead use charts and other tools to identify patterns that can suggest future activity. Technical analysis can be summarized as a quote by Paul Tudor Jones, one of the most successful hedge fund managers, who believes that "prices move first and fundamentals come second."

The concept of trend refers to the general direction of a market or of the price of an asset. Trends can vary in length from short, to intermediate, to long term. Identifying a trend can be highly profitable, because the trend can be traded. Next, I'm introducing some of the most common tools in technical analysis used to estimating and trading potential trends.

2.3.1. Breakout

At breakout the price moves through a pre-determined level of support or resistance. This action is also usually followed by heavy volume and increased volatility. Commonly the strategy is to buy the asset when the price breaks above a level of resistance and sell when it breaks below support. Once a resistance level is broken, it is regarded as the next level of support when the price experiences a pullback. In the Figure 4 is represented downward resistant line. Another way to implement the breakout strategy is to go long (short) if the current price is the highest (lowest) quote of the pre-determined period – for example 20 or 40 days.

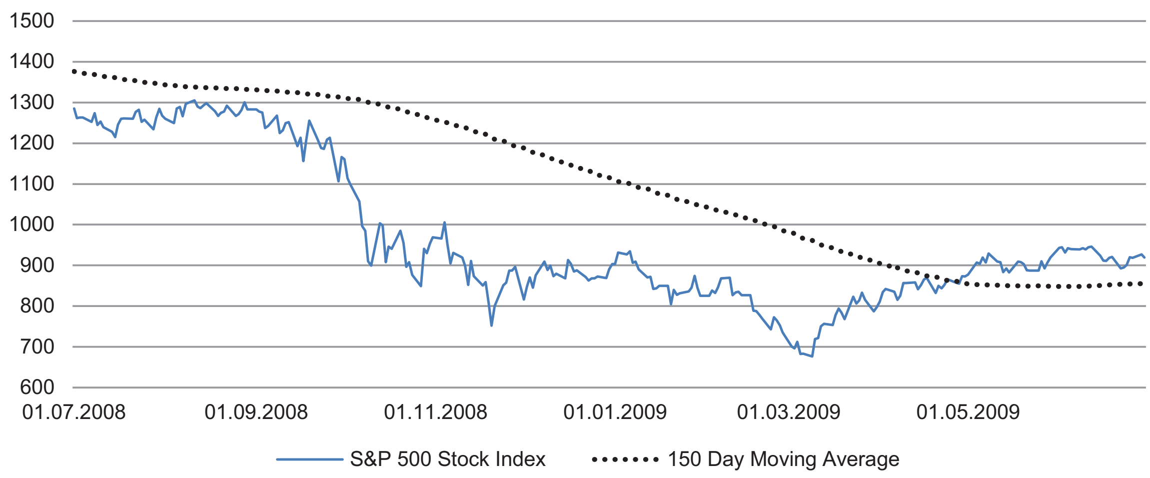
Figure 4 - S&P 500 Stock Index (1.7.2007-30.6.2009) and Downward Resistant Line



2.3.2. Moving Averages

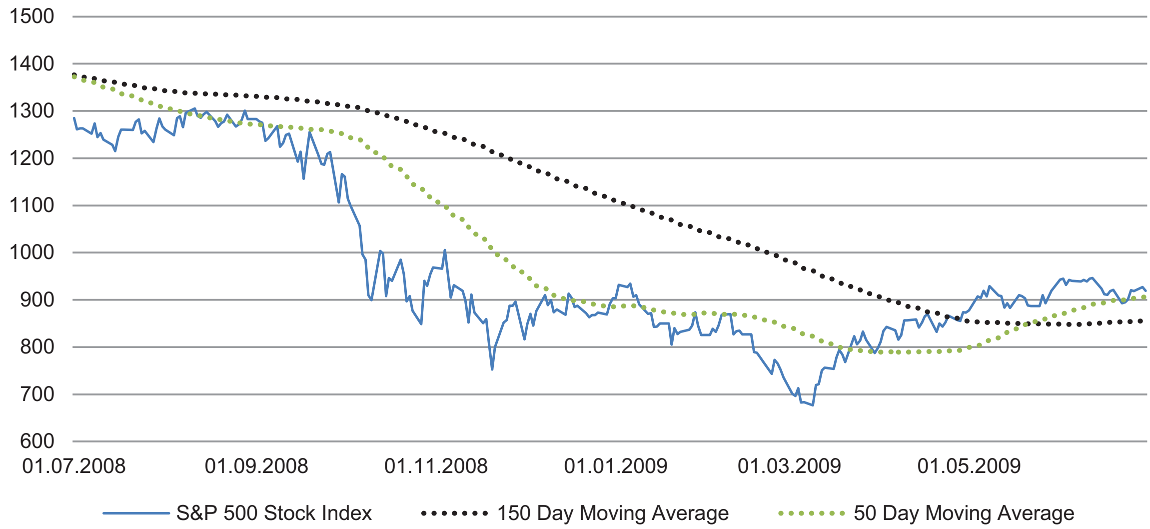
The most used variation of moving averages is a crossover. The most basic type of crossover is when the price of an asset moves from one side of a moving average and closes on the other. Price crossovers are used to identify shifts in momentum and can be used as a basic entry or exit strategy.

Figure 5 - S&P 500 Stock Index (1.7.2008-30.6.2009) and 150 Day Simple Moving Average



The second type of crossover occurs when a short-term average crosses through a long-term average. This signal is used to identify that momentum is shifting in one direction and that a strong move is likely approaching. A buy signal is generated when the short-term average crosses above the long-term average. Similarly, a sell signal is triggered by a short-term average crossing below a long-term average.

Figure 6 - S&P 500 Stock Index (1.7.2008-30.6.2009), 150 Day Simple Moving Average and 50 Day Simple Moving Average



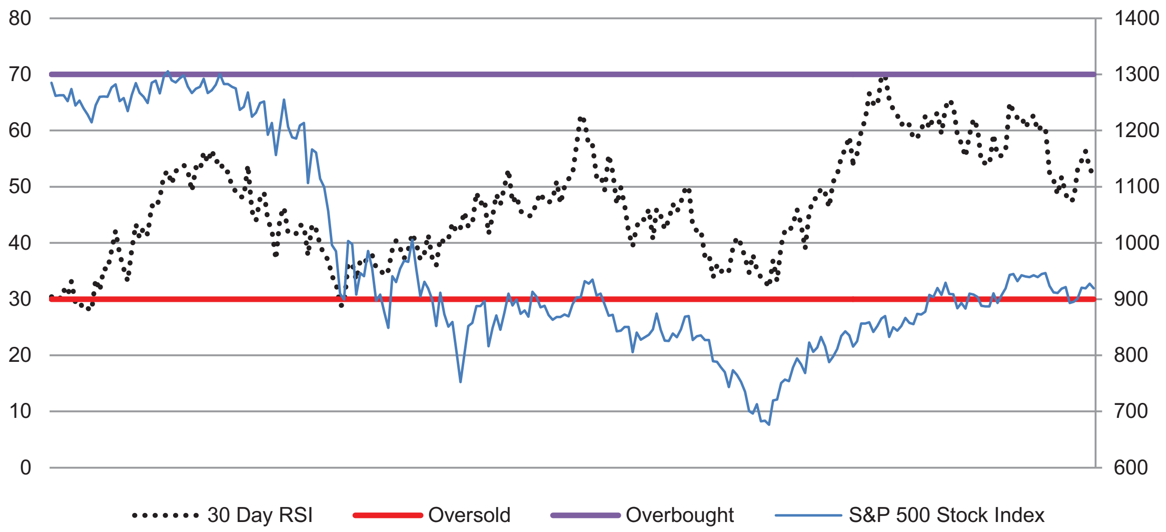
2.3.3. Relative Strength Index (RSI)

RSI is a technical momentum indicator that compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset. The RSI signal ranges from 0 to 100.

$$RSI = 100 - \frac{100}{1 + \frac{Average\ days\ of\ x\ days\ up\ closes}{Average\ days\ of\ x\ days\ down\ closes}}$$

An asset is considered to be overbought when the RSI approaches the 70 level. This means that it may be getting overvalued and there will be a possible pullback in near future. Respectively, if the RSI approaches 30, it is an indication that the asset may be getting oversold and therefore likely to become undervalued. Large surges and drops in the price of an asset will affect the RSI by creating false buy or sell signals. Hence, the RSI is best used as a valuable complement to other stock-picking tools.

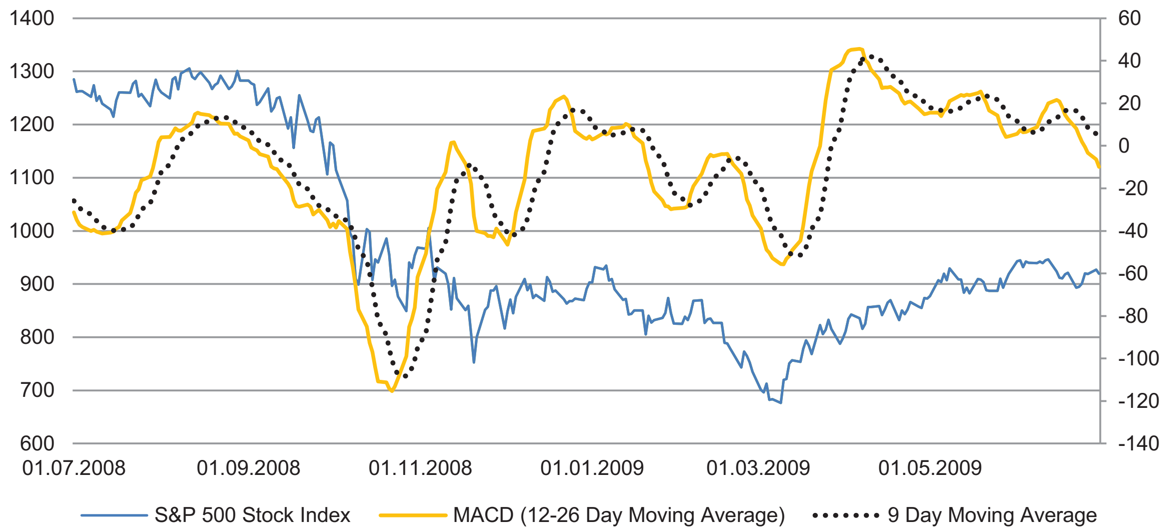
Figure 7 - S&P 500 Stock Index (1.7.2008-30.6.2009) and 30 Day RSI



2.3.4. Moving Average Convergence/Divergence (MACD)

MACD is a trend-following momentum indicator that shows the relationship between two moving averages of prices. The MACD is usually calculated by subtracting the 26-day moving average from the 12-day moving average. 9-day moving average of the MACD, signal line, is then plotted on top of the MACD, functioning as a trigger for buy and sell signals.

Figure 8 - S&P 500 Stock Index (1.7.2008-30.6.2009) and MACD



There are three common methods used to interpret the MACD. Firstly, crossover occurs when the MACD falls below the signal line, it is a bearish signal, which indicates that it may be time to sell. Likewise, when the MACD rises above the signal line, the indicator gives a bullish signal, which suggests that the price of the asset is likely to experience upward momentum. Secondly, divergence is the situation when the security price diverges from the MACD. It signals the end of the current trend. Thirdly, when the MACD rises dramatically it is a signal that the security is overbought and will soon return to normal levels. This occurs when shorter moving average pulls away from the longer-term moving average.

In addition, the zero line plays an important role as it equals the position of the short-term average relative to the long-term average. When the MACD is above zero, the short-term average is above the long-term average, which signals upward momentum. The opposite is true when the MACD is below zero. The zero line often acts as an area of support and resistance for the indicator.

2.3.5. Stochastic oscillator

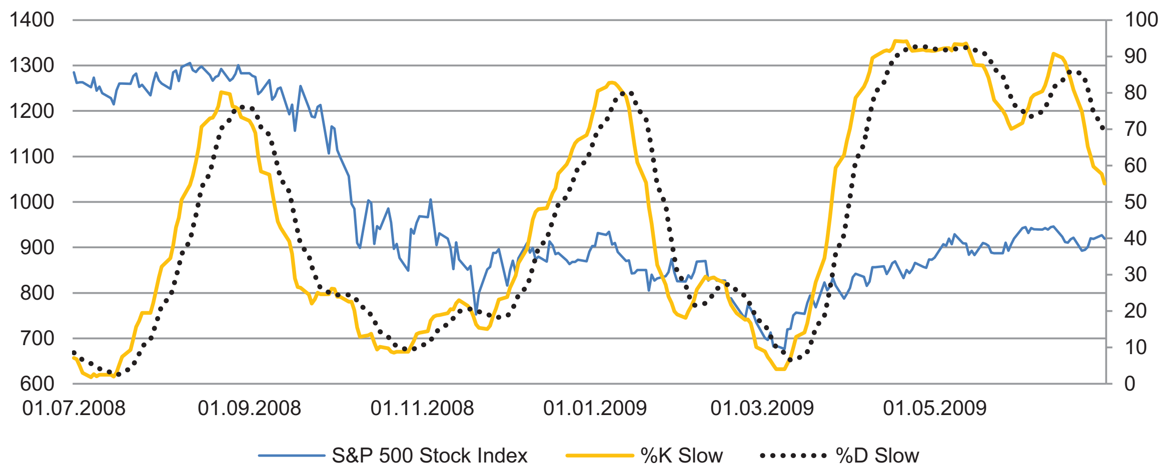
Stochastic oscillator compares a security's closing price to its price range over a given time period. The oscillator's sensitivity to market movements can be reduced by adjusting the time period or by taking a moving average of the result. The theory behind this indicator is that in an upward-trending market, prices tend to close near their high, and during a downward-trending market, prices tend to close near their low. Transaction signals occur when the %K Slow crosses the %D Slow, where

$$\%K = 100 * \frac{Price - Lowest\ price\ (n\ periods)}{Highest\ price\ (n\ periods)\ -\ Lowest\ price\ (n\ periods)}$$

$$\%K\ Slow = x\ period\ moving\ average\ of\ \%K$$

$$\%D\ Slow = y\ period\ moving\ average\ of\ \%K$$

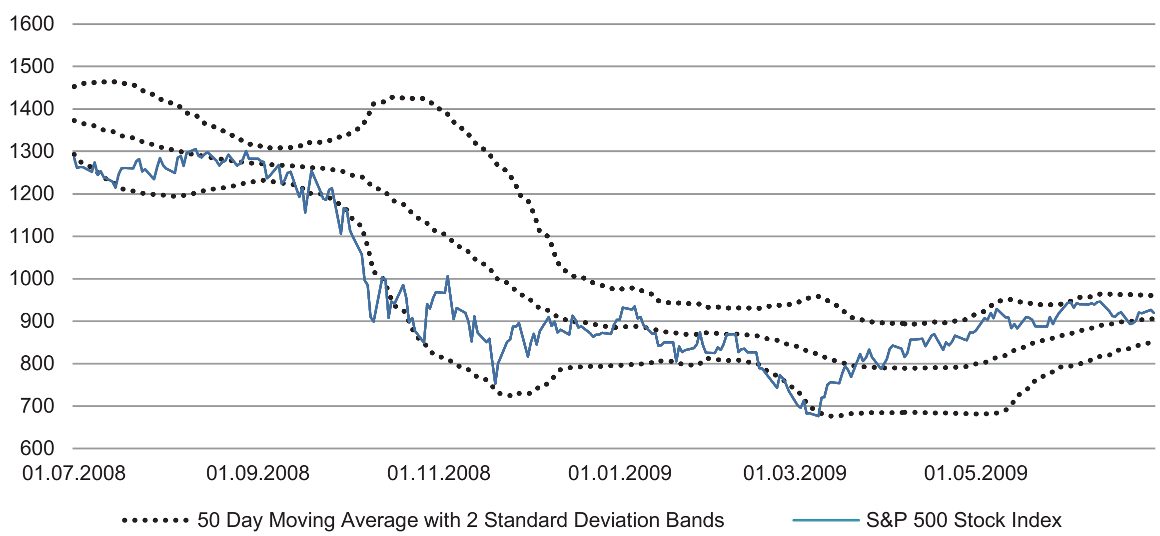
Figure 9 - S&P Stock Index, %K (30-Day Average), %K Slow (14-Day Average), %D Sloq (9-Day Average)



2.3.6. Bollinger Bands

Bollinger bands are a band plotted two standard deviations away from a simple moving average. Due to standard deviation is a measure of volatility, Bollinger bands adjust themselves to the market conditions. (Hence, this will be also the technical analysis tool to be used in this thesis.) In practice, when the markets become more volatile, the bands move further away from the average and during less volatile periods the bands move closer to the average. The tightening of the bands is often used as an early indication that the volatility is about to increase sharply. The interpretation is that closer the prices move to the upper band, the more overbought the market, and the closer the prices move to the lower band, the more oversold the market. On the other hand, by crossing upper/lower two standard deviation bands may also signal a momentum towards given direction.

Figure 10 - S&P Stock Index and 50 Day Moving Average with 2 Stands Deviation Bands



2.4. Efficient Markets

If excessive returns can be generated by technical and/or fundamental analysis, that contradicts with the theory of efficient markets. However, before proceeding, efficient markets should be defined.

2.4.1. Market Conditions and Assumptions

Fama (1970) provides three market conditions consistent with efficiency. Firstly, it must be easy to determine sufficient conditions for capital market efficiency. Secondly, all available information is available without any cost to all market participants. Thirdly, all market participants agree on the implications of current information for the current price distribution of each security. Consequently, in such a market, the current price of a security fully reflects all available information.

Fama also suggests few more important assumptions. An efficient market requires a large number of competing profit-maximizing participants that analyze and value securities. In addition Information regarding securities arrives in the market in randomly, and the timing of announcements is independent of others. Also competing investors must trade and try to adjust security prices rapidly to reflect the effect of new information and rational investors immediately exploit any arbitrage possibilities. The result is that numerous competitors that analyze and adjust stock prices to news will result in random and unpredictable price changes and all information will be reflected in security prices.

2.4.2. Forms of Market Efficiency

There are three forms of efficiency, which are weak, semi-strong and strong. In weak-form efficiency, future prices cannot be predicted by analyzing prices from the past. Excess returns cannot be earned in the long run by using investment strategies based on historical share prices or other historical data. Technical analysis techniques will not be able to consistently produce excess returns, though some forms of fundamental analysis may still provide excess returns.

In semi-strong-form efficiency, it is implied that share prices adjust to publicly available new information very rapidly and in an unbiased fashion, such that no excess returns can be earned by trading on that information. Semi-strong-form efficiency implies that neither fundamental analysis nor technical analysis techniques will be able to reliably produce excess returns. In strong-form efficiency, share prices reflect all information, public and private, and no one can earn excess returns. If there are legal barriers to private information becoming public, as with insider trading laws, strong-form efficiency is impossible, except in the case where the laws are universally ignored.

2.5. Previous Research on Technical Analysis' Profitability

Even though a large number of studies on the predictability of asset returns exist, the amount of studies that concentrate on technical analysis' predicting power of price movements and a method of testing market efficiency is relatively small. It has been generally noted that the studies from 1980s onwards have generally improved on the deficiencies of the earlier studies in terms of incorporating risk, transaction costs, out of sample tests and accounting for curve fitting. Hence, the main focus here will be on previous research after 1980s.

In general, there is more research focused on foreign exchange markets than the stock markets. Most studies in the foreign exchange markets indicate that by exploiting technical trading rules positive net returns in the range of 3%-11% for major currency futures markets can be achieved. Neely (1997) tested specific filter and moving average rules on exchange rates over the 1974-1997 period and reported positive net returns most of the cases. Only 2 out of the 40 cases didn't yield positive returns including transaction costs. Moreover, Neely, Weller and Dittmar (1997) investigated six foreign exchange rates over the 1974-1995 period. These results indicated that average annual net returns from each portfolio of 100 optimal trading rules for each exchange rate ranged 1%-6%. These results were also statistically significant. Also LeBaron (1999), Neely (2002), and Saacke (2002) reported the profitability of moving average rules in currency markets. LeBaron (1999) found that for the mark and yen, a 150-day moving average rule generated twice as large sharpe ratios compared to buy-and-hold strategies on US stock portfolios. However, Sapp (2004) reported that trading rule profits in currency markets could be explained by risk premia using capital asset pricing model.

Generally, there has been disagreement about the nature of technical trading profits in the foreign exchange market. According to LeBaron (1999) and Sapp (2004) technical trading returns were reduced after intervention periods of the Federal Reserve were eliminated, but Neely (2002) and Saacke (2002) claimed that trading returns were actually uncorrelated with foreign exchange interventions of central banks. Study by Qi and Wu (2002) also found technical trading rules to generate significant excess returns. They found mean excess returns of 7.2%-12.2% against the buy-and-hold strategy for major currencies over the period 1973-1998.

Lukac and Brorsen (1990) investigated 30 futures markets with 23 technical trading systems over the 1975-1986 period. The results indicated that only 7 out of 23 trading systems generated positive monthly net returns after transaction costs. Wang (2000) and Neely (2003) reported that genetically optimized trading rules failed to outperform the buy-and-hold strategy in both S&P 500 spot and futures markets. For example, Neely (2003) showed that genetic trading rules generated negative returns versus buy-and-hold strategy during the entire out-of-sample periods. Brock et al. (1992) found trading rule that generated substantially higher excess returns than the average of trading rules formed by genetic programming for the 1963-1986 period. Other studies, Allen and Karjalainen (1999), Ready (2002), and Neely (2003) all suggested that genetic trading rules underperformed buy-and-hold strategies for the S&P 500 index or the Dow Jones Industrial Average index in the long run.

The results of the different studies that were replicating Brock et al. (1992) are different across markets and sample periods. In general, for stock indices in emerging markets, technical trading rules were profitable after transaction costs according to Raj et al. (1996) and Gunasekarage et al. (2001). Ratner and Leal (1999) documented that Brock et al.'s (1992) moving average rules generated statistically significant net returns in four emerging equity markets in 1982-1995. However, most studies that replicated the original study by Brock et al. have similar problems: trading rule optimization, out-of-sample verification, and curve-fitting were not properly taken into account, although several recent studies incorporated parameter optimization and transaction costs into their testing procedures. Compared to emerging markets, trading profits were not found on stock indices in developed markets or they were substantially decreasing over time. This is suggested for example by Bessembinder et al. (1998) and Day et al. (2002).

The overall profitability of technical analysis has been more concentrating on the second part of the 1980s and the first half of the 1990s. Less profitability is reported for sample periods from around 1995 to the very present. (Consequently, this thesis focuses on time period 2000-2012.) This finding has been linked to improved market efficiency and curve fitting. Despite the decline in profitability, some recent studies have been trying to find explanations for these rather anomalous profits from trading rules. For example data snooping, risk premium, inappropriate transaction costs, temporary market inefficiency and market microstructure deficiencies. The most notable and strongly emerging explanations have been data snooping and risk premium.

3. Data and Methodology

3.1. Sample Selection and Data Sources

In order to have a broad view on the markets, I have selected three different asset types, of which one can be further divided into four different asset classes. The instruments I selected are:

1. Stock market index futures
    - S&P 500
    - Euro Stoxx 50
    - Hang Seng
2. FX futures (against USD)
    - CAD
    - JPY
    - CHF
    - GBP
    - AUD
3. Commodity futures
    - Agriculture
        - i. Corn
        - ii. Cotton
        - iii. Soybeans
        - iv. Sugar
        - v. Wheat
        - vi. Live cattle
        - vii. Coffee
        - viii. Lean hogs
        - ix. Cocoa

- Energy
    i. Natural Gas
    ii. Heating Oil
    iii. Crude Oil Brent
- Interest Rate
    i. T-Bond
    ii. 5Y Note
    iii. 10Y Note
    iv. Eurodollar
- Metal
    i. Gold
    ii. Silver
    iii. High Grade Copper

After these instruments have been selected, I have created a composite for each subgroup: Stock market future composite includes 3 instruments, fx futures composite includes 5 instruments, agriculture futures composite includes including 9 instruments etc. Each instrument has an equal portion in the corresponding composite. These composites are used to analyze the data of the underlying instruments. Moreover, the composites are compared to buy-and-hold strategies. The results of buy and hold strategies for different composites are presented in Appendix.

The data for instruments is collected on Bloomberg using futures' generic contract close prices and by selecting the most traded future contract for each month/quarter depending on the instrument for time period 31.12.2009-31.12.2012.

3.2. Methodology

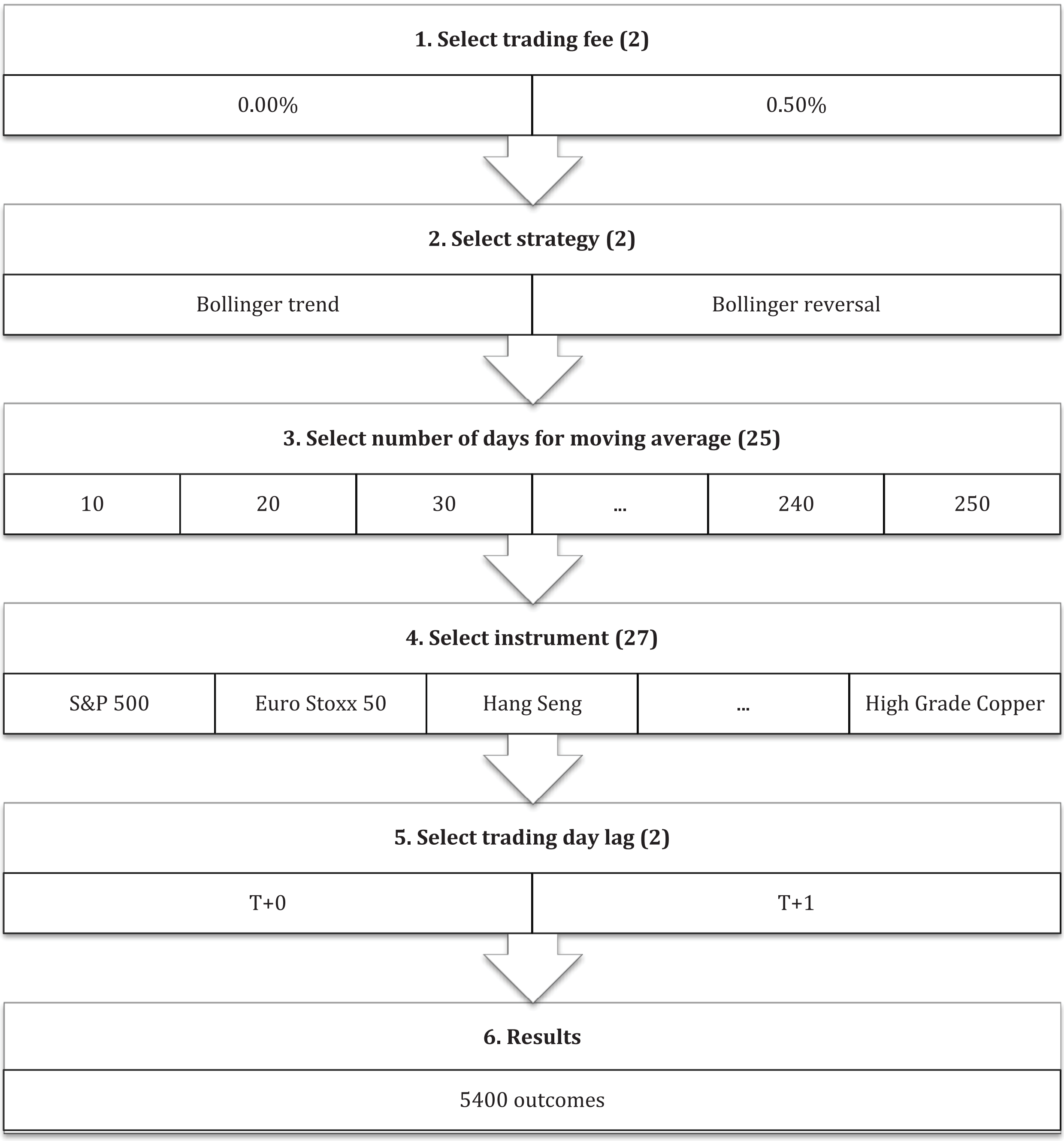
As mentioned before, I study can Bollinger bands yield excess returns and consequently are there market inefficiencies from this point of view. I use both trend following strategy and trend reversal strategy, in other words, I'm trying to answer the simple question should the current market trend of given instrument be sold or bought – nor neither? This is done for every of the 27 selected instruments.

I go through different values for moving average from 10 to 250 with interval of 10 meaning 25 different scenarios. I also study what kind of effect does the transaction fees have on the overall profitability. I estimate opening and closing a transaction resulting a transaction fee of both 0.00% and 0.50%. In addition, I study the transaction date effect on the profitability. I use two cases, in which the trade is executed in the same day the trading signal occurred, T+0 in other words, or on the next day, T+1 in other words.

As there's no available ready-to-made software (at least some I could afford), I have constructed a user interface in Excel with coding VBA in order to examine Bollinger bands profitability starting from simple text files with close prices and ending to table of results. This is also done due to focus in this thesis is focuses in general on automated system trading, algorithms and programming.

The code in more detail is presented in Appendix and the big picture is presented in Figure 11 – Steps of the Analysis.

Figure 11 - Steps of the Analysis



4. Empirical Results

The following table is used in this chapter to discuss the results. Hence, it will be explained here, before entering any deeper analysis.

The title ("X Futures") states the basket introduced in chapter *3.1. Sample Selection and Data Sources*. On the second row *Strategy* states if the column values are results from trend following strategy (*Trend*) or trend reversal strategy (*Reverse*). The third row is the amount of fee used in calculations. The fee used in calculations is *0.00%* or *0.50%*., which means in practice that the return of opening and closing a position will be deducted by the fee. Trade signal delay tells when the trade will be done after trade signal is noticed by algorithm. The trade will be done on the same day's close price (*0* or *T+0*) or the next (*1* or *T+1*). This applies also buy, sell and close signals. The figures *10* to *250* refer to the days of moving average used in analysis.

Table 1 - Trading results table model

X Futures								
Strategy	Trend	Trend	Trend	Trend	Reverse	Reverse	Reverse	Reverse
Fee	0,00%	0,00%	0,50%	0,50%	0,00%	0,00%	0,50%	0,50%
Trade Signal Delay	0	1	0	1	0	1	0	1
10	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
20	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
30	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
40	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
50	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
60	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
70	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
80	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
90	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
100	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
110	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
120	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
130	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
140	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
150	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
160	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
170	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
180	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
190	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
200	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
210	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
220	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
230	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
240	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
250	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%

4.1. Stock market index futures

In short term, 10 to 40 days, Bollinger bands strategy, trend nor reversal, don't yield any positive returns after fees. Before fees it appears that markets tend to overreact in short term and buying at the lower Bollinger band and selling at the higher Bollinger band is a profitable trading strategy. However, when the fees are considered, this trading strategy isn't profitable either due to large amount of trades, which results a huge amount of trading fees.

Using higher band as a buying signal and lower band as selling signal results positive returns, especially around 160-240 area. Ones of the most used values calculating the simple moving average is 150, 200 and 250. In Table 2 it is shown that the return area much higher when we are using different values (160, 170, 180, 190 or 210, 220, 230, 240) regardless the execution day. One very interesting finding is that taking or closing the position T+1 leads actually to better returns than T+0 in most cases.

In general, following the trend of equity futures with Bollinger bands seems to be a good trading strategy. Many of these variations, also after fees, beat a buy and hold strategy. This is against weak-form of market efficiency and it can be summarized that stock market index future market is not efficient. Buy and hold strategy yielded cumulative return of -5.2% during the given time frame (31.12.1999 - 31.12.2012) for an unbalanced portfolio with each of chosen 3 future contracts being equally weighted (1/3). However, equity markets peaked around 2000-2001, so very broad interpretations should not be concluded and more research should be done due to selected time frame.

Table 2 - Trading results for stock market index futures composite 31.12.1999 - 31.12.2012

Stock Market Index Futures								
Strategy	Trend	Trend	Trend	Trend	Reverse	Reverse	Reverse	Reverse
Fee	0,00%	0,00%	0,50%	0,50%	0,00%	0,00%	0,50%	0,50%
Trade Signal Delay	0	1	0	1	0	1	0	1
10	-48,19%	-40,69%	-71,54%	-67,39%	68,63%	62,72%	-5,90%	-9,12%
20	-4,62%	-14,57%	-43,10%	-49,08%	11,18%	18,75%	-35,18%	-30,90%
30	-16,84%	-23,46%	-45,45%	-49,77%	0,08%	4,96%	-34,12%	-30,93%
40	-0,95%	3,66%	-28,27%	-24,89%	-17,76%	-23,04%	-40,73%	-44,57%
50	20,62%	30,12%	-6,91%	0,48%	-29,84%	-34,13%	-45,92%	-49,25%
60	16,36%	21,86%	-6,21%	-1,83%	-25,11%	-32,71%	-40,20%	-46,25%
70	44,63%	46,67%	20,94%	22,42%	-38,07%	-42,68%	-49,36%	-53,06%
80	36,04%	50,57%	15,92%	28,41%	-42,43%	-46,84%	-51,46%	-55,17%
90	51,36%	72,52%	31,22%	49,81%	-49,33%	-54,04%	-56,43%	-60,53%
100	59,03%	58,36%	39,67%	39,13%	-49,74%	-48,11%	-56,33%	-54,94%
110	47,32%	50,74%	30,37%	33,48%	-47,86%	-47,41%	-54,30%	-53,91%
120	48,03%	52,06%	33,02%	36,63%	-51,71%	-53,52%	-56,89%	-58,51%
130	42,29%	41,08%	28,63%	27,54%	-48,46%	-46,42%	-53,82%	-51,97%
140	38,24%	40,22%	25,80%	27,66%	-45,27%	-45,09%	-50,59%	-50,45%
150	48,88%	55,03%	36,03%	41,63%	-48,91%	-51,17%	-53,83%	-55,87%
160	63,80%	73,59%	51,14%	60,13%	-48,80%	-52,88%	-53,53%	-57,23%
170	68,11%	78,73%	56,13%	65,93%	-48,44%	-53,44%	-52,86%	-57,42%
180	74,28%	78,32%	62,78%	66,52%	-48,33%	-50,56%	-52,53%	-54,58%
190	75,99%	93,45%	65,00%	81,39%	-51,87%	-58,19%	-55,35%	-61,23%
200	64,04%	77,53%	53,74%	66,36%	-48,59%	-54,56%	-52,28%	-57,83%
210	62,74%	79,66%	53,21%	69,17%	-49,67%	-55,18%	-53,02%	-58,17%
220	74,99%	89,92%	65,52%	79,64%	-53,87%	-57,23%	-56,88%	-59,99%
230	71,86%	71,91%	63,02%	62,92%	-53,23%	-52,54%	-56,10%	-55,39%
240	66,58%	70,83%	58,43%	62,39%	-52,23%	-55,51%	-55,00%	-58,09%
250	56,34%	55,24%	48,79%	47,68%	-49,46%	-51,15%	-52,26%	-53,87%

4.2. FX futures (against USD)

With FX futures the results are quite easy to interpret. After transaction fees positive returns can't be achieved using Bollinger bands. However, it can be concluded that currency composite seems to continue trending after crossing upper or lower band with 110-130 days of simple moving average. Even though, this doesn't work as a trading strategy after fees, this may be valuable information for risk management and hedging fx positions. These results support that fx futures markets are efficient.

Buy and hold strategy yielded cumulative return of -6.3% during the given time frame (31.12.1999 - 31.12.2012) for an unbalanced portfolio with each of chosen 5 future contracts being equally weighted (1/5).

Table 3 - Trading results for FX futures composite 31.12.1999 - 31.12.2012

FX Futures

Strategy	Trend	Trend	Trend	Trend	Reverse	Reverse	Reverse	Reverse
Fee	0,00%	0,00%	0,50%	0,50%	0,00%	0,00%	0,50%	0,50%
Trade Signal Delay	0	1	0	1	0	1	0	1
10	-4,98%	-3,03%	-51,65%	-50,64%	8,00%	4,72%	-45,17%	-46,89%
20	-2,73%	-4,51%	-43,72%	-44,74%	-0,67%	0,46%	-42,46%	-41,81%
30	-10,39%	-7,05%	-41,89%	-39,78%	8,75%	3,21%	-29,72%	-33,24%
40	-0,52%	-2,48%	-28,81%	-30,23%	-0,51%	1,12%	-29,46%	-28,28%
50	-3,98%	0,21%	-27,45%	-24,28%	-1,85%	-6,67%	-25,96%	-29,60%
60	-6,48%	-3,65%	-26,70%	-24,45%	-0,65%	-2,75%	-22,20%	-23,86%
70	4,49%	1,74%	-14,16%	-16,48%	-9,13%	-8,06%	-25,80%	-24,91%
80	-3,22%	-3,80%	-19,15%	-19,62%	-3,13%	-2,25%	-19,07%	-18,33%
90	3,45%	4,01%	-11,59%	-11,09%	-9,58%	-8,65%	-22,81%	-22,03%
100	7,89%	5,78%	-6,37%	-8,17%	-11,87%	-8,90%	-23,65%	-21,08%
110	13,18%	9,36%	-0,54%	-3,87%	-16,62%	-12,90%	-26,77%	-23,51%
120	14,52%	11,79%	1,69%	-0,72%	-18,71%	-16,09%	-27,90%	-25,58%
130	11,94%	8,86%	0,00%	-2,76%	-17,32%	-14,28%	-26,23%	-23,50%
140	5,77%	7,24%	-4,67%	-3,30%	-11,13%	-11,48%	-19,97%	-20,33%
150	6,23%	5,66%	-3,60%	-4,10%	-11,83%	-10,28%	-20,03%	-18,63%
160	5,59%	7,33%	-3,54%	-1,96%	-10,92%	-12,06%	-18,62%	-19,64%
170	0,79%	1,18%	-7,94%	-7,58%	-6,06%	-6,15%	-14,16%	-14,25%
180	1,54%	1,82%	-6,38%	-6,11%	-5,20%	-6,24%	-12,62%	-13,59%
190	4,64%	4,73%	-2,85%	-2,76%	-8,09%	-9,05%	-14,69%	-15,60%
200	0,66%	3,45%	-6,36%	-3,75%	-4,47%	-7,16%	-11,16%	-13,67%
210	2,08%	1,99%	-4,64%	-4,74%	-5,49%	-5,25%	-11,74%	-11,51%
220	-0,03%	-0,17%	-6,55%	-6,68%	-3,04%	-2,29%	-9,35%	-8,64%
230	-1,17%	-0,50%	-7,25%	-6,61%	-2,30%	-3,05%	-8,28%	-9,00%
240	-0,09%	0,49%	-5,94%	-5,37%	-2,64%	-2,70%	-8,35%	-8,41%
250	-1,35%	0,48%	-6,90%	-5,15%	-0,78%	-1,45%	-6,43%	-7,07%

4.3. Commodity Futures

4.3.1. Agriculture

The results of agriculture futures composite can be divided roughly into three subgroups: 10-50 days, 60-160 days and 160 – 250 days. Firstly, using moving average of 10-50 days, it can be seen that markets tend to overreact as trend reversal strategy is profitable. However, due these parameters also result in high amount of trades and hence the profitability after transactions fees is not certain even though odds for positive returns do increase if trading signal date T+1 is being used.

Secondly, using moving average of 60-160 days, generates positive return despite the trading date (T+0 or T+1) or transaction fees. There seems to a stronger momentum towards trending especially when breaking the upper/lower band of 110-150 days. Thirdly, using moving average of 160-250 days shows that the agriculture composite tends to overreact and trend reversal strategy yield positive returns.

Moreover, the outcome can be summarized that agriculture futures composite seems to overreact in the short and long run, but in the between the market seems to establish a trend. However, none of the tested parameters did beat the buy and hold strategy. Buy and hold strategy yielded cumulative return of 139.7% during the given time frame (31.12.1999 - 31.12.2012) for an unbalanced portfolio with each of chosen 9 future contracts being equally weighted (1/9). Hence, it can be concluded that agriculture futures market are efficient.

Table 4 - Trading results for agriculture futures composite 31.12.1999 - 31.12.2012

Commodity futures: Agriculture								
Strategy	Trend	Trend	Trend	Trend	Reverse	Reverse	Reverse	Reverse
Fee	0,00%	0,00%	0,50%	0,50%	0,00%	0,00%	0,50%	0,50%
Trade Signal Delay	0	1	0	1	0	1	0	1
10	-21,68%	-28,99%	-61,37%	-65,01%	19,97%	36,19%	-41,87%	-33,82%
20	-25,28%	-35,01%	-56,49%	-62,14%	19,88%	30,70%	-31,61%	-25,51%
30	-31,96%	-35,80%	-55,37%	-57,86%	54,23%	76,47%	0,76%	15,35%
40	-9,85%	1,30%	-34,82%	-26,57%	21,13%	48,90%	-12,33%	7,84%
50	2,51%	0,82%	-22,43%	-23,67%	49,24%	54,84%	13,26%	17,48%
60	28,17%	36,24%	2,11%	8,76%	-6,29%	0,48%	-25,40%	-20,00%
70	32,81%	44,93%	9,13%	19,08%	-23,10%	-23,86%	-37,09%	-37,65%
80	32,88%	36,57%	11,71%	14,74%	-30,56%	-18,68%	-42,30%	-32,28%
90	23,77%	28,84%	5,68%	9,85%	-23,78%	-20,30%	-35,99%	-32,99%
100	17,45%	19,77%	1,42%	3,44%	0,98%	14,64%	-14,33%	-2,67%
110	51,68%	68,53%	33,94%	48,97%	-15,92%	0,84%	-27,41%	-12,85%
120	60,26%	68,13%	42,80%	50,01%	-1,30%	4,03%	-13,88%	-9,18%
130	83,44%	77,22%	66,18%	60,62%	-12,25%	-0,06%	-22,69%	-11,88%
140	54,60%	73,41%	40,12%	57,47%	16,85%	23,28%	3,68%	9,40%
150	33,91%	29,95%	21,48%	17,86%	32,13%	38,30%	18,08%	23,73%
160	18,87%	15,09%	8,18%	4,70%	24,59%	27,39%	12,16%	14,84%
170	13,87%	12,41%	4,20%	2,85%	20,98%	26,62%	9,68%	15,00%
180	9,68%	19,02%	0,71%	9,38%	20,78%	20,26%	10,11%	9,68%
190	13,14%	22,77%	4,75%	13,74%	55,83%	57,26%	42,43%	43,83%
200	2,07%	8,99%	-5,39%	1,12%	33,02%	37,57%	22,75%	26,97%
210	-5,94%	-3,25%	-12,37%	-9,82%	62,13%	63,31%	50,03%	51,13%
220	-14,03%	-11,91%	-19,59%	-17,52%	65,75%	72,02%	53,63%	59,47%
230	-12,89%	-12,24%	-18,27%	-17,67%	42,76%	48,40%	33,02%	38,35%
240	-12,16%	-14,83%	-17,44%	-19,96%	36,76%	44,37%	27,66%	34,83%
250	-12,09%	-13,86%	-17,14%	-18,79%	29,27%	39,24%	20,90%	30,32%

4.3.2. Energy

Energy futures composite didn't yield almost any profitable returns (1 out of 25) when trending markets was explored with transaction fees. In the very short time period of 10 days trend reversal strategy did yield profitable results. These results (+72.34%) were substantially lower (49.73%) if the trading was executed T+0 compared to T+1. Two of the most used values for moving average (150 and 250 days) were not profitable after fees for trend reversal strategy, but every parameter between these was. This may be explained that this reversal strategy is being executed by many market participants and hence there are no excess returns available.

Even though the best reversal trading strategy did yield decent cumulative profit of +129.53% using 190 days of moving average, it still didn't beat the buy and hold strategy. Buy and hold strategy yielded cumulative return of 214.6% during the given frame (31.12.1999 - 31.12.2012) for an unbalanced portfolio with each of chosen 3 future contracts being equally weighted (1/3). Hence, it can be concluded that energy futures markets are efficient.

Table 5 - Trading results for energy futures composite 31.12.1999 - 31.12.2012

Commodity futures: Energy								
Strategy	Trend	Trend	Trend	Trend	Reverse	Reverse	Reverse	Reverse
Fee	0,00%	0,00%	0,50%	0,50%	0,00%	0,00%	0,50%	0,50%
Trade Signal Delay	0	1	0	1	0	1	0	1
10	-82,50%	-80,30%	-90,90%	-89,68%	230,74%	188,73%	72,34%	49,73%
20	-22,85%	-17,77%	-54,50%	-51,92%	21,97%	-27,55%	-31,11%	-59,10%
30	13,86%	20,12%	-25,61%	-21,38%	-7,07%	15,96%	-40,60%	-25,68%
40	-48,80%	-53,32%	-64,05%	-67,38%	16,37%	5,48%	-19,40%	-26,82%
50	-57,51%	-48,91%	-68,55%	-62,10%	-6,05%	-16,92%	-30,87%	-38,88%
60	-29,18%	-23,73%	-44,56%	-40,19%	-46,34%	-44,80%	-58,47%	-57,26%
70	-34,83%	-25,60%	-47,52%	-39,94%	-41,05%	-38,56%	-53,38%	-51,27%
80	-24,62%	-22,78%	-37,74%	-36,26%	-55,02%	-54,50%	-63,09%	-62,65%
90	-29,88%	-24,05%	-41,11%	-36,18%	-44,64%	-50,95%	-53,55%	-58,90%
100	-25,22%	-8,35%	-35,93%	-21,26%	-39,87%	-53,50%	-48,52%	-60,32%
110	-5,31%	-8,04%	-17,58%	-19,89%	-45,04%	-52,57%	-52,09%	-58,80%
120	-10,41%	-14,24%	-21,16%	-24,53%	-37,83%	-40,60%	-45,44%	-47,99%
130	30,39%	25,70%	16,81%	12,62%	-58,19%	-69,27%	-62,62%	-72,67%
140	-20,81%	-22,09%	-29,19%	-30,34%	-7,42%	-21,80%	-15,83%	-29,12%
150	-37,03%	-28,50%	-43,52%	-35,84%	15,50%	-2,67%	5,50%	-11,22%
160	-42,54%	-37,80%	-48,32%	-43,97%	16,11%	15,03%	6,27%	5,17%
170	-45,10%	-51,45%	-50,36%	-56,11%	43,46%	63,54%	31,73%	50,34%
180	-41,50%	-43,65%	-46,40%	-48,40%	133,23%	94,93%	115,15%	79,57%
190	-50,10%	-48,89%	-54,33%	-53,21%	168,06%	148,82%	147,43%	129,53%
200	-52,27%	-51,18%	-56,09%	-55,09%	82,53%	57,28%	70,10%	46,35%
210	-41,91%	-41,17%	-46,28%	-45,59%	31,59%	22,15%	22,68%	13,72%
220	-49,47%	-50,79%	-53,25%	-54,47%	56,09%	45,32%	45,86%	35,59%
230	-21,68%	-18,27%	-26,19%	-22,99%	39,00%	19,80%	29,93%	11,73%
240	-23,51%	-24,45%	-27,87%	-28,75%	19,91%	19,85%	12,75%	12,55%
250	-16,73%	-16,91%	-21,07%	-21,19%	-3,28%	-6,96%	-8,19%	-11,82%

4.3.3. Interest Rate

Interest rate futures composite didn't yield any positive returns after fees. The behavior of the interest futures may be seen by the trading results before fees and the decision of the trade date. When the system is trying to follow the trend changing the trade date from T+0 to T+1 has a positive result on returns. Vice versa, in reversal strategy executing trades T+0 yields better results than T+1 in every case. Hence, it can be concluded that in the case of mean reversion markets acts faster, than if the markets are trending according to simple moving average.

Buy and hold strategy yielded cumulative return of 19.2% during the given frame (31.12.1999 - 31.12.2012) for an unbalanced portfolio with each of chosen 4 future contracts being equally weighted (1/4). Consequently, none of Bollinger bands trading strategies were able to achieve that figure and interest rate futures markets are efficient.

Table 6 - Trading results for interest rate futures composite 31.12.1999 - 31.12.2012

Commodity futures: Interest Rate								
Strategy	Trend	Trend	Trend	Trend	Reverse	Reverse	Reverse	Reverse
Fee	0,00%	0,00%	0,50%	0,50%	0,00%	0,00%	0,50%	0,50%
Trade Signal Delay	0	1	0	1	0	1	0	1
10	-1,93%	2,79%	-44,75%	-41,80%	1,47%	-3,41%	-42,52%	-45,53%
20	1,39%	3,40%	-35,59%	-34,09%	-2,18%	-4,09%	-37,48%	-38,92%
30	-2,82%	-2,10%	-30,90%	-30,19%	2,35%	2,21%	-27,62%	-27,93%
40	0,41%	1,89%	-23,05%	-21,83%	-1,02%	-2,28%	-24,32%	-25,36%
50	0,88%	3,41%	-19,86%	-17,80%	-1,19%	-3,61%	-21,69%	-23,65%
60	-2,07%	0,07%	-21,24%	-19,49%	1,93%	-0,05%	-18,37%	-19,99%
70	-2,05%	-1,01%	-19,11%	-18,19%	1,70%	1,08%	-16,40%	-16,97%
80	-1,53%	1,33%	-16,82%	-14,38%	1,14%	-1,65%	-14,81%	-17,18%
90	2,53%	4,39%	-10,92%	-9,26%	-3,19%	-4,90%	-16,02%	-17,54%
100	1,31%	2,67%	-11,04%	-9,80%	-1,85%	-2,91%	-14,04%	-15,02%
110	-1,77%	0,53%	-13,21%	-11,17%	1,69%	-0,37%	-10,57%	-12,40%
120	-1,85%	0,75%	-12,43%	-10,12%	1,67%	-0,79%	-9,67%	-11,85%
130	-1,69%	0,40%	-11,44%	-9,56%	1,45%	-0,39%	-8,92%	-10,58%
140	-1,60%	1,03%	-10,70%	-8,30%	1,48%	-0,92%	-8,21%	-10,39%
150	-0,65%	1,37%	-9,51%	-7,66%	0,48%	-1,26%	-8,76%	-10,35%
160	-1,40%	0,85%	-10,11%	-8,06%	1,48%	-0,59%	-7,72%	-9,61%
170	-1,52%	0,07%	-9,79%	-8,33%	1,67%	0,39%	-7,07%	-8,25%
180	-3,32%	-2,21%	-11,30%	-10,28%	4,30%	3,65%	-4,58%	-5,19%
190	-4,55%	-2,84%	-12,31%	-10,74%	6,10%	4,69%	-2,83%	-4,12%
200	-1,45%	1,07%	-8,69%	-6,36%	2,39%	-0,03%	-5,39%	-7,62%
210	-1,13%	1,38%	-8,13%	-5,81%	2,34%	-0,16%	-5,23%	-7,53%
220	1,50%	3,82%	-4,95%	-2,79%	-1,34%	-3,49%	-7,73%	-9,74%
230	1,01%	2,58%	-5,19%	-3,72%	-0,81%	-1,90%	-6,99%	-8,02%
240	1,78%	3,49%	-4,11%	-2,51%	-1,84%	-3,27%	-7,61%	-8,94%
250	2,03%	3,56%	-3,64%	-2,20%	-2,15%	-3,30%	-7,67%	-8,74%

4.3.4. Metal

Trend strategy yielded positive returns for metal futures composite with both T+0 and T+1 execution strategies. However, the time frame was somewhat biased as it was a great bull market for metals: copper +323%, silver +457% and gold +474%. Consequently none of Bollinger band strategies was able to achieve these results and due to strong bull market trend reversal strategies with different parameters all generated substantial losses. Buy and hold strategy yielded cumulative return of 418.4% during the given frame (31.12.1999 - 31.12.2012) for an unbalanced portfolio with each of chosen 3 future contracts being equally weighted (1/3). Under this circumstances metal futures market can be claimed to be efficient.

Table 7 - Trading results for metal futures composite 31.12.1999 - 31.12.2012

Commodity futures: Metal								
Strategy	Trend	Trend	Trend	Trend	Reverse	Reverse	Reverse	Reverse
Fee	0,00%	0,00%	0,50%	0,50%	0,00%	0,00%	0,50%	0,50%
Trade Signal Delay	0	1	0	1	0	1	0	1
10	18,43%	49,32%	-40,73%	-24,83%	-42,62%	-46,10%	-71,39%	-73,39%
20	-10,28%	-17,55%	-49,56%	-53,85%	-37,02%	-24,85%	-64,21%	-57,20%
30	16,58%	0,08%	-23,34%	-34,75%	-45,10%	-21,41%	-64,25%	-48,41%
40	26,68%	45,53%	-8,57%	4,50%	-41,67%	-38,38%	-58,02%	-55,49%
50	58,53%	46,95%	22,32%	13,23%	-51,87%	-51,04%	-62,83%	-62,19%
60	20,05%	42,32%	-4,86%	12,74%	-48,57%	-52,89%	-59,15%	-62,58%
70	18,04%	38,89%	-3,61%	13,51%	-47,89%	-44,71%	-57,46%	-54,86%
80	87,39%	103,89%	58,25%	72,25%	-56,17%	-53,56%	-62,88%	-60,66%
90	122,43%	135,65%	90,96%	102,42%	-70,54%	-71,83%	-74,53%	-75,66%
100	49,64%	68,80%	28,71%	45,07%	-68,01%	-67,36%	-72,20%	-71,62%
110	56,39%	80,80%	36,55%	57,91%	-62,02%	-61,72%	-66,84%	-66,55%
120	63,02%	103,63%	44,02%	80,08%	-58,08%	-64,42%	-63,35%	-68,84%
130	73,44%	101,73%	55,91%	81,54%	-64,62%	-64,06%	-68,68%	-68,21%
140	56,05%	75,24%	40,74%	58,06%	-64,35%	-65,84%	-68,21%	-69,52%
150	72,23%	84,03%	57,20%	67,93%	-74,75%	-77,02%	-77,29%	-79,32%
160	52,02%	60,34%	39,24%	46,84%	-71,26%	-72,93%	-74,00%	-75,43%
170	57,75%	71,02%	45,10%	57,27%	-81,65%	-69,54%	-83,33%	-72,12%
180	148,08%	149,92%	132,98%	134,76%	-85,04%	-74,25%	-86,25%	-76,10%
190	90,88%	86,29%	79,31%	74,95%	-82,50%	-67,80%	-83,95%	-70,17%
200	78,04%	77,23%	67,34%	66,49%	-66,12%	-67,22%	-68,67%	-69,69%
210	86,98%	90,23%	76,45%	79,48%	-74,04%	-74,67%	-75,87%	-76,46%
220	64,58%	67,03%	55,38%	57,69%	-72,85%	-71,98%	-74,71%	-73,90%
230	61,36%	51,27%	52,88%	43,22%	-70,14%	-69,64%	-72,12%	-71,66%
240	136,21%	137,84%	125,82%	127,39%	-81,55%	-80,13%	-82,64%	-81,28%
250	118,20%	102,98%	109,30%	94,55%	-78,36%	-77,91%	-79,54%	-79,11%

5. Conclusions

This study focuses on trend following and trend reversal strategies by using Bollinger bands to find optimal trading parameters. Bollinger bands are a band plotted two standard deviations away from a simple moving average. Due to standard deviation is a measure of volatility, Bollinger bands adjust themselves to the market conditions.

Firstly, my hypothesis is that volatility is a key driver for profitable trading strategy. This hypothesis naturally includes the assumption that there are market inefficiencies. Secondly, I assume that certain instruments behave in the same way, i.e. have high level of correlation regarding volatility, and hence, they can be combined and analyzed as an asset class composite.

In general, following the trend of equity futures with Bollinger bands seems to be a good trading strategy. Many of these variations, also after fees, beat a buy and hold strategy. This is against weak-form of market efficiency and it can be summarized that stock market index future market is not efficient. However, all the other markets (fx, agriculture, energy, interest rate, and metal) seemed to be efficient and Bollinger band trading strategy, trend or reversal, didn’t yield any excess returns. This is also supported by other recent studies, which have been focused on technical analysis’ profitability. Still, even though these strategies were not more profitable than buy and hold strategies, these results may give important information on market dynamics and potential trend patterns which can be exploited in the field of risk management and hedging market exposure.

It should be mentioned, that this thesis underlines only one figure, the overall profit during the period. Hence, very broad interpretations are hard to conclude as the simulated portfolio's volatility is not calculated during this period. In other words, even though buy and hold strategy wins (loses) Bollinger band strategy, it still may have significantly lower (higher) Sharpe ratio - usually an risk averse investor prefers, or at least should prefers, a portfolio with 9.0% yield and volatility of 3.0% to a portfolio with 9.5% yield and volatility of 6.0%, for example.

In addition, how is the overall performance generated, is still a bit mystery. Is it a result of only a few great trades or are most of the executed trades contributing to the performance? It might be that a great portion of the return was made with few trades and in the meantime the money was lying in the bank account, even though it could be invested in some other profitable strategy. Hence, more detailed attribution analysis would give us beneficial information for comprehensive portfolio construction purposes.

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Appendix

Buy and hold strategies' returns

Future	Asset Class	31.12.1999	31.12.2012	Return %	Portion	Return Attr.	Buy and hold
Corn	Agriculture	204,5	698,25	241%	1/9	26,83%	
Cotton 2	Agriculture	50,74	75,14	48%	1/9	5,34%	
Soybeans	Agriculture	461,75	1418,75	207%	1/9	23,03%	
Sugar 11	Agriculture	6,12	19,51	219%	1/9	24,31%	
Wheat	Agriculture	248,5	778	213%	1/9	23,68%	
Live Cattle	Agriculture	68,475	129,9	90%	1/9	9,97%	
Coffee	Agriculture	125,9	143,8	14%	1/9	1,58%	
Lean Hogs	Agriculture	54,5	85,725	57%	1/9	6,37%	
Cocoa	Agriculture	837	2236	167%	1/9	18,57%	139,67%
SP500	Equity	1469,25	1426,19	-3%	1/3	-0,98%	
HSI	Equity	16962,1	22656,92	34%	1/3	11,19%	
ESTX50	Equity	4904,46	2635,93	-46%	1/3	-15,42%	-5,20%
CAD	FX	1,4461	0,9948	-31%	1/5	-6,24%	
JPY	FX	102,51	86,1	-16%	1/5	-3,20%	
CHF	FX	1,5907	0,9154	-42%	1/5	-8,49%	
GBP	FX	1,6182	1,6176	0%	1/5	-0,01%	
AUD	FX	0,6567	1,0378	58%	1/5	11,61%	-6,33%
Natural Gas	Energy	2,329	3,351	44%	1/3	14,63%	
HeatingOil	Energy	69,03	304,51	341%	1/3	113,71%	
Crude Oil Brent	Energy	25,6	91,82	259%	1/3	86,22%	214,56%
T-Bond	Interest Rate	94,5	99,27	5%	1/4	1,26%	
5Y Note	Interest Rate	98,0156	124,5625	27%	1/4	6,77%	
10Y Note	Interest Rate	95,8594	132,7813	39%	1/4	9,63%	
Eurodollar	Interest Rate	93,835	99,7	6%	1/4	1,56%	19,22%
High Grade Copper	Metal	86,3	365,25	323%	1/3	107,74%	
Silver	Metal	5,413	30,173	457%	1/3	152,47%	
Gold	Metal	289,76	1664,46	474%	1/3	158,14%	418,36%

VBA Code for Analysis

First we start by initiating the simulation and clearing previous data on all output sheets.

```
Sub SimulationStart()
      Application.ScreenUpdating = False

      TradesAmount = 0 'How many trades done
      TradeFreq = 0 'Trade date after signal
      Call GetInitialSetup 'Initial values for multiple variables
      Call StartMachineLearning 'This initites to find trades according to
      strategy
End Sub
```

Next we define all the necessary variables in order to make our simulation act accordingly.

```
Sub GetInitialSetup()
      Application.StatusBar = "Sub GetInitialSetup()"

      'Initial Setup
      InitialCash = Range("InitialCash")
      MaxLoss = Range("MaxLoss")
      StartDate = Range("StartDate")
      EndDate = Range("EndDate")
      LookbackYears = Range("LookbackYears")
      TradingYears = Range("TradingYears")
      MaxLeverage = Range("MaxLeverage")
      TradeFee = Range("Fee")

      'Additional Setup
      RunGroups = Range("RunGroups")
      ScreenUpdateFreq = Range("ScreenUpdateFreq")
      AllowedCorr = Range("AllowedCorr")
      CorrelationUpdate = Range("CorrelationUpdate")
      MonteCarlo = Range("MonteCarlo")

      'Reporting
      SendingEmail = Range("SendingEmails")
      SendEmailFreq = Range("SendEmailFreq")
      EmailTo1 = Range("EmailTo1")
      EmailTo2 = Range("EmailTo1")
      RepFolder = Range("Folder")

End Sub
```

The actual loop where algorithm goes through different moving average options for Bollinger band for every instrument starts here. *Strategies* range includes two variables (trend, reversal) and *instruments* range includes all the 27 different instruments.

```
Sub StartMachineLearning()
      Set Rng = Range("Strategies")
      For Each s In Rng
          Strategy = s
          Call MultipleSetup
          LoopSMA = SMAStart
          Range("SMA") = LoopSMA
              Do Until LoopSMA > SMAStop 'Start SMA/ Days Lookback Loop
                  Set Rng2 = Range("Instruments")
                  For Each i In Rng2
                      InstrumentForFile = i
                      If IsEmpty(i) = False Then Call RunSimulation
                  Next i
              LoopSMA = LoopSMA + SMADelta
              Loop
      Next s
      MachineLearning = False
End Sub
```

```
Sub MultipleSetup()
    SMAStart = Range("SMAStart")
    SMAStop = Range("SMAStop")
    SMADelta = Range("SMADelta")
    StDevStart = Range("StDevStart")
    StDevStop = Range("StDevStop")
    StDevDelta = Range("StDevDelta")
End Sub
```

Here the actual simulation starts. The general logic is following: First we have to clear data related previous simulation, define the close price for the instrument for given interval, which in this case is 31.12.1999-31.12.2012 and ensure that our data is valid between those dates.

```
Sub RunSimulation()

      ThisWorkbook.Activate
      Application.ScreenUpdating = False
      Application.Calculate
```

```
    Application.Calculation = xlCalculationManual

    'Fixed VBA
    RunDayInt = 1
    CumProfit = 1
    StrategyTrades = 0

    Application.StatusBar = "Sub RunSimulation()"

    If MonteCarlo = "Yes" Then Call MonteCarloSimulation 'Randomizing daily
    ln returns etc.
    Call ClearPreviousData 'Clearing Previous Data
    Call CreateArClosePr 'Create Price Array
    Call ValidateData 'Check that dates are valid
    Call CreateArFixed 'Create Other Arrays
    Call CreateArTargets 'Create Target Prices for Trading
    Call StartBacktest 'Start Backtest
    Call ShowResultsNew 'Start Combining Results
    Call WriteLog
End Sub
```

```
Sub ClearPreviousData()
    Application.StatusBar = "Sub ClearPreviousData()"

    Erase ArClosePr
    Erase ArShortTF
    Erase ArShortTarget1
    Erase ArShortTarget2
    Erase ArShortTarget3
    Erase ArLongTF
    Erase ArLongTarget1
    Erase ArLongTarget2
    Erase ArLongTarget3

    Erase ArVolatility
    Erase ArWorkingArray
    Erase ArActiveTrades
    Erase ArDailyAum
    Erase ArActiveTrades
    Erase ArMTM
    Erase ArClosed
    Erase ArExitTarget
    Erase ArStopTargetLong
    Erase ArStopTargetShort
    Erase ArDailyCumAum
    Erase ArAssetTypeCumPL
    Erase ArAssetTypeCumLN
    Erase ArDays
    Erase ArNominal
    Erase ArClosedTradesDetail
End Sub
```

```
Sub CreateArClosePr()
Application.StatusBar = "Sub CreateArClosePr()"
```

```
        'Open ClosePrices.txt
        PriceFile = RepFolder & "\Price Data\" & InstrumentForFile & ".xlsx"
        Workbooks.Open (PriceFile)

        'Create ArClosePr
        ArrayEndY = Range("A1").End(xlDown).Row
        ArrayEndX = Range("A1").End(xlToRight).Column

        'Dim here all the matrix to be same size aka. day rows and instrument
        columns
        ReDim ArClosePr(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArLongTarget1(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArLongTarget2(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArLongTarget3(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArShortTarget1(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArShortTarget2(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArShortTarget3(1 To ArrayEndY, 1 To ArrayEndX) As Variant

        ReDim ArVolatility(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArMTM(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArClosed(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArNominal(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArStopTargetLong(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArStopTargetShort(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArDailyCumAum(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArAssetTypeCumLN(1 To ArrayEndY, 1 To ArrayEndX) As Variant
        ReDim ArClosedTradesDetail(1 To 100000, 1 To 20)
        ReDim ArStrategies(1 To 8, 1 To 5)

        'Set ArClosePr
        ArClosePr = Range(Range("A1"), Range("A1").Offset(ArrayEndY - 1,
        ArrayEndX - 1))
        ActiveWorkbook.Close False

End Sub
```

```
Sub ValidateData()
        'Check StartDate
        For j = 1 To UBound(ArClosePr(), 1)
            Z = Format(ArClosePr(j, 1), "dd.mm.yyyy")
            If Format(ArClosePr(j, 1), "dd.mm.yyyy") = StartDate And
        IsDate(Format(ArClosePr(j, 1), "dd.mm.yyyy")) Then
                StartDate = Format(ArClosePr(j, 1), "dd.mm.yyyy")
                StartDateOk = 1
                Exit For
            End If
        Next j
        For j = 1 To UBound(ArClosePr(), 1)
            Z = Format(ArClosePr(j, 1), "dd.mm.yyyy")
            If Format(ArClosePr(j, 1), "dd.mm.yyyy") = EndDate And
        IsDate(Format(ArClosePr(j, 1), "dd.mm.yyyy")) Then
                EndDate = Format(ArClosePr(j, 1), "dd.mm.yyyy")
                EndDateOk = 1
                Exit For
            End If
```

```
      Next j
      If StartDateOk = 1 And EndDateOk = 1 Then
          Else:
          MsgBox ("Check dates!" & vbNewLine & "- Startdate: " & StartDateOk
      & vbNewLine & "- Enddate: " & EndDateOk)
          Stop
          End
End If
End Sub
```

Secondly, we create a matrix to monitor active trades and flag the first trade. This is due to the signal may have occurred before our initial trading date 31.12.1999. Hence, every first trade of every instrument is blocked to keep the results unbiased. Here also the strategy matrix is introduced, which will be referred later in the code as we proceed.

```
Sub CreateArFixed()
      Application.StatusBar = "Sub CreateArFixed()"

      'ArActiveTrades
      jEnd = Range("oArActiveTrades").End(xlDown).Row -
      Range("oArActiveTrades").Row + 1
      ReDim ArActiveTrades(1 To jEnd, 1 To ArrayEndX) As Variant
          For i = 1 To ArrayEndX
              ArActiveTrades(1, i) = ArClosePr(1, i)
          Next i
          For j = 1 To jEnd
              ArActiveTrades(j, 1) =
      Sheets("Wheel").Range("oArActiveTrades").Offset(j - 1, 0)
          Next j
          'Fill in "First Trade Ignore"
          For j = 1 To jEnd
              If ArActiveTrades(j, 1) = "First Trade" Then
              For i = 2 To ArrayEndX
                  ArActiveTrades(j, i) = "TRUE"
              Next i
              End If
          Next j

      'ArDays
      ReDim ArDays(1 To UBound(ArClosePr, 1) - 1)
      For j = 2 To UBound(ArClosePr, 1)
          ArDays(j - 1) = ArClosePr(j, 1)
      Next j

      'ArStrategies
      jEnd = Range("oArStrategies").End(xlDown).Row -
      Range("oArStrategies").Row + 1
      ReDim ArStrategies(1 To jEnd, 1 To 5) As Variant
```

```
        For j = 1 To jEnd
            For i = 1 To 5
                ArStrategies(j, i) = Range("oArStrategies").Offset(j - 1, i
      - 1)
            Next i
        Next j

End Sub
```

Thirdly target prices are created. In practice these target prices are later used to define if algorithm should go long or short.

```
Sub CreateArTargets()
      Application.StatusBar = "Sub CreateArTargets()"

      RunDate = StartDate
      For j = 1 To UBound(ArClosePr, 1)
          If RunDate = Format(ArClosePr(j, 1), "dd.mm.yyyy") Then
              DayRow = j
              Exit For
          End If
      Next j
      'For each instrument and day get strategies and make an array
      For i = 2 To UBound(ArClosePr, 2)
      InstrumentX = i
      For j = DayRow To UBound(ArClosePr, 1)
      DateY = j
          'Subs for different strategies
              If Strategy = "Bollinger Trend" Or Strategy = "Bollinger Rev"
      Then
                  Call Bollinger
              Else:
                  MsgBox ("Unrecognized strategy!")
                  Stop
              End If
          DoEvents
      Next j 'Next day
      Next i 'Next instrument
End Sub
```

```
Sub Bollinger()

      'Constant
      xStDev = 2

      'Exit Sub if the price is null
      If ArClosePr(DateY - 250, InstrumentX) = "" Then Exit Sub

      'Target prices
      ReDim ArWorkingArray(1 To LoopSMA) As Double
      For t = 1 To LoopSMA
```

```
            ArWorkingArray(t) = ArClosePr(DateY - t + 1, InstrumentX)
        Next t
            SMA = Application.Average(ArWorkingArray)
            StDev = Application.StDev(ArWorkingArray)
            If Strategy = "Bollinger Trend" Then
                ArLongTarget1(DateY, InstrumentX) = SMA + xStDev * StDev
                ArShortTarget1(DateY, InstrumentX) = SMA - xStDev * StDev
            ElseIf Strategy = "Bollinger Rev" Then
                ArLongTarget1(DateY, InstrumentX) = SMA - xStDev * StDev
                ArShortTarget1(DateY, InstrumentX) = SMA + xStDev * StDev
            Else: Stop
            End If
End Sub
```

Fourth step is to go through each day between 31.12.1999-31.12.2012 and check if the close price has crossed long or short target. If the target has been crossed the position is taken T+0 or T+1 depending on our initial setup. In this thesis both variations are examined. Also the exit price and the close price for every trade are updated daily. If these prices are crossed when position is open, we liquidate the position – on the same day (T+0) or next (T+1) - depending on selected preference. Moreover the cumulative performance of the trade is monitored by "Sub TradeClosed()"

```
Sub StartBacktest()
        Application.StatusBar = "Sub StartBacktest() | Strategy: " & Strategy &
        " | Lookback: " & LoopSMA & " Days"

        'First Row is DayRow (Already got)
        'Get Last Row For Period
        For j = 1 To UBound(ArClosePr, 1)
            If EndDate = Format(ArClosePr(j, 1), "dd.mm.yyyy") Then
                EndRow = j
                Exit For
            End If
        Next j

        '1) Go Throgh Each Day For Selected Backtest Days
        For j = DayRow To EndRow

        'Show RunDate
        RunDate = ArClosePr(j, 1)

        Application.StatusBar = "Cumulative Profit: " & Format(CumProfit - 1,
        "Percent") & " | Date: " & RunDate

             '2) Go Throgh Each Instrument For Date (j)
```

```
    For i = 2 To UBound(ArClosePr, 2)
    Instrument = ArClosePr(1, i)
    TradeSignalLong = False
    TradeSignalShort = False

        '2a) Check If Trade Signal Is Generated:
        'Long Strategies:
        If Strategy = "Bollinger Trend" And ArClosePr(j, i) >
ArLongTarget1(j, i) _
        Or Strategy = "Bollinger Rev" And ArClosePr(j, i) <
ArLongTarget1(j, i) Then
            TradeSignalLong = True
            Direction = 1
        'Short Strategies:
        ElseIf Strategy = "Bollinger Trend" And ArClosePr(j, i) <
ArShortTarget1(j, i) _
        Or Strategy = "Bollinger Rev" And ArClosePr(j, i) >
ArShortTarget1(j, i) Then
            TradeSignalShort = True
            Direction = -1
        End If

        '2b) Check no previous position
        If TradeSignalShort = True Or TradeSignalLong = True Then
'Signal is generated
            If ArActiveTrades(7, i) = "" Or ArActiveTrades(7, i) = "0"
Then 'There is no previous trade
                If Direction = 1 Then Call GetLongStopPrice Else Call
GetShortStopPrice
                ArActiveTrades(1, i) = Instrument
                ArActiveTrades(2, i) = ArClosePr(j + TradeFreq, 1)
'Fill Trade Date
                ArActiveTrades(4, i) = ArClosePr(j + TradeFreq, i)
'Fill Trade Price
                ArActiveTrades(5, i) = StopPrice 'Fill Stop Price
                ArActiveTrades(7, i) = Direction 'Fill Long/Short
                ArActiveTrades(15, i) = AssetType 'Remove somewhere
else...
            End If
        End If

        '2c) Update Exit Price for Trades
        If ArActiveTrades(7, i) <> "" And ArActiveTrades(7, i) <> "0"
Then
            If ArActiveTrades(7, i) > 0 Then Call GetLongStopPrice Else
Call GetShortStopPrice
            ArActiveTrades(5, i) = StopPrice
        End If

        '2d) Check if trade shoudl be exited
        ExitTrade = False
        If ArActiveTrades(7, i) <> "" And ArActiveTrades(7, i) <> "0"
Then
            If Strategy = "Bollinger Trend" And ArClosePr(j, i) <
StopPrice And ArActiveTrades(7, i) = 1 _
            Or Strategy = "Bollinger Rev" And ArClosePr(j, i) >
StopPrice And ArActiveTrades(7, i) = 1 Then
```

```
                ExitTrade = True
            'Short Strategies:
            ElseIf Strategy = "Bollinger Trend" And ArClosePr(j, i) >
StopPrice And ArActiveTrades(7, i) = -1 _
            Or Strategy = "Bollinger Rev" And ArClosePr(j, i) <
StopPrice And ArActiveTrades(7, i) = -1 Then
                ExitTrade = True
            End If
                If ExitTrade = True Then
                    ArActiveTrades(12, i) = ArClosePr(j + TradeFreq, 1)
'Close Date
                    ArActiveTrades(13, i) = ArClosePr(j + TradeFreq, i)
'Close Price
                        Instrument = ArActiveTrades(1, i)
                        TradeDate = ArActiveTrades(2, i)
                        Volatility = ArActiveTrades(3, i)
                        EntryPrice = ArActiveTrades(4, i)
                        StopPrice = ArActiveTrades(5, i)
                        ExitPrice = ArActiveTrades(6, i)
                        Nominal = ArActiveTrades(7, i)
                        Step = ArActiveTrades(8, i)
                        FirstTrade = ArActiveTrades(9, i)
                        PLCCY = ArActiveTrades(10, i)
                        PLPcnt = ArActiveTrades(11, i)
                        CloseDate = ArActiveTrades(12, i)
                        Closeprice = ArActiveTrades(13, i)
                        PcntOfP = ArActiveTrades(14, i)
                        AssetType = ArActiveTrades(15, i)
                        CloseDtVol = ArActiveTrades(17, i)
                    Call TradeClosed
                    'Update ArClosed
                        If FirstTrade <> True Then ArClosed(j, i) =
ArActiveTrades(10, i)
                    'Clear ActiveTrade for Instrument
                    For r = 2 To UBound(ArActiveTrades(), 1)
                        ArActiveTrades(r, i) = "0"
                    Next r
                End If
        End If

    'Next Instrument
    Next i
'Next Day
DoEvents
RunDayInt = RunDayInt + 1
Next j

End Sub
```

```
Sub GetLongStopPrice()
        If Strategy = "Bollinger Trend" Or Strategy = "Bollinger Rev" Then
            For i = 1 To UBound(ArClosePr(), 2) 'Find Instrument Column
                If ArClosePr(1, i) = Instrument Then
                    iClmn = i
                    Exit For
```

```
                End If
            Next i
            jStart = DayRow + RunDayInt - LoopSMA
            ReDim ArWorkingArray(1 To LoopSMA)
            For j = 1 To LoopSMA
                ArWorkingArray(j) = ArClosePr(jStart + j - 1, iClmn)
            Next j
            StopPrice = Application.Average(ArWorkingArray())
        Else:
        MsgBox ("Define new long stop price")
        Stop
    End If
End Sub
```

```
Sub GetShortStopPrice()
        If Strategy = "Bollinger Trend" Or Strategy = "Bollinger Rev" Then
            For i = 1 To UBound(ArClosePr(), 2) 'Find Instrument Column
                If ArClosePr(1, i) = Instrument Then
                    iClmn = i
                    Exit For
                End If
            Next i
            jStart = DayRow + RunDayInt - LoopSMA
            ReDim ArWorkingArray(1 To LoopSMA)
            For j = 1 To LoopSMA
                ArWorkingArray(j) = ArClosePr(jStart + j - 1, iClmn)
            Next j
            StopPrice = Application.Average(ArWorkingArray())
        Else:
        MsgBox ("Define new short stop price")
        Stop
    End If
End Sub
```

```
Sub GetLongExitPrice()
        If LongStrategy = "Bollinger Trend" Then 'And LongStrategyType =
      "Momentum" Then
            '1a) Bollinger: Momentum
            For i = 1 To UBound(ArClosePr(), 2) 'Find Instrument Column
                If ArClosePr(1, i) = Instrument Then
                    iClmn = i
                    Exit For
                End If
            Next i
            jStart = DayRow + RunDayInt - BollingerLongSMA
            ReDim ArWorkingArray(1 To BollingerLongSMA)
            For j = 1 To BollingerLongSMA
                ArWorkingArray(j) = ArClosePr(jStart + j - 1, iClmn)
            Next j
            ExitPrice = Application.Average(ArWorkingArray())
        Else: Stop
        End If
End Sub
```

```
Sub GetShortExitPrice()
          If LongStrategy = "Bollinger Trend" Then 'And ShortStrategyType =
      "Momentum" Then
              '1a) Bollinger: Momentum
              For i = 1 To UBound(ArClosePr(), 2) 'Find Instrument Column
                  If ArClosePr(1, i) = Instrument Then
                      iClmn = i
                      Exit For
                  End If
              Next i
              jStart = DayRow + RunDayInt - BollingerLongSMA
              ReDim ArWorkingArray(1 To BollingerLongSMA)
              For j = 1 To BollingerLongSMA
                  ArWorkingArray(j) = ArClosePr(jStart + j - 1, iClmn)
              Next j
              ExitPrice = Application.Average(ArWorkingArray())
          Else: Stop
          End If
End Sub
```

```
Sub TradeClosed()

      'ArClosed days + instruments' update one field
      If FirstTrade = True Then
          DoEvents
      Else:

      TradePL = 1 + (Closeprice / EntryPrice - 1) * Nominal - TradeFee
      CumProfit = CumProfit * TradePL

      StrategyTrades = StrategyTrades + 1
      TradesAmount = TradesAmount + 1
      'Closed Trades Details
          ArClosedTradesDetail(TradesAmount, 1) = Instrument
          ArClosedTradesDetail(TradesAmount, 2) = TradeDate
          ArClosedTradesDetail(TradesAmount, 3) = EntryPrice
          ArClosedTradesDetail(TradesAmount, 4) = CloseDate
          ArClosedTradesDetail(TradesAmount, 5) = Closeprice
          ArClosedTradesDetail(TradesAmount, 6) = Nominal
          ArClosedTradesDetail(TradesAmount, 7) = (Closeprice / EntryPrice -
      1) * Nominal
          ArClosedTradesDetail(TradesAmount, 8) = Strategy
          ArClosedTradesDetail(TradesAmount, 9) = LoopSMA
          DoEvents
      End If

End Sub
```

After these procedures the results are ready for analysis.

```
Sub ShowResultsNew()
```

```
Sheets("DataLearningResults").Select
'If MachineLearningRound = 1 Then
    i = UBound(ArClosedTradesDetail, 2)
    j = UBound(ArClosedTradesDetail, 1)
    Range(Range("A1").End(xlDown).Offset(1, 0),
Range("A1").End(xlDown).Offset(1, 0).Offset(j - 1, i - 1)) =
ArClosedTradesDetail()
'End If
'Call WriteArrayToSheet

Sheets("Wheel").Select
End Sub
```