Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

BACHELOR THESIS

Application of technical analysis on algorithmic trading

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

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Prague, May 16, 2014

Signature

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Abstract

The thesis takes on the question of profitability of algorithmic trading based on trend and momentum indicators and examines whether or not it is possible to acquire systematic profits. It reviews the development of relevant literature over the last 100 years to determine whether the inner workings of the market can be quantified and plausibly modelled. On three major U.S. stock indices are then tested several different strategies to determine whether in the long-term, passive investment can be outperformed by active trading. Merit of the work lies in backtesting several strategies and interpreting the results according to unique characteristics of the indices.

JEL Classification	G14, G15, G17
Keywords	technical analysis, algorithmic trading, back-testing, stock markets

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Abstrakt

Tato bakalářská práce se zabývá otázkou výnostnosti algortimického obchodování založeného na trendových indikátorech a indikátoru momenta a zdali je možno obdržet systematický profit. Práce shrnuje relevantní literaturu za posledních 100 let ke zjištění toho, zdali fundamentální procesy mohou být kvantifikovány a modelovány. Na třech zásadních amerických akciových indexech je poté testováno několik strategií k určení, zdali v dlouhém období může aktivní obchodování předčit pasivní investici. Přínos práce leží v backtestingu několika strategií and interpretaci výsledků vzhledem k unikátním vlastnostem jednotlivých indexů.

Klasifikace JEL	G14, G15, G17
Klíčová slova	technická analýza, algoritmické obchodování, backtesting, akciové trhy

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Acronyms

EMH Efficient Market Hypothesis

FMH Fractal Market Hypothesis

DJI The Dow Jones Industrial Average

NASDAQ NASDAQ Composite

SP 500 The Standard & Poor's 500

Bachelor Thesis Proposal

Author	Jan Šíla
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Proposed topic	Application of technical analysis on algorithmic trading

Topic characteristics The development of financial markets has been enormous over the past few decades and the trading moves from large halls full of paper orders to trading stations capable of making billions calculations per second. This puts a spotlight on technical analysis of the markets. The bachelor thesis aims to understand price-based indicators and their use in technical analysis of equity markets. It will focus on their application in mid-term and short-term price predictions and consecutively assessing profitability of algorithmic trading when they are present. I will attempt to construct a trading algorithm myself which will be tested on historical price developments of selected listed American companies and indexes. I would like to see whether or not the profitability of such systems is influenced by unexpected market volatilities. Moreover, I would like to inspect differences in algorithms and their efficiency used for relatively shortly hold positions against long-term decisions.

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Author Supervisor

Chapter 1

Introduction

It appears to be in the very nature of men to invent in order to facilitate whatever goal is ahead. Financial markets and the lure of substantial profits from speculation are no exception to that. Furthermore, since the markets are gaining the interest of the public as they have become more accessible over the last decades, many people have tried to grasp the essence of their nature and then monetize it. Yet, the very inner characteristics of the markets seem to be of a rather erratic nature.

Regardless of the true motivation of anyone participating in the financial markets, be it an academic curiosity or commercial incentives, understanding and taming the markets have been a rather elusive enterprise. The mainstream economic society have not supported the notion of existence of any general rules to effectively outperform the market for about the last 150 years. The collective opinion was, that it is even impossible to systematically, in the long run, somehow measure and predict the market progress. The foundation of this belief stems from the well known Efficient Market Hypothesis.

This thesis takes on the question of financial markets behaviour and examines theoretical attempts to describe, or somehow quantify its nature. In the aftermath of major academic discussion concerning this topic that was sparked with popularization of Fractal Market Hypothesis, this thesis attempts to understand basic workings of the stock market and test trading strategies. Algorithms are then created in order to test the hypothesis on historical data, discuss their significance and evaluate the obtained results by several metrics.

Chapter 2 summarizes the development of fundamental financial and related economic theory, with major attention to Efficient and Fractal Market Hypotheses. Third part is concerned with the methodological and theoretical foundations of technical analysis, its merits and possible drawbacks and introduces basic indicators. Chapter 4 then describes the data and markets on which the algorithms were tested and discusses the obtained results. The last part concludes the findings.

Chapter 2

Literature review

2.1 Efficient or Fractal Market Hypothesis?

> There can be no ultimate statements in science: there can be no statements in science which can not be tested, and therefore none which cannot in principle be refuted, by falsifying some of the conclusions which can be deduced from them.
>
> *Karl Sigmund Popper*

The first important piece of work related to the Efficient Market Hypothesis (EMH), comes in the 1900 as a dissertation of Louis Bachelier. In this thesis, the author well describes the general principles of options and forwards and concludes with a couple of groundbreaking ideas. Firstly, Bachelier asserts after inspecting the price changes of Rentes on Paris Bourse, that "The mathematical expectation of a speculator is nil" (Bachelier 1900, p. 10). Since the author considers the ultimate outcome and the expectation of it, rather than distribution of prices as such, we talk about a fair game defining the series.

Those were later on followed by a many other authors. (Sewell 2011) states that Bachelier's work was lost for around 50 years before rediscovered by Leonard J. Savage who brought it to the attention of Paul Samuelson and others. To put it a bit sentimentally, it was Savage's postcard who led several academics such as Fisher Black[1], Myron Scholes and Robert Merton, directly or indirectly, to win a Nobel Prize in Economics, according to (Davis *et al.* 2011)

[1] Black died 2 years before he would have accepted the Nobel Prize for his contribution on Black-Scholes formula on option pricing from 1973

Random Walk as a price driving process is inspected in (Kendall & Hill 1953) on variety of 22 price series and he does state that the weekly data "behave almost like wandering series" and hence confirms the randomness. He also points out that "There is experimental evidence and theoretical support for the belief that aggregative index numbers behave more systematically than their components. This might be due to the reduction of the random elements by averaging and the consequent emergence of systematic constituents; but it could equally well be due to chance".

Furthermore, the author finds a notable exception to the Random Walk and that is the development of cotton prices from 1816 to 1951 (War periods excluded) at New York for which Kendall finds some predictability.

Kendall's paper made serious impact in the academia. (Alexander 1961) follows his hypothesis for further evaluation. Alexander even takes on cotton prices as the exception from Kendall's paper, which demonstrate a degree of serial correlation in their respective changes. The paper in conclusion claims, that the autocorrelation was a consequence of first differences of monthly averages Kendall considered in his paper. Alexander also elaborates on (Osborne 1959), where the author demonstrates that common stock prices in logarithmic forms follow Brownian motion and also supported the square-root of time rule as described in Bachalier's dissertation. Yet, the author presents an indication of some sort of trend as he concludes that once an index rises by some proportion, it is more likely to move even further in the same direction, than the other way around.

Visually the randomness is inspected in (Roberts 1959) as the paper suspects the securities of prices to be random as well. Roberts considers weekly price changes of the Dow Jones and then compares them visually to simulated series generated by the Random Walk. He notices only two patterns; "the relative frequency of different outcomes and the clustering tendency of similar outcomes."

This is reported by (Mandelbrot 1963b) as well, however with a fundamentally different conclusion and this observation led to the Fractal Market Hypothesis.

(Samuelson 1965) elaborates on the idea of price movement described as a Random Walk process and comes up with a definition of efficient markets as a martingale process. This particular process as such was first introduced by

(Ville 1939), but the more important is Samuelson's Proof. He points out, nonetheless, that "from nonempirical base of axioms you never get empirical results". However, his theorem of martingale property of stock prices has been one of the founding stones for the Hypothesis.

The theorem does not imply that the sequence of future prices of a security shows strictly Brownian motion. It does not imply, that today's price change given the past prices is statistically independent of a forecasted change based on more historical prices; it only implies that given today's figure and historical figures, the Pearsonian correlation coefficient of increments will be zero.

Samuelson explains, that the prices do not perform a Brownian random walk, since they are somehow bounded because of supply and demand, despite our limited knowledge about the future.

Yet, it appears, that martingale process as the corner stone for the Efficient Market Hypothesis might not be that flawless. One of the reasons might be that the price increments need not follow Gaussian distribution as expected. (Larson 1960) reports that inspecting corn futures and measuring goodness of fit to Normal distribution, it fits 80% of the data, yet there are "excessive number of extreme values, being 8 or 9 standard deviations from the mean". Larson also confirms mean-reverting propertyof corn futures, but it is later refuted in (Lo & MacKinlay 1988).

Let us point out, that Futures is a different kind of market than Equity market which this thesis considers. Still, this contribution is relevant, since we started on Futures market with (Bachelier 1900) on Bourse. It also provides direct connection to (Mandelbrot 1963b), who was not a very loud voice opposing the EMH in the 1960's, when the mainstream economical theory regarding the financial markets was created.

"I shall replace the Gaussian distributions throughout by another family of probability laws, to be referred to as "stable Paretian"" states Benoit Mandelbrot in The Variation of Certain Speculative Prices, (Mandelbrot 1963b, p. 395) and lays the founding stone to a completely different perspective to examine the financial markets, which later on took the name the Fractal Market Hypothesis (FMH).

Mandelbrot studies the development of closing cotton prices in New York in the period of 1880 to 1940. He innovatively disregards the then considered Gaussian distribution of price increments. Instead, Mandelbrot considers them to follow Cauchy distribution, where the individual extreme value can substantially affect the parameters of the distribution. Furthermore, as a consequence prices do not change in a smooth infinitesimal changes, but their variation is rather performed by discontinuous jumps, then the process is "almost surely almost everywhere discontinuous"(Mandelbrot 1963b, p. 417). Mandelbrot later gives a broader and less technical view of his approach in (Mandelbrot & Hudson 2014) where he describes, that "the results were $\cdots$ far from being well-behaved and normal as the standard theory then predicted, cotton prices jumped wildly around. Their variance, rather than holding steady as expected, gyrated a hundred-fold and never settled down to a constant value." (p.95).

Not only does Mandelbrot provide a different perspective which does not intend to enwrap itself in comfort of Gaussian smoothness and continuity, he moreover develops a method how to find and measure degree of disorder in somewhat messy environment, besides other things,of financial markets. Mandelbrot describes them as a system of stable distributions with heavy tails and long-run persistence. (Mandelbrot 1963b;a; 1967)

This theory were along with Hurt's ideas transformed into a method to quantify market efficiency. Edwin Hurst created the fundamental tool for detecting long-term memory in series of any kind(Hurst 1951). Hurst's original concern was design of a water dam on the river Nile in the 1950's.

To put it rather simply, the method of Rescaled range analysis (R/S), later elaborated on by Mandelbrot and nicknamed "The Joseph effect"(Mandelbrot & Wallis 1968). Its core idea lies in measuring how the observed phenomenon varies from its maxima to minima compared to independent series. If the hypothesis of similarity is statistically rejected, it implies a degree of importance of the particular series(Mandelbrot & Hudson 2014).

Several papers and books were published supporting the Efficient Market Hypothesis from different angles and inspection of all is beyond the scope of this thesis.

In general, the studies vary from Random Walk as a descriptive process of price changes to asserting price increments follow some sort of normal distribution. Even though there does not exist any widely valid and codified definition, two of them are of a rather great importance. According to(Fama 1965):

"An *"efficient"* market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants.

This definition focuses rather on market agents and their behaviour, but for the purpose of this thesis a bit more technical definition is suitable.

Let us conclude this part with widely accepted definition as presented by (Malkiel & Fama 1970) in three forms; The *weak form* which assumes that future development of prices cannot be predicted based on knowing historical prices. *Semi-strong form* that considers the inability to make predictions based on historical prices as well as available public information. And lastly the *strong form* under which prices cannot be predicted even when insider information is available to an agent.

However attractive the Efficient Market Hypothesis might appear, it is not of any extraordinary nature among other hypothesis and ideas and as well is subjected to critique and falsification from various angles. This section hence focuses on the contra-arguments to EMH and will offer several different hypothesis to describe market behaviour. Furthermore, it will present the contemporary evidence on technical analysis and its theoretical as well as empirical results.

On the other hand, let us point out, that finding some degree of dependence in the price developments does not necessarily imply finding profitable trading strategy. The world as we know it always carries some degree of risk despite the efforts to minimize it, therefore we talk about decision under uncertainty, where each ultimate state of the world has its probability.

Hence, even the best model will possess unexplained variance to some extent and even low probability is still a probability, with limited correctness of the estimation. And the financial markets are unequivocally no exception to that, experiencing crashes in the last century which, according to a classic Gaussian model should not have repeated as they did in the 1980's and 90's. The worst

Dow Jones Index performance of the century closed on October 19^{th}, 1987 with a plunge of 29.2 had the probability of occurrence less than 1 in 10^{50}, (Mandelbrot & Hudson 2014, p. 34).

This thesis nonetheless does not have the ambition to model the markets to present actual dependence.It attempts to measure how profitable an algorithm based on certain statistical indicators can be.

The EMH claims that there is no serial correlation in the prices of financial markets. (Jegadeesh 1990) on the other hand finds empirical evidence, that this statement might not be entirely true.

Furthermore, Eugene Fama, one of the most well known proponents of the Hypothesis further examines the EMH in terms of autocorrelation and finds, that there is up to 40% predictability of 3-5 years variation of portfolios of small firms (Fama & French 1988). This is later followed by (Jegadeesh 1990) who finds that first order serial correlation is highly significant in monthly returns.

Challenges falling upon the EMH did not focus solely on Random Walk or autocorrelation property. (LeRoy 1973) relaxes exogeneity of expected rate of return as presented by (Samuelson 1965) and examines if it leads to similar result. The underlying assumption for portfolio composition is that investors have a choice between a risk free asset yielding exogenous return and risky stock. The author concludes, that in general, under risk aversion, rates of return on stock will not exhibit martingale property of unconditional expectation

The last assumption of the Efficient Market Hypothesis that will be critically reviewed, is rationality of its agents and their consequent behaviour on the markets. Let us briefly examine this as well. Two fundamental pillars of behavioural finance are described in (Barberis & Thaler 2003): Firstly, *limits to arbitrage* argues that it is difficult for agents attempting to trade as rational traders, to undo the allocation inefficiencies of the traders behaving less rationally.

Specifically, an arbitrage is an investment strategy that offers riskless profits at no cost. While irrational traders are often known as "noise traders", rational traders are typically referred to as "arbitrageurs". The authors argue, that mechanisms which would arbitrageurs adopt to utilize the misallocation are not necessarily risk-free. They assume, there is a certain probability that the prices would deviate further away from the fair price causing losses to rational traders. In effect, the mean-reverting condition assumed in the EMH does not hold in this theory.

Moreover, there are other factors such as spread and transaction costs making the opportunities less profitable or riskier at least.

The second pillar of behavioural economics is the *psychology* of the agents. There are various factors such as overconfidence in their opinions (higher for alleged experts), belief perseverance or anchoring of their estimates which together make people susceptible to biased, or rather irrational behaviour.

Moreover, people tend to use statistical inference improperly, such utilizing too small samples. Also, there is evidence that people tend to poorly assess when it comes to estimating probabilities: events they think are certain to occur actually appear only 80% of the time, and events they deem impossible occur approximately 20% of the time[2]

The economists who are cautious of such experimental results tend to account for them in their research by the following measures, or beliefs: (i) through repetition, people will learn their way out of biases; (ii) experts in a field, such as traders in an investment bank, will make fewer errors; and (iii) that with more powerful incentives, the effects will disappear. However, the effects might be mitigated to some extent, the authors do not find any evidence that they can be wiped out completely.

Furthermore, recent literature takes on the question, if technical analysis can be a self-fulfilling analysis. "Some chartists even claim their discipline does not contradict the efficient-market hypothesis: if prices already reflect all past publicly available information, one may skip the hassle of dissecting balance sheets or mastering pricing models, focusing instead on candlestick or diagram patterns which, by conjecture, contain all the necessary information to explain

[2]Dale Griffin, Amos Tversky, The weighing of evidence and the determinants of confidence, Cognitive Psychology, Volume 24, Issue 3, July 1992, Pages 411-435, ISSN 0010-0285, http://dx.doi.org/10.1016/0010-0285(92)90013-R. (http://www.sciencedirect.com/science/article/pii/001002859290013R)

price movements." appears in the abstract for lecture by Frédéric Claisse, Ticks of the trade: technical analysis self-justified [3]

The Keynes's effect of beauty contest, published in (Keynes 2006) might apply as well in the creation of prices in equity markets. The growing adoption of technical analysis is well documented and surveyed (Carter 1990; Gehrig & Menkhoff 2006). The effect of evaluating not one's opinion, but acting on what one thinks the public opinion is, might drive the prices as the technical analysis assumes. It would be true, if traders relied solely on technical analysis, but according to the (Carter 1990), it is rather a guiding or confirmations tools for the final decision. Moreover, more recent studies report less profitability for longer established stocks and indices, when applying the same technical parameters as for newcomers of the equity markets.

2.1.1 Measurment of efficiency & LT dependence

Despite the practical characteristics of the thesis focusing primarily on technical analysis, let us briefly conclude the broader theoretical literature review with applying the theory.

As hinted in previous reference to (Hurst 1951), developing a measure of effectiveness if attempted in (Kristoufek & Vosvrda 2013) or (Barkoulas & Baum 1996). The first paper evaluates 41 stock indices and introduces Efficiency Index (0 for perfectly efficient market), where the poorest performance shows Peruvian IGRA index (EI of 0.36). U.S. indices scored 0.13, 0.15 and 0.17 for DJI, NYSE and NASDAQ respectively and took middle places.

(Barkoulas & Baum 1996) tests for long-term dependence in US stocks analysing individual securities as well as sectoral indices. The paper does not detect fractal dimension in indices, but in firm's returns it does. The authors use spectral regression method but the results do not reject the martingale model hypothesis, since it finds some evidence on long-term memory only in five company stocks and intermediate in case of three. It concludes, that fractal structures in indices might be only a result of aggregation of individual stocks.

[3]available http://orbi.ulg.ac.be/handle/2268/148439 HOW TO PROPERLY QUOTE UNAVAILABLE LECTURE?

To sum up, it has been shown in several studies that the Efficient Market Hypothesis is not generally very fitting description of the financial markets and there is no universal concordance on how the markets price mechanisms really work. The Fractal Market Hypothesis tackles directly the Weak Form of EMH and this thesis takes it as basis to test whether technical analysis can be profitable on real data.

The development of relevant literature concerning technical analysis dates back to 17^{th} century to (Penso de la Vega 1957). Since then various academic studies have been documenting the widespread use of technical analysis, (Gehrig & Menkhoff 2006) find significant increase in application of those methods in the nineties among currency traders.

(Park & Irwin 2007) offers a broad review of technical analysis studies from 1960 to 2004. Among a total of 95 modern studies (1988-2004), where advanced methods and tools are available, from 95 papers, 56 finds positive results when using technical analysis and 19 indicate mixed results. Also, studies of older dates did not, according to this particular paper, very much consider the risk variable in their testing.

Apart from statistical and precaution-measures summary, the authors also stress the difference about views of market participants and academics as a result of publication bias. If an academic believes to find a method which generally outperforms the market, they are more likely to sell it rather than publish it for a fraction of the potential profit. Or in other case, file drawer effect is a result of unpublished reports for their insignificance. Nevertheless,one of the most influential and impacting article by (Brock *et al.* 1992) takes on a similar issue as this thesis. This study has grown in significance for various others took on the methods and achieved positive results in various other studies e.g. (Bessembinder & Chan 1998)

The authors test two trading rules - moving average and trading range breaks - on the Dow Jones Index in selected periods of its history. For statistical inferences, bootstrap methodology inspired by (Efron 1979) is used. The authors believe that combining technical analysis with bootstrapping helps to achieve a better description of the series. For a lot data is used, the authors control for data snooping problem with three precautions: reporting results from all trading strategies; utilizing very long data series (1897-1986); emphasizing the robustness of results across non-overlapping subperiods of time.

The results are inconsistent with any of the three tested hypothesis about returns: a random walk; an AR (1); a GARCH-M model or an Exponential GARCH. Since after generating alternative time series akin to the Dow Jones Index with similar properties (mean, variance) and applying same rules, results performed worse than the real scenario. For the GARCH-M process, the average result of the real scenario was in the upper 10-percent bound of the range of the average results of the 17 hypothetical scenarios. For the others, the real scenario did even better. Hence, the results are unlikely to be obtained by data snooping or coincidence. Still, transaction costs might delete some proportion of the extra returns, so again we assume that they are very low.

In terms of financial results, they generally show higher returns for buy periods than sell periods. For buy periods the average year return was about 12% (daily 0.042, SD(0.89%)), which is in contrast with average -7% per year return on sell periods(daily -0.025, SD(1.34%)).

The use of intra-day technical analysis is in U.S. equity market is examined in (Marshall *et al.* 2008). The shorter period is chosen, since technical analysis is preferred, by responding traders, to fundamental supposedly particularly in the short run (Carter 1990).

Marshall et al. take into account the hypothesis of clustering and assuming its effect is more profound over briefer periods, they examine 7846 rules on SPDR exchange-traded fund over 2002-2003. Using previously well-documented strategies from Filters, Moving Averages, Support and Resistance, Channel Breakout, and On-Balance Volume, data snooping bias is minimized and the paper concludes that none of those rule families produced statistically significant results in favour of profitability of the technical analysis.

If the technical analysis is defined as purely applied statistics, then chartists rely solely on subjective opinion about the graphical formations. (Lo *et al.* 2000) attempts, however, to combine those approaches and statistically determine the chartists formations and then investigate their usefulness.

The authors reject the easier programmable indicators such as Moving Averages in order to examine the power of smoothing techniques in automating technical analysis. Using nonparametric kernell regression, the study aims to remove non-linear noise from the data. The conclusion is, that "certain technical patterns, when applied to many stocks over many time periods, do provide incremental information, especially for Nasdaq stocks"(Lo *et al.* 2000, p. 49). The paper does not state that the analysis as such generates substantial extra profit, but it rather adds value the investment process.

Recently, (Shynkevich 2012) published a study on technical analysis and its profitability on stocks with small market capitalization, or so called "small cap" companies. For the period of 1995-2002, the technical analysis yielded superior returns on several tech industries and other small cap sector portfolios even when discounted for moderate size of transaction costs.

Yet, in already described paper, (Brock *et al.* 1992) show that historically MA rules have been profitable even for large firms for which market efficiency is generally presumed to hold.(Hsu & Kuan 2005) find that most of the profitable rules and strategies are based on either filter rules or moving average.

Moreover, (Hsu & Kuan 1999; Hsu *et al.* 2010; Hsu & Kuan 2005) examine the profitability of technical analysis using White's reality check as described in (White 2000), and Hansen's SPA test that reveal the data snooping bias. Compared to previous studies they examine more complex universe of trading techniques, including not only simple rules but also complex trading strategies and test it on four indices.

It is found that significantly profitable simple rules and complex trading strategies do exist in the data from relatively "young" markets (NASDAQ Composite and Russell 2000) but not in the data from relatively "mature" markets Dow Jones Industrial Average (DJIA) and S&P 500. Moreover, after taking transaction costs into account, they find that the best rules for NASDAQ Composite and Russell 2000 outperform the buy-and-hold strategy in most periods.

As previously mentioned, researchers might incline to take wishful thinking for relevant results. (Hsu & Kuan 1999) also takes on the data snooping bias and uses White's Reality Check.

On another note, (Kuang *et al.* 2010) examines almost 26 000 trading strategies in emerging forex markets. Despite finding several profitable rules with mean excess return of over 30%, they reject general profitability of technical analysis as when controlled for data snooping bias (using StepM, SSPA tests and White's Reality Check) the returns disappear.

The oldest stock index, the DJI is examined in (Bajgrowicz & Scaillet 2012) as well. False discovery rate (FDR) method is used to control for data snooping bias and the paper concludes that even studies testing earlier periods and finding profitability of technical analysis, should be disregarded as relevant. Majority of the papers presented in this review detects profitability, if any, mostly in previous century periods and its returns decreasing over time when adoption of those methods booms.

(Azizan & M'ng 2010) focuses on Bollinger Bands Z-test (BBZ), closely related to Moving Average indicator. This study as several other goes the way paved by (Brock *et al.* 1992) and it directly follows (Bessembinder & Chan 1998) on FKLI, FCPO, Soyoil, Soybean and Corn futures since 1995 to 2008, so we move from Stock market to Futures. The mechanical buy signal is above +1 standard deviation of the index and sell signal below -1 S, which means that bands used in BBZ are 1 SD bands from the MA.

The paper concludes, that BBZ is, for the respective markets, a robust trading system which can be applied for live trading. The paper also offers results for live trading over the year 2005 on FKLI in which passive buy-and-hold strategy yielded -6.5 points loss, whereas BBZ adjusted for transaction costs performed +44 points (the parameters were BBZ(21MA, 1 SD)).

Just to show that technical analysis has spread not just in the Stock market of Futures market, but also in the Foreign exchange, let us briefly mention a paper by (Reitz 2002). It provides theoretical evidence that Moving Average rules can detect possible shifts in currently unobservable fundamentals in the forex markets by analysing past prices developments. The authors use general filter rules as a proxy for Bayesian learning and prove that the past indeed can provide useful information about the underlying fundamentals, which can be observed with certain lags. However, they again do not consider actual transaction costs. Also the authors work with statistical expectations which might or might not have practical application as for instance one of the assumptions is stationarity of the exchange rate stochastic process.

Chapter 3

Methodology

3.1 Trading strategies and market rationale

This part of the thesis will cover the nature of strategies, in particular from financial markets perspective. Strategy as such, can be loosely defined as a plan to achieve one or several goal under the conditions of uncertainty. Predominantly, the ultimate goal of each trader is to beat the markets. Since passive investing is always an option, the underlying motivation to trade is to take advantage of market changes and capitalize on them to one's profit. Therefore, trading strategies in this case essentially aim to somehow predict the direction in which market is going to develop.

Then if the investor believes the market prices will go up, they buy the instrument, or enter the so called long position. And if indeed the prices has risen over time, they then sell the asset with profit, or it is said that they exit long position. The other case is, when the investor expects the prices to go down, then the mechanism is a bit more complicated. It requires them to rent the asset from a broker at the current price and sell it to another market participant willing to buy at the price and later on repurchase it at lower price, provided the price has indeed fallen. Then, when returning the instrument to the lender, trader might make a profit.

This is overly simplified, as we do not take into account costs of the transaction or spreads, of the prices. On a market, the buy-sell spread, or also known as the bid-ask spread, occurs when there is a difference between the buy and sell price. In effect it means, that a trade to become profitable, the price needs to move the desired way to some extent. Naturally, the offer price is not lower than the bid price, in other words, non-holder of the security buys it for a higher price that the holder can sell at the same point in time to a broker. In our analysis, we limit ourselves only to close prices of different stock indices as we disregard transaction costs of trades completely to simplify demonstration of the results. The impact of introducing transaction costs will be discussed in the results evaluation subsection.

Let us return to the key topic at hand. The strategy of the simplest form is the Buy & Hold, or passive trading strategy. Technically, an asset is bought and held for some period of the before, usually rather long period, in order to capitalize on the perceived growing nature of the markets. The assets targeted by the this strategy are usually indices, as they comprise of a many individual stocks selected by a certain mechanism. As a large group, they are perceived to be less likely to drop significantly in value, though recent turmoil do not support this idea.

It is questionable to label the Buy & Hold a strategy, as it does not contain much of a plan in the sense of trading automatizatin. Although, picking the stocks do consist of some portfolio optimization, or rather fundamental analysis, which attempts to evaluate the intrinsic value of a stock and trades the differences between its findings and market price. Nevertheless, Buy and Hold will suffice to serve as performance benchmark for tested strategies.

Shall we distinguish in the terminology about what is an investor and what is a speculator, Edwards *et al.* (2001) points out that there have been a cultural shift. Days of investors who bought and held stock in order to collect its dividends, and speculators were slightly suspicious men, are gone. Nowadays, people are more concerned with the price increments than dividends payouts. For our purposes, defying each subject with different trading habits is redundant, therefore, let us consider investors and speculators as synonyms. However, for Buy & Hold strategy, the term investor seems more appropriate.

As for the perceived generally growing markets, when looking at a chart in nominal values of an index and looking in deep history, the then figures are really a fraction of today's values, therefore, any short term upswing or downswing is barely visible. However, when looking at logarithmic scale of values of the Dow Jones Average, since the Black Monday of 1929, the index still goes up in pretty much the same pace. Nevertheless, if looked more closely, major deviations would be found in intraday or weekly prices for sure, but this works well to describe the general idea of market behaviour over the last century. Hence, trend indicators triggering long positions in particular, would probably yield high profitability statistics.

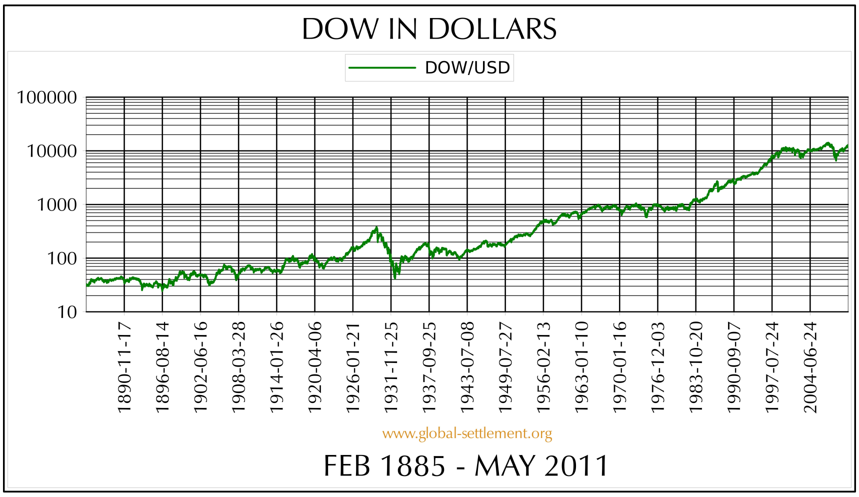

Figure 3.1: The Dow Jones Industrial Average in log-scale 1885-2011
Source: www.global-settlement.com

An interesting question was left hanging, and that is of the importance of growing market for profitability. Clearly, if the DJI is considered as benchmark of the market, it has risen great deal since its introduction in 1896 and simple passive investment would be substantially rewarded, assuming it would survive all drawdowns. Not to mention, that expansion is mentioned all the time from different market angles, be it newspaper or analytics commenting on the latest developments. In terms of behavioural sciences and psychology, people are simply more inclined to look for growing patterns than the other way. This effect is also magnified by news releases, PR of companies and generally press around stocks focuses more one the bright side. Edwards *et al.* (2001) comments on this affirmatively:"...various factors might explain why "the public" is always Bullish. The public is always hoping and expecting the stocks to go up all the time."

However, the same book claims that examination of long term charts reveals that "stock levels rise and fall about the same amount" and since they go up about two thirds of the time, the downfall must be much faster then the climbing. Therefore, short positions might be profitable much faster than orders with label 'long'.

But such a quick profit is hard to acquire, at least using technical analysis, even more in the example this thesis has tested. In the next chapter it will be demonstrated, that strategies suffer predominantly from the lags between the actual market turn and before triggering an order. Moreover, as indicators are inherently a bit behind market and sell signals tend to be initiated when the market is reversing to trend upwards, therefore, ending up as less profitable, or more likely, loss-making. In particular, short positions are highly recommended to be paired with a stop-loss order, which specifies the maximum amount the trade can incur to its issuer as they can be truly substantial, again due to growing markets.

Despite ethical conundrums, that by going short in a market, trader is benefiting from someone else's misfortune, as discussed in Edwards *et al.* (2001), there are also upsides to the issue. As the short selling was described above, the trader has the obligation to repurchase borrowed security and hence brings liquidity to the market, regardless of their profit. Furthermore, declining stocks attract buyer as a promising opportunity to buy cheaper. Also, after a decline, upswing can be expected since the traders causing this effect need to buy the stock to cover for them, pushing the prices back again.

Effectively, long and short orders are necessary complements to each other, however, markets tend to fall rapidly for shorter periods of time, therefore, making it harder to capitalize on those movements.

3.2 Active trading

Let us define financial trading strategy as "A set of objective rules designating the conditions that must be met for trade entries and exits to occur. A trading strategy includes specifications for trade entries, including trade filters and triggers, as well as rules for trade exits, money management, timeframes, order types, etc..."[1]

Characterising the workings of strategies based on technical indicators requires at least basic notation of them. Let us briefly present the most common kinds and examples, whereas the tools tested in this thesis will be formally, and mathematically more precisely, introduced in the following subsection. Quite interestingly, a few were introduce by the same author Wilder (1978) such as

[1]Available at http://www.investopedia.com/terms/t/trading-strategy.asp

ATR, Parabolic SAR, RSI or Directional Movement Concept. Although developed quite long before the computer age, all those stood the test of time and are widely popular on trading floors.

- **<u>Trend indicators:</u>**

  ◇ **Moving averages (MA)** - Average previous periods, smoothing price data as a discrete equivalent of derivation, to create a trend following indicator, define market direction with a lag.

    ∗ Simple (SMA) just averages the latest values,

    ∗ Weighted (WMA) puts different emphasis on each observation

    ∗ Exponential (EMA) puts more weight on most recent prices

  ◇ **Moving Average Convergence-Divergence (MACD)** - Also a momentum indicator, MACD line is the difference of two EMAs and fluctuates around 0 as they converge/diverge. Positive MACD means upside momentum, negative downside (growing/declining market)

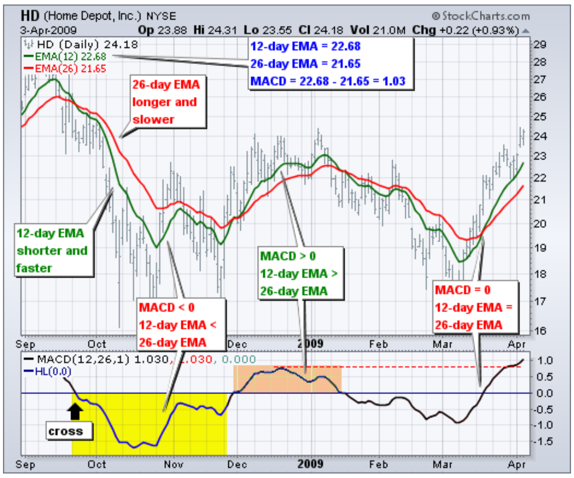

Figure 3.2: SMA, EMA and MACD example

Source: stockcharts.com

  ◇ **Parabolic Stop and Reverse (SAR** - Follows trend and works as trailing stop, or profit guard, since for growing market it never decreases and vice versa. Therefore, it discourages to move with stop-loss orders and protects the profits. Its sensitivity can be altered.

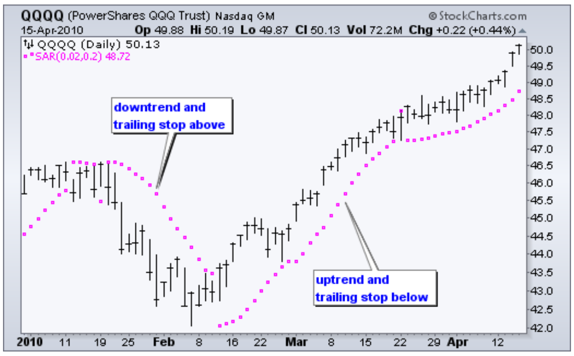

Figure 3.3: Parabolic SAR example

Source: stockcharts.com

- **<u>Momentum indicators</u>**
  - ◇ **Relative Strength Index (RSI)** - Measures if a market is overbought or oversold by comparing averages of the latest gains and losses, usually of 14 past periods.

Figure 3.4: RSI example

Source: stockcharts.com

  - ◇ **Stochastic oscillator** - follows speed of price changes by two measures. Firstly, difference of the latest close and lowest low, to the maximum amplitude of the prices in a period (high-low range). Then compares it with 3 day SMA of the series. Strong series of positive returns makes low RSI, which indicates overbought market and vice versa.

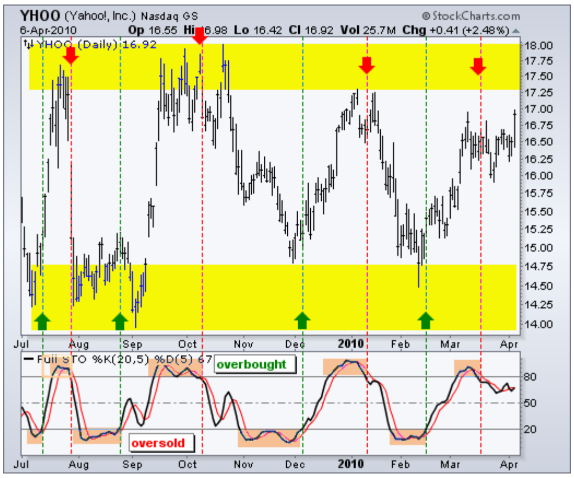

Figure 3.5: Stochastic oscillator example

Source: stockcharts.com

- ◇ **Commodity Channel Index (CCI)** - is used to identify new trend or extreme movement of the current trend as it measures the present price level change relatively to average price level change over time. High values indicate prices above their average and vice versa.

Figure 3.6: Commodity Channel Index

Source: stockcharts.com

- **Volatility indicators**

  - ◇ **Bollinger bands** - Very simple indicator, which creates bands below and above a moving average by adding 2 standard deviations of the prices in respective period to them.

Figure 3.7: Bollinger bands example

Source: stockcharts.com

- ◇ **Average True Range (ATR)** - intended particularly for more volatile commodity market and does not provide any evidence of price movement, only volatility measure. It takes into account differences between current high and previous close and previous close and current low. Strong movements in either direction are accompanied by large True range

Figure 3.8: Average True Range example

Source: stockcharts.com

- ◇ **Standard Deviation (SD-** rather straightforward statistical tool which measures dispersions of price from their mean. It is used to measure expected risk and to determine significance of the price changes.

Figure 3.9: Standard Deviation example

Source: stockcharts.com

- **Volume indicators**

  ◇ **Chaiking Osciallator** - is basically an indicator of money flow in or out of a stock by combining price and volume.It is based on difference of two EMAs of Accumulation Distribution Line that comprises of volume and ratios of high, close and lowest price of the period.

Figure 3.10: Chaikin Oscillator, hint of the construction

Source: stockcharts.com

  ◇ **On Balance Volume (OBV)** - based on idea that volume precedes price. This indicator adds up volumes if the intraday change is positive and vice versa. Value of the indicator is not important, as it serves to chartists for spotting patterns in graphical form, which should then apply to price development.

Figure 3.11: Average True Range example

Source: stockcharts.com

The choice of those conditions, respectively values of their parameters, are solely arbitrary to the trader and can be derived from personal tastes or randomized. Yet, several combinations of figures and indicators have become broadly used. Such are popular combination of SMA's (10,100; 50,150 etc.), or RSI of the last 14 periods with benchmarks of 30 and 70. Nevertheless, combinations and parameters do not make themselves a strategy as such. There needs to be precisely defined what is to be done when the indicators behave in a such a way and how they will be interpreted. The vector of parameters also depends on trader's attitude towards risk and trading style. Investors focusing mostly on long-term transactions of larger quantities, would more likely pick trend indicators such as Moving Average, where again, the growing tendency of the markets will play a substantial role. On another hand, someone who prefers smaller transactions and gains might be looking into volatility based bag of tools, such as the Bollinger bands.

Job of the indicators is, that by interacting with the prices or between them, to identify trading opportunity and send signals to enter a position. If the trader takes it only as secondary guideline and puts more emphasis on different angle of examination or whatever else, we rather speak about technical analysis as such. When the machine trades according to the signals, and acts on each of them, then we speak about algorithmic trading. Undoubtedly, the signals generated do not necessarily generate a profitable trade. In order to improve the strategy, or rather minimize the number of losses, various kinds of indicators can serve also as filter rules to confirm or refute the signal. That basically means that more than one conditions have to be satisfied so that the order is placed. In order to avoid multicollinearity, as a statistical issue of creating redundant results and making other variables seem unimportant. Hence, instead of using 5 differently parametrized Moving Averages that serve as trend indicators, momentum can be evaluated by Stochastic oscillator, or RSI.

The endeavour to improve the performance of the strategy can lead to misinterpretation of the results. Needless to say that the opportunity to test vast amounts of combinations is, thanks to advanced computational power, rather attractive.

Backtesting, as presented also in this thesis, is testing the scenarios on historical prices to determine the profitability, should keep in mind one very important thing. That is that the results do not, and highly likely never will, conclude universal rule to beat the market. Hardly, it can be concluded, that two crossing Moving Averages are consistent and systematically lucrative to use. Rather, they shall be perceived as a mere calculation outcome of individual setup and state of the world. Otherwise, data snooping bias, as mentioned in the Literature review occurs, and corrupts validity of the results.

At the end of this section, let us present a strategy that incorporates three of previously mentioned indicators of different kind. Underneath, this figure represents a moving momentum strategy, that is based on three independent rules to trigger a trade on an ETF of S&P 500.

Long positions are initiated when those criteria are met:

- 20-period simple moving average (SMA) is above 150-period SMA
- Slow Stochastic (14,3) is not greater than 20
- MACD Histogram (12,26,9) is positive

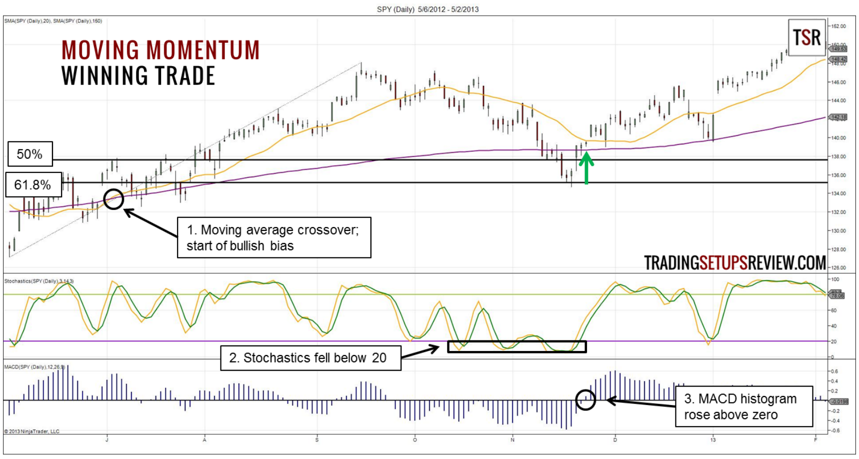

Figure 3.12: Example of strategy based on technical analysis
Source: http://www.tradingsetupsreview.com

The moving averages as trend indicators suggest that the market is going up as the 20-period SMA crosses from below the 150-period SMA. At this point, Stochastic oscillator does not indicate oversold market, therefore, the signals is not triggered just yet. After Stochastics plunged bellow the 20 points benchmark, MACD was still in the negative figures for a while. When it crossed the zero line, long position was entered and exited when moving averages crossed again in opposite way.

3.3 Trend-momentum trading: EMA, SMA, RSI

As was mentioned above, trading strategists have a portfolio of several indicators, which add up to myriads of possible combinations. Nevertheless, the author has chosen to test a strategy linked to his previous participation in student trading competitions. As it yielded mixed results, but overall performed quite well even for intraday and intraweek, the author was interested how it would perform over longer terms, since the success of the then performance might be attributed to mere chance.

The period chosen for backtesting starts in the January of 1990 and ends on 14^{th} May 2014. It was taken into account that in order to produce signals, indicators need certain degree of volatility in the markets. Moreover, as is stated in the Literature review, even basic strategies performed well halfway through the last century, mostly those based on trend following. It might be credited to the fact, that more or less, the markets rose steadily, with relatively few pullbacks compared to today. At least, we might find graphical evidence that suggests that.

The author chose to backtest the strategy on indices encompassing more technological areas as new and dynamic environment to see if the predictive power of technical analysis takes out any significant profits against Buy and Hold. Furthermore, over those 24 years, there was a huge boom in information and market accessibility to the public in general, therefore, the markets has experienced a lot of traffic and volatility.

The rules tested are based on three kinds of indicators only. Two moving averages to indicate a trend and then the RSI as a filter rule to determine whether profitability rises due to limiting loss-making positions. Let us make present formal definitions to properly understand their workings, which, for lack of relevant sources, were all created by the author.

Definition 1. *Let us have a series of prices $P_1, \cdots, P_m$, then we denote Simple Moving Average of n periods as*

$$SMA(n) = \tfrac{P_n + \cdots + P_{m-n}}{n}, n \leq m.$$

Definition 2. *Let us have a series of prices $P_1, \cdots, P_m$, then we denote Exponential Moving Average of n periods as*

$$EMA(n) = (P_n - EMA(n-1)) \cdot M + EMA(n-1),$$

where $M = 2/(n+1)$ as the exponential multiplier.

Definition 3. *Let us have a series of n price increments and let us denote P_i^1, $i \in \{1, \cdots, l\}$ positive increment, P_j^2, $j \in \{1, \cdots, m\}$ as negative increments, where $l + m = n$. Then,*

$$RSI = 100 - \tfrac{100}{1+RS}$$

where $RS = \frac{\frac{\sum_1^l P_i^1}{l}}{\frac{\sum_1^m P_j^2}{j}}$.

Now, let us describe fundamental working scheme of the strategies used and tested in his thesis. There are altogether 3 basic algorithms with slight amendments to compare between them.

Strategy 1.1: The first strategy tested is based on solely one rule and that is to go long whenever the current price is higher than EMA(10), shorts are excluded from this model. The Exponential Moving Average is a smoothing indicator, that cancels out some variance over the last 10 periods. As it is exponential, it puts more emphasis on the most recent price. In other words, considering EMA and SMA of the same sample periods, the identical price increment will have more profound impact on the value of EMA.

The buy order is triggered if the price cross over the EMA and that means, the upswing has to be rather significant compared the latest development. Each order is executed once the price jumps over and is bought for the current price and hold for as long the price is above the EMA(10), then once the price drops below, it is sold for that price the plunge occurred. This concept si illustrated in Figure 3.13

This strategy is theoretically underpinned in Osborne (1959) or Wilder (1978) that once prices move one way, they are more likely to preserve that trend than to turn around. Nevertheless, just because it focuses on long positions only, it does not necessarily mean that they cannot be loss-making as well. Simply, the prices can cross the EMA from below and then carry on steadily next to each other with another cross below the initial price level. As it is now binded with another indicator, there are expected a lot of orders and therefore, in the next part, it will be discussed how the profitability would be affected, should transaction costs take place.

Strategy 1.2: The same concept as Strategy 1.1 was tested also for EMA(20) and is expected to yield less transactions, as this indicator will take longer to follow the price development, which would limit the number of crosses. Indeed, smaller upswing would be sufficient to indicate transaction order, compared to EMA(10) given same initial conditions, as EMA would be burdened with past prices as well.

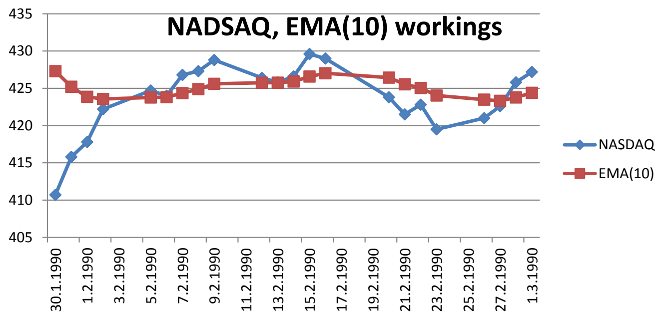

Figure 3.13: Illustration of workings of the price above EMA strategy

Source: Author's computations

Strategy 2.1: This strategy adds another moving average, but this time it is a Simple Moving Average of 100 previous days, SMA(100). It follows widely used strategy of crossing Moving Averages, that is based on two trend indicators that confirm or contradict the trend direction. EMA(10) serves as the 'quick average', whereas SMA(100) is an example of 'slow average'.

The mechanism itself is quite similar to one of Strategy 1 but prices as such are represented by EMA(10) and the crossing threshold is represented by SMA(100). When the 'quick' crosses from below the SMA, it triggers entering a long positions, which lasts until the opposite crossing appears where EMA goes over the SMA from above. Again, a rather straightforward concept, which is visualized below in Figure 3.14

The SMA(100) serves to confirm underlying long-term trend, however, it might also be to a disadvantage as it carries along old figures which values might not be relevant anymore if the trend is currently changing. On another note, it can also limit false signal as short term quick deviations would be smoothed out. Hence, according to aforementioned nature of short positions, it is expected it might be of more efficient use for long positions. Figure 3.14 shows the problem moving averages lag for executing quickly a short trade. As NASDAQ goes down for about 10 days, the strategy triggers signal on day 6 of the drop. Close order occurs 6 trading days since the dip, where price has swung quite above the price level of the order.

Strategy 2.2: Similar scheme as Strategy 2.1, but with 20-day Exponential Moving Average as the 'quick', which is expected to behave less volatile, as the tail would hold back the most recent values a little bit. AS an upside, it is expected to filter more reliably strong market growth, but will be even more vulnerable to situations illustrated in Figure 3.14, once it enters such a position, for the upswing would take more time. For direct comparison, Figure 3.16 shows the graphical interpretation.

EMA(20) enters this particular position 2 days later in lower price level and exits, however 2 days earlier than EMA(10). Nonetheless, EMA(20) incurs a loss of -6.18%, whereas EMA(10) only 4.2%. Althought Strategy 2.2 has lower amplitude between respective averages, it takes longer time to initiate the signal, while the price is still droping. Therefore, the entering position is worse than in the case of Strategy 2.1 and the ultimate loss is higher.

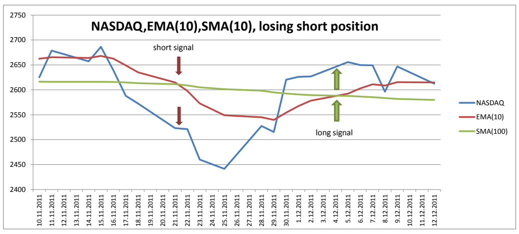

Figure 3.14: EMA(10),SMA(100)

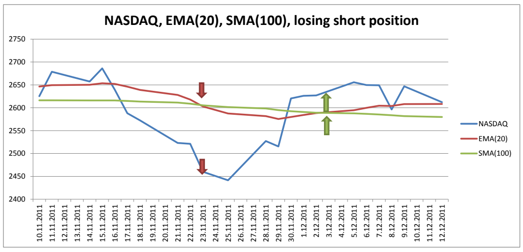

Figure 3.15: EMA(20), SMA(100)

Figure 3.16: NASDAQ comparions Strategy 2.1 and Strategy 2.2

Source: Author's computations

Strategy 3.1: This set of trading rules is the answer to the last remark about short sales and their profitability. This strategy is the same as set of Strategies 2.1 and 2.2, however, permits to initiate only long market orders. The positions are then open when EMA(10) surpasses SMA(100) and is hold until opposite crossing occurs. Therefore, we obtain direct comparison to determine how profitable or loss-making going short was in the Strategy 2 set.

Strategy 3.2: It is essentially same as the one previously mentioned, but with slightly different setup. EMA(10) is substituted for EMA(20), but trend confirming SMA(100) does not change. In Figure 3.17

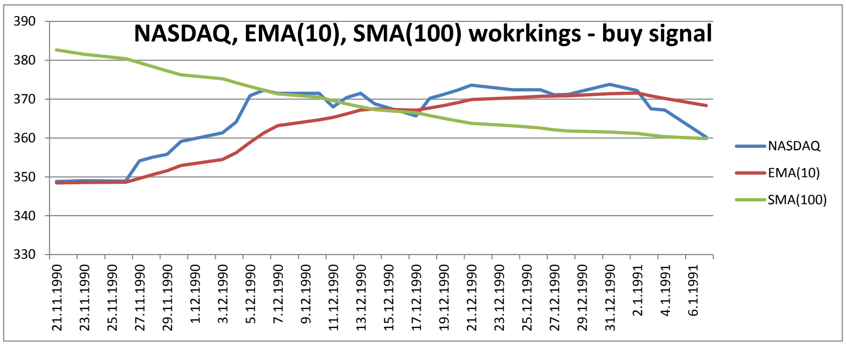

Figure 3.17: Illustration of workings of the price above EMA strategy

Strategy 4: The last strategy is using trend indicators EMA and SMA, but adds a filter rule, a momentum indicator of Relative Strength Index. RSI is computed for the previous 14 days and is set up to filter only short trades. The idea is, that RSI would identify overbought market and trigger short signal if it the momentum is going to be in favour of it. Quite likely, there are going to be few signals, depending on the threshold RSI needs to go over. In our case it is 50, which is rather low, but let it consider as compensation to 14 days period to allow for some volatility.

Once a long position is initiated, it is hold until the opposite si signalled. Therefore, we discover, that a single position goes over several buy signals and also, all the orders take up all available equity. Figure 3.18 is showing the practical workings in a bit of a heavy traffic. In this case, two sell signals are created that pass the RSI filter, as it is below its benchmark. Let us also point out very high correlation between RSI and NASDAQ itself, that highlights RSI as good momentum indicator, being close in its relative development (NASDAQ,EMA,SMA on the left axis, RSI on the right axis).

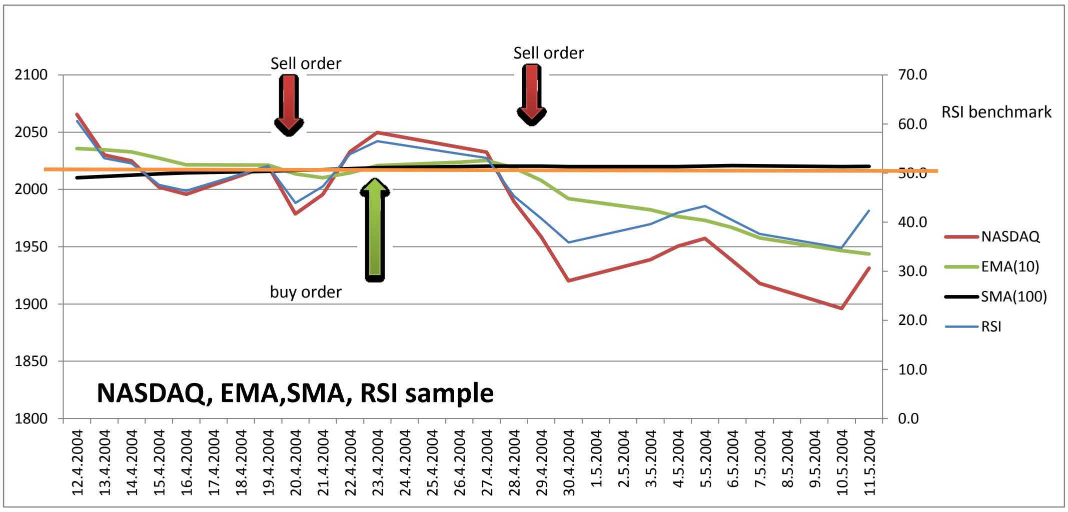

Figure 3.18: Two signals on NASDAQ, including RSI filter

3.4 Strategies evaluation

Evaluating strategy is as arbitrary as is its formation and parametrization. There are no predefined metrics that would evaluate if one has beaten the market or not, or how far they have come to that. Since, purely theoretically, the markets might produce infinite wealth, it does not seem as the best performance management to look only on the final payslip, or in case of backtesting, a hypothetical payslip.

Indeed, the profits could be highly rewarding. The maximum return, that could be accomplished on NASDAQ Composite over the period examined in this thesis is $1.16 \cdot 10^{27}$, if every intraday change was bet on correctly. Of course, as substantial and overwhelming this number is, as equally low is the probability of such event happening, which is about $7 \cdot 10^{9}$, given market going up or down, never sideways.

Risk is an inseparable component of financial market and can never be avoided. As it is depicted as an independent and rather erratic, it is hard to predict or suppress. Financial analysts and specialists use models to minimize risk in investment, which as well under serious scrutiny after the 2008 crisis, particularly the Value at Risk model. Nevertheless, not even the best model would produce single figures, there is always an element of insecurity and dealing with that would suffice as autonomous topic. For our purposes, we would consider the Standard Deviation or returns as sufficient measure of risk. As a main profitability characteristics, let us define Sharpe ratio as in Edwards *et al.* (2001), with little author's amendments.

Definition 4. *Let us have $r_1, \cdots, r_i$, $i \in \{1, \cdots, n\}$ as returns of a security. Then we denote,*

$$\textit{Sharpe ratio} = \frac{E(r_1, \cdots, r_i) - r_f}{\sigma_r}$$

where $E(r_1, \cdots, r_i)$ is the expected value of returns, r_f is the risk-free rate and σ_r is the standard deviation of the returns.

In the strategy assumptions as presented in the next section, no risk free rate is considered, as the thesis is not concerned with portfolio optimization, it seemed redundant, as there would be no optimization between portfolio and risk free assets. As for the expected value of returns, it is calculated as arithmetic average of respective means. In computations, the expected value would be underestimated, or rather biased in favour of zero. Since for objective results, all values over current period were taken into account, to receive relevant ratio for Buy & Hold strategy, which comes into effect immediately. Whereas strategies took much more time to produce any movement in the portfolio for two reasons.

Firstly, SMA of 100 observations needed those 100 day prices to compute first value and Strategies 2-4 needed it as necessary condition. Secondly, even when all indicators had values, it again took a few periods to produce first signal where return would be different of zero. Hence, 0 would have overestimated relative frequency.

Returns as such have come to the author's attention, particularly their distribution, as stock and option returns are interestingly examined in Mandelbrot & Hudson (2014). It was examined, as a side hypothesis, what is the effect of strategy on distribution of returns. The idea was that, considering Mandelbrot's interpretation of power-law distribution, that strategies would cancel out the negative tail and rather form a power-law, or Poisson-like (for low sigmas) distribution shape.

Let us briefly present results for Russell 2000 and first set of strategies, where the effect is most significant.

Table 3.1: Returns summary statistics - Russell 2000

Variable	Mean	Std. Dev.	Min.	Max.	N
Buy & Hold	0	0.013	-0.119	0.119	6099
Buy above EMA(10)	0	0.009	-0.119	0.084	6099
EMA(10),SMA(100) cross, buy	0	0.008	-0.061	0.119	6019
EMA(10),EMA(100) cross	0	0.014	-0.093	0.119	6019
EMA(10),SMA(100),RSI filter	0	0.011	-0.09	0.119	6019

The results show that strategies, apart from crossing moving averages, lowered Standard Deviation and that non of the strategies utilized both of the extremes. Inspection of histograms did not conclude any major alternations, apart from higher relative frequency around 0, as justified above. Further returns summaries, comparison of Buy and Hold to the most complex strategy including histograms are in Appendix.

Nonetheless, Sharpe ration, despite flawed, as it does not consider Maximum Drawdown, fluctuations of gains and losses, or maximum retracement and sequences of those indicators. The thesis has disregarded those not for ignorance but due to limited computational and programming skill set and it will be reflected in result discussion.

Third evaluation metric, along with Net Profit & Loss and Sharpe Ratio, will Compound Annual Growth Rate. It gives smoothed out rate of return, such that it would steadily obtain the ultimate return, but without fluctuation. It will be considered as stability of returns rate.

Definition 5. *For any two different time periods t_0, t_1 and initial and final price of a security $P(t_0), P(t_1)$, the Compound Annual Growth Rate is defined as:*

$$CAGR = (\tfrac{P(t_1)}{P(t_1)})^{\frac{1}{t_1 - t_0}} - 1$$

Chapter 4

Data and results

4.1 Data and algorithm description

The stock indices that are inspected in this thesis are: NASDAQ Composite, Standard & Poor's 500 and Russell 2000.

NASDAQ is also a New York based stock exchange, which issues NASDAQ Composite index that enlists all securities that are traded on the exchange. It was launched in 1970 with starting value of 100 and peaked on intraday high 5,132 over the dot-com bubble in 2000. The index lists U.S. as well as overseas companies and is one of the oldest and most influential of its kind. It is predominantly used to measure performance of technological and growth companies.

Standard & Poor's 500 is a selection of the most capitalized companies traded on NASDAQ and NYSE exchanges, comprises of 500 securities and founded in 1957 rank amongst the well established. It reach intraday high of 1890.9 recently in May.

Russell 2000 comprises of 2000 least capitalized companies of Russell 3000 as serves as benchmark for so called small-cap companies and represent about 9% of capitalization of Russell 3000. It was founded in 1984 and is the youngest of the selected indices and reached all-time high of 1208.65 at the beginning of March.

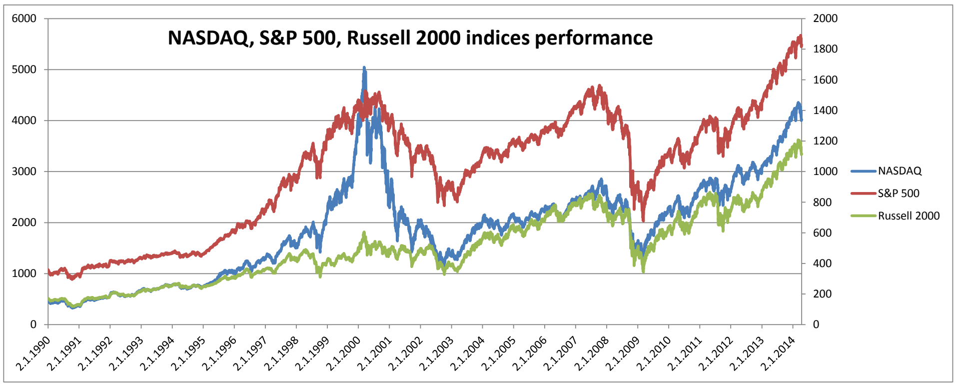

Figure 4.1: NASDAQ, S&P 500, Russell 2000 performances
Source: Authors's computation

Performance of the indices had to be split and depicted agains two y-axis, as MS Excel would scale Russell 2000 and S&P 500 to seemingly very similar indices. NASDAQ with significantly higher figures si depicted agains the left axis, and the rest against the right axis. The respective correlation coefficients are in Table 4.1 below. The correlations are rather high, partially because of spurious correlation of growing stocks, however, more in-depth analysis is beyond the scope of this thesis. The correlations are rather high, partially because

Table 4.1: Cross-correlation table

Variables	NASDAQ	S& P500	Russell 2000
NASDAQ	1		
S&P 500	0.949	1	
Russell 2000	0.853	0.906	1

of spurious correlation of growing stocks, however, more in-depth analysis is beyond the scope of this thesis.

Let us also present basic descriptive statistics of the actual prices:

Table 4.2: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
NASDAQ	1880.416	968.354	325.4	5048.62
S&P500	1002.254	398.026	295.46	1890.9
Russell 2000	504.986	238.291	118.82	1208.65
N		6120		

As previously mentioned, the period examined is from 1990 to 14/4/2014 and are taken from server finance.yahoo.com and Adjusted Close part of them was selected to account for dividends and stock splits. Data as such has not been otherwise modified. Although the period starts the first business day of 1990, the benchmark date is considered 30.1.1990, for the dates before were used to compute the first EMA(10).Nevertheless, in the sample of total 6115 day prices, this is an insignificant reduction. Therefore this is the date of commencement of trading activities. The starting point was not shifted because of other lagged indicators and Buy & Hold strategy starting at this point is the benchmark to each algorithm.

The underlying model assumptions are summarized as follows:

Assumption 1: Let us present few underlying assumptions for the back-testing to facilitate the results interpretation

Assumption 2: There are no transaction costs or carrying out an order

Assumption 3: There are no dividends as they are accounted for by working with Adjusted Close figures

Assumption 4: Equity is not withdrawn - each order is 'all in'

Assumption 5: There no specified exit rules - once market is entered, positions switch from long to short and vice versa

Assumption 6: The risk free-rate of the markets is nil

Assumption 7: The trading equity budget, starting at $100 is possibly infinite, therefore the srtrategy account cannot go bankrupt no matter the drawdown.

4.2 Results description and evaluation

	NASDAQ				S&P 500				Russell 2000			
	prices> EMA(10)	EMA(10), SMA(100)	EMA(10),SMA (100),long	EMA(10),SMA (100),RSI(14)	prices> EMA(10)	EMA(10), SMA(100)	EMA(10),SMA (100),long	EMA(10),SMA(100),RSI(14)	prices> EMA(10)	EMA(10), SMA(100)	EMA(10),SMA(100),long	EMA(10),SMA (100),RSI(14)
Txns	*533*	(45,46)	(45,0)	(45,6)	*585*	(50,50)	(50,0)	(50,1)	*519*	(45,46)	(45,0)	(45,6)
Sharpe	.0459	.0388	.0405	.0416	0.0061^	.0217	.0305	.0304	.0376	.0345	.0333	.0334
CAGR	26.5%*	19.01%	20.14%	21.16%	1.13%^	6.87%	11.19%	11.13%	18.97%	14.75%	14.40%	14.40%
Net P&L	$940	$1,620	$1,594	2099*	11^	$196	$451	$448	$469	$845	$762	$767
	prices> EMA(20)	EMA(20) cross SMA(100)		EMA(20),SMA (100),long	prices> EMA(20)	EMA(20) cross SMA(100)		EMA(20),SMA (100),long	prices> EMA(20)	EMA(20) cross SMA(100)		EMA(20),SMA(100) long
Txns	*383*	(39,39)		(39,0)	*399*	(41,41)		(41,0)	*354*	(38,37)		(38,0)
Sharpe	.0467	.0258		0.0473*	.0196	.0183		.0394	.0377	.0231		.0433
CAGR	25.66%	10.56%		24.74%	6.88%	5.36%		14.20%	18.23%	8.27%		20.02%
Net P&L	$939	$415		$971	$96	$134		$356	$459	$266		$605
	BUY & HOLD				BUY & HOLD				Buy & Hold			
Sharpe	0.0322				0.0304				.0309			
CAGR	14.65%				10.95%				12.66%			
Net P&L	**$879**				**$466**				**$631**			

Notes: * denotes the **best performing** strategy in respective parametr
^ denotes the **worst performing** strategy in respective parametr
Txns denotes the number of **transactions** (long, short)

Colors:

Performing in **top 25%:**	**Sharpe ratio**	.0
	CAGR	%
	Net Profit & Loss	$
Performing in **bottom 25%:**	**Sharpe ratio**	.0
	CAGR	%
	Net Profit & Loss	$

Figure 4.2: Overall performance under strategies
Source: Author's computations

The benchmark, Buy & Hold strategies performed in all metrics between the top and bottom 25%, but for example NASDAQ outperforms it in all rules, expect for one.

The best performance over variety of testes strategies and metrics has shown NASDAQ index having 16 figures in top 25 % of the categories altogether. whereas the algorithms did not do well on the S&P 500, which has 14 values in the bottom 25%. Russell 2000 performed in the middle, being in the bottom quarter on for EMA(20), SMA(100) cross strategy.

Taking a closer look at NASDAQ only, in terms of Sharpe ratio as the leading statistic, 6 out of 9 strategies performed in the top 25%, including the highest ratio of all, 0.0473 belonging to Strategy 3.2, which is EMA(20),SMA(100) crossing each other when only long positions are allowed. Compared to Strategy 3.1 as the closest algorithm, which is different only in using EMA(10),it is less profitable, losing about $600. However, most of the rules are earning more than 20% a year of return compared to 15% of the index itself.

NASDAQ holds the overall winners in all three metrics, only the cross rule using longer EMA is performing below the passive investment. Let us present the best equity peformance in the figure below, the second set in Figure A.10 can be found in the Appendix

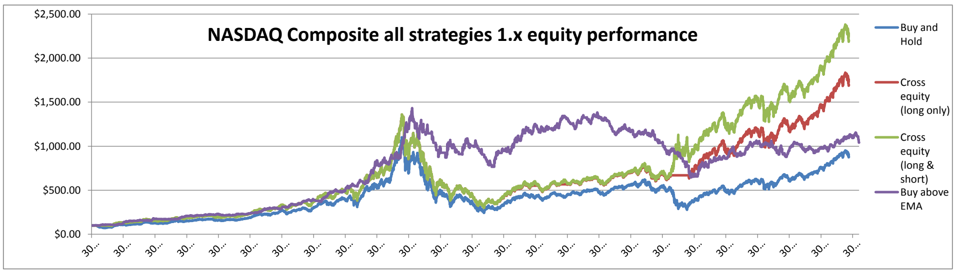

Figure 4.3: NASDAQ Equity, Strategies 1.x
Source: Authors's computation

S&P 500 did not perform very well, when in terms of Sharpe ratio, only one strategy did better than Buy and Hold. This index also holds the worst results, which is the first strategy, performing very badly, bordering on zero profitability as such, compared to B&H as a significant loss. The number of transactions, in this case number of times prices grew over EMA(10) is comparable to others, however, it was predominantly in stagnation, as the rule did not use the upswings, or rather the prices fell quickly back again yielding for example only one or two day returns instead of holding the positions longer. The same holds for the other EMA(10) based strategies. Even eliminating short orders did not improve the results, therefore, not even the long orders perform well on the S&P. Let us visualize equity performance of the better set of strategies, the other half can be found in the Appendix as Figure **??**.

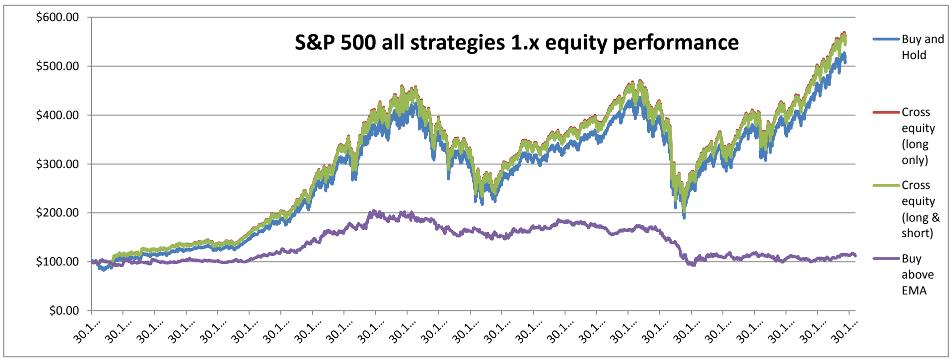

Figure 4.4: S&P 500 Equity performance, Strategies 1.x
Source: Authors's computation

Russell 2000 as the youngest amongst the selected indices performed similarly to its benchmark in most of the strategies, with the exception of EMA(20) cross, which did exceptionally badly. Evidence suggests, that it is due to discussed short positions, since eliminating them resulted in double of the Net

Profit, Sharpe ratio and more than double of CAGR. Otherwise, Russell quite interestingly did worse for EMA(10), SMA(100) in terms of CAGR, but almost doubled redoubled the Net Profit. It would be explained by steadier, but more stable returns over the period.

Notably, EMA(20) over prices strategy was doing very well in terms of Net Profit & Loss indicator, was growing even over the dot-com bubble period around 2000, but huge unstoppable decline occured since 2006, as the index went down as well, however, the upswing did not occur. Again, let us present the better perfoming half of the strategies in Figure **??** and point to the Appendix to the second half in Figure **??**

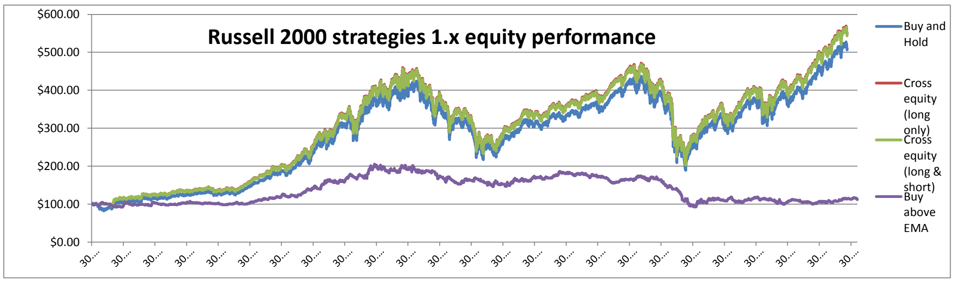

Figure 4.5: Russell 2000 Equity performance, Strategies 1.x
Source: Authors's computation

Transaction costs were omitted as assumption. In reality, the downside effect would of course depend on the commission level of brokerage. Since the advent of online trading, demand for cheap brokers caused the price of those services to drop. According to internet research, commision vary around 0.2%, depending on the type of market order and provider. Since there have not been that many transaction in strategies, other than the set of Strategy 1, they were disregarded from the calculation.

Concerning the expectations outlined in 3, results suggest, that strategies based on trend and momentum indicators performed altogether quite well. The variation in presented metrics also respond well to the changes in parameters, market orders and filter rule. As discussed in the relevant literature, short orders generally undermine the performance as they are often loss-making. It also follows the reasoning that those kind of indicators, with lagged responses, are not the best choice for speculating short, however, generate substantial reward on long orders.

Chapter 5

Conclusion

This bachelor thesis focused on nowadays financial markets with main scope revolting around popular topic of algorithmic trading based on technical analysis. It tests on historical data of three major U.S. indices, whether it is possible to systematically made profit, taking risk into account, compared to passive investment strategies over period 1990-2014. As there is not codified how to formally evaluate trading strategies, three metrics were introduced; Sharpe ratio, Compound Annual Growth Rate and Net Profit & Loss. Strategies were primarily assessed on Sharpe ratio and CAGR basis, as Net Profit does not reflect market volatility or stability of returns.

The results quite precisely reflected theoretical foundations of trend based lagged indicators of Simple Moving Average, Exponential Moving Average and Relative Strength Index as a filter rule with the purpose to eliminate loss-making sell market orders.

The best performance was achieved on NASDAQ Composite index in all of the introduced metrics. One of the possible explanations is derived from the price development, which is very trend-friendly. NASDAQ grows in the measured period quite systematically with the exception of 1998 recession up until the burst of the dot-com buble in 2000. Then it reverses the drop after 3 years and goes again 6 years later to switch the main trend for the last time.

The evolution of NASDAQ is pretty straightforward in terms of trend and, therefore, Moving Averages take of this to signal long positions.

On another hand, S&P 500 had quite similar advancement, with lower amplitudes, but strategies did not perform much close to figures obtained on NASDAQ.

Lastly, Rusell 2000 goes up in steady and major uptrend, without high volatility compared to the other two with the exception of 2008 crisis and performance on this index is between the extreme 25% of results.

The thesis inspected how strategies based on trend and momentum technical indicators perform on U.S. stock indices. It has shown that there are conditions, which are favourable to technical analysis in order to make substantial profits. However, evidence shows, that those profits are liable to risk and fluctuations no different to those applied to stocks themselves. Therefore the excessive returns would be attributed to chance, rather than systematic outperformance. Hence, the thesis cannot conclusively determine, that technical analysis is systematically profitable on U.S. stock markets. If there is a method to empirically measure the systematic element of profits from strategies,is left for further research.

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Appendix A

Title of Appendix One

Table A.1: Summary NASDAQ Composite returns

Variable	Mean	Std. Dev.	Min.	Max.	N
Returns Buy & Hold	0	0.015	-0.097	0.142	6099
Returns Cross + RSI filter	0.001	0.015	-0.142	0.097	5973

Source: Authors's computation

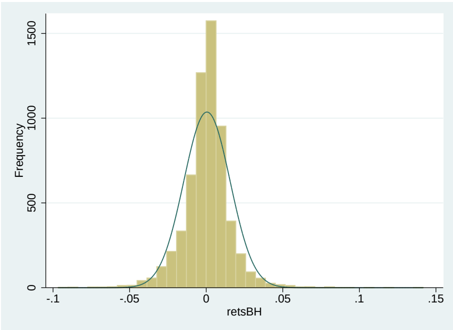
0.4 

Figure A.1: Buy & Hold

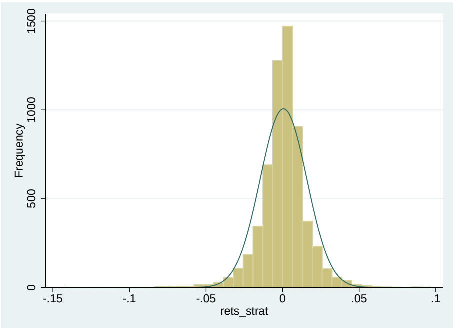
0.4 

Figure A.2: EMA(10),SMA(100),RSI(14)

Figure A.3: NASDAQ returns comparison

Source: Authors's computation

Table A.2: Summary S&P 500 returns

Variable	Mean	Std. Dev.	Min.	Max.	N
Returns Buy & Hold	0	0.012	-0.09	0.116	6099
Returns Cross + RSI filter	0	0.012	-0.116	0.09	6019

Source: Authors's computation

0.4

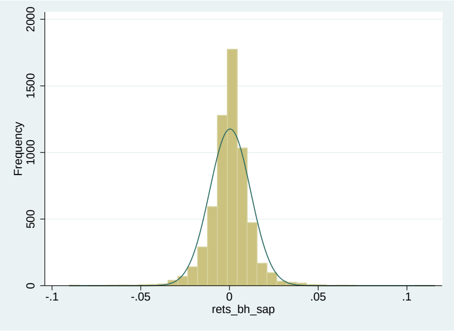


Figure A.4: Buy & Hold

0.4

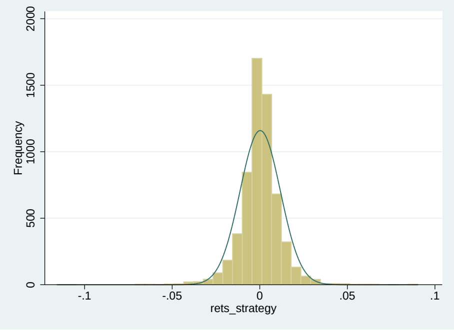


Figure A.5: EMA(10),SMA(100),RSI(14)

Figure A.6: S&P 500 returns comparison

Source: Authors's computation

Table A.3: Summary Russell 2000 returns

Variable	Mean	Std. Dev.	Min.	Max.	N
Returns Buy & Hold	0	0.013	-0.119	0.093	6099
Returns Cross + RSI filter	0	0.014	-0.093	0.119	6019

Source: Authors's computation

Source: Authors's computation 0.4

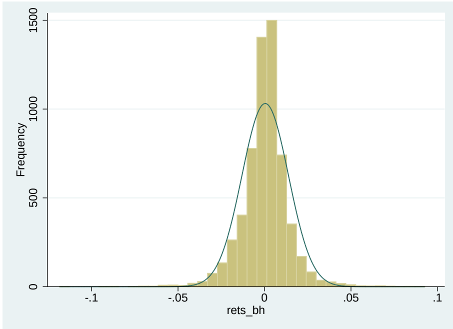


Figure A.7: Buy & Hold

0.4

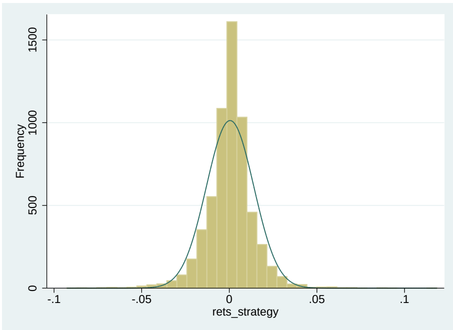


Figure A.8: EMA(10),SMA(100),RSI(14)

Figure A.9: Russell 2000 returns comparison

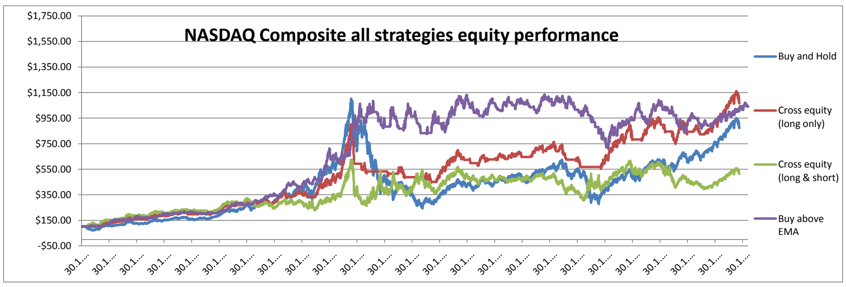


Figure A.10: NASDAQ Equity, Strategies 2.x

Source: Authors's computation

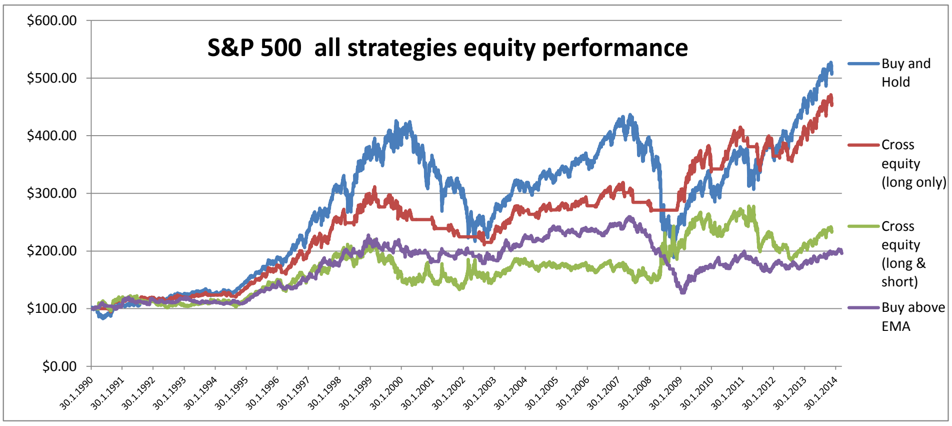


Figure A.11: S&P 500, Equity, Strategies 2.x

Source: Authors's computation

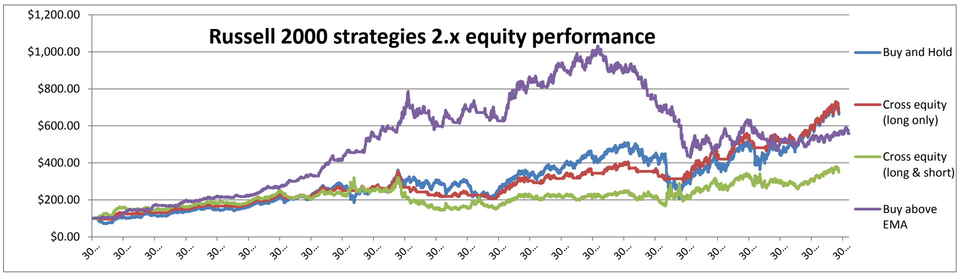


Figure A.12: Russell 2000, Equity, Strategies 2.x

Source: Authors's computation

Table A.4: NASDAQ Composite, 1990-2014

NASDAQ Composite Buy Hold	
gross profit	16006
gross loss	-15127
net profit	**879.47**
# winning	3341
# losing	2753
% winning	54.82%
Max win	$79.09
Max loss	-$86.56
CAGR	**14.65%**
Sharpe Ratio	**0.032294717**

Table A.5: NASDAQ Composite, 1990-2014

Buy above EMA (10) stats	
gross profit	12940
gross loss	-12000
net profit	**940.27**
# winning	2066
# losing	1571
% winning	56.81%
Max win	$73.64
Max loss	-$74.12
CAGR	**26.50%**
Sharpe Ratio	**0.045929923**

Table A.6: NASDAQ Composite, 1990-2014

EMA(10) SMA(100) cross buy only	
gross profit	19149.8404
gross loss	-17555.03815
net profit	**1594.80**
# winning	3097
# losing	2533
% winning	55.01%
Max win	$87.44
Max loss	-$95.69
CAGR	**20.14%**
Sharpe Ratio	**0.040525855**

Table A.7: NASDAQ Composite, 1990-2014

EMA(10) SMA(100) cross + RSI filter	
gross profit	23340.45291
gross loss	-21241.43768
net profit	2099.02
# winning	3219
# losing	2657
% winning	54.78%
Max win	$87.44
Max loss	-$113.65
CAGR	**21.16%**
Sharpe Ratio	**0.041566003**

Table A.8: NASDAQ Composite, 1990-2014

EMA(10) SMA(100) cross	
gross profit	24476.48
gross loss	-22856.1
net profit	**1620.40**
# winning	3235
# losing	2733
% winning	54.21%
Max win	$103.58
Max loss	-$130.40
CAGR	**19.01%**
Sharpe Ratio	**0.038898**

Table A.9: NASDAQ Composite, 1990-2014

Buy above EMA(20) stats	
gross profit	11940.10561
gross loss	-11000.81508
net profit	**939.29**
# winning	2121
# losing	1620
% winning	56.70%
Max win	$72.71
Max loss	-$53.93
CAGR	**25.66%**
Sharpe Ratio	**0.046697288**

Table A.10: NASDAQ Composite, 1990-2014

EMA (20) SMA(100) cross buy only stats	
gross profit	9384.601009
gross loss	-8413.545339
net profit	**971.06**
# winning	2208
# losing	1707
% winning	56.40%
Max win	$38.62
Max loss	-$63.49
CAGR	**24.74%**
Sharpe Ratio	**0.047314827**

Table A.11: NASDAQ Composite, 1990-2014

EMA(20) SMA(100) cross	
gross profit	12200.1
gross loss	-11784.7
net profit	**415.44**
# winning	3197
# losing	2764
% winning	53.63%
Max win	$39.14
Max loss	-$57.81
CAGR	**10.56%**
Sharpe Ratio	**0.025871**

Table A.12: NASDAQ Composite, 1990-2014

EMA(20) SMA(100) cross	
gross profit	12200.1
gross loss	-11784.7
net profit	**415.44**
# winning	3197
# losing	2764
% winning	53.63%
Max win	$39.14
Max loss	-$57.81
CAGR	**10.56%**
Sharpe Ratio	**0.025871**

Table A.13: S&P 500 1990-2014

S&P 500 Buy Hold	
gross profit	7803
gross loss	-7336
net profit	**466.79**
# winning	3259
# losing	2836
% winning	53.47%
Max win	$32.24
Max loss	-$33.08
CAGR	**10.95%**
Sharpe Ratio	**0.030455443**

Table A.14: S&P 500 1990-2014

Buy above EMA (10) stats	
gross profit	1632
gross loss	-1620
net profit	**11.88**
# winning	1892
# losing	1755
% winning	51.88%
Max win	$8.77
Max loss	-$10.71
CAGR	**1.13%**
Sharpe Ratio	**0.006164959**

Table A.15: S&P 500 1990-2014

EMA(10) SMA(100) cross buy only	
gross profit	7505.411664
gross loss	-7053.980893
net profit	**451.43**
# winning	3136
# losing	2739
% winning	53.38%
Max win	$31.37
Max loss	-$32.19
CAGR	**11.19%**
Sharpe Ratio	**0.030532415**

Table A.16: S&P 500 1990-2014

EMA(10) SMA(100) cross + RSI filter	
gross profit	7458.883021
gross loss	-7011.101702
net profit	447.78
# winning	3138
# losing	2742
% winning	53.37%
Max win	$31.16
Max loss	-$31.97
CAGR	**11.13%**
Sharpe Ratio	**0.030430644**

Table A.17: S&P 500 1990-2014

EMA(10) SMA(100) cross	
gross profit	4172.484
gross loss	-3976.07
net profit	**196.41**
# winning	3112
# losing	2854
% winning	52.16%
Max win	$18.16
Max loss	-$25.26
CAGR	**6.87%**
Sharpe Ratio	**0.02171**

Table A.18: S&P 500 1990-2014

Buy above EMA(20) stats	
gross profit	2162.281593
gross loss	-2066.415534
net profit	**95.87**
# winning	1996
# losing	1805
% winning	52.51%
Max win	$9.22
Max loss	-$14.43
CAGR	**6.88%**
Sharpe Ratio	**0.019694367**

Table A.19: S&P 500 1990-2014

EMA (20) SMA(100) cross buy only stats	
gross profit	3518.761842
gross loss	-3162.601985
net profit	**356.16**
# winning	2248
# losing	1923
% winning	53.90%
Max win	$15.37
Max loss	-$15.80
CAGR	**14.20%**
Sharpe Ratio	**0.039414876**

Table A.20: S&P 500 1990-2014

EMA(20) SMA(100) cross	
gross profit	4142.704
gross loss	-4008.28
net profit	**134.43**
# winning	3102
# losing	2856
% winning	52.06%
Max win	$17.36
Max loss	-$24.10
CAGR	**5.36%**
Sharpe Ratio	**0.018332**

Table A.21: S&P 500 1990-2014

EMA(20) SMA(100) cross	
gross profit	4142.704
gross loss	-4008.28
net profit	**134.43**
# winning	3102
# losing	2856
% winning	52.06%
Max win	$17.36
Max loss	-$24.10
CAGR	**5.36%**
Sharpe Ratio	**0.018332**