Testing Simple Technical Trading Rules

Master Thesis Finance

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If all it took to beat the markets was a Ph.D. in mathematics, there would be a hell of a lot of rich mathematicians out there.

Bill Dries, unknown trader

Abstract

This thesis tests three simple technical trading indicators which are the foundation to the trading systems described by Michael Covel in his bestselling book *Trend Following, how great traders make millions in up or down markets* (2004). The Dual Exponential Moving Average (DEMA), Moving Average Convergence Divergence (MACD) and the Relative Strength Index (RSI) generate the buy and sell signals for the profitable trading systems examined in *Trend Following*. I attempt to replicate these technical indicators using the AEX Index as benchmark. Furthermore an out-of sample dataset, comprised of global, currency and FOREX markets is included to provide more detailed observations on the characteristics of the indicators. The results show that the indicators are unable to generate significant positive alpha for the 2000 – 2012 period. Conversely I find that the indicators are able to provide significant alpha on certain sub-periods. I attempt to explain these alpha's by using the Small Minus Big (SMB), High Minus Low (HML) and Momentum (MOM) factor. None of these factors are able to explain the positive alpha's for the sub-period analysis.

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1. Introduction

Technical analysis fascinates many investors, lured by the idea of outsmarting the market. This 'study of price charts' has been popular for decades and is likely to remain popular among investors due to its simplicity, clearly defined technical trading indicators and readily available software models that can take over the actual trading decisions. Technical analysis' use is widespread, especially in speculative markets. Smidt (1965) studied its use among amateur traders in US commodity futures and finds that more than 50% of the survey's respondents use this form of analysis either as sole indicator or as part of a bigger trading system. More recently, Menkhoff and Gehrig (2006) find that technical analysis is seen as the 'workhorse' among Foreign exchange traders.

Although there is sufficient evidence that technical analysis is widely used in speculative markets, the financial literature on the profitability of technical analysis is still dispersed. This dispersion stems from the discrepancy of proclaimed profits in technical trading systems versus the notion of efficient markets. The efficient market hypothesis is still a dominant theory in the academic world and states that security markets are efficient and therefore reflect all information available into security prices without significant delay. This would leave no room for predictive factors in the time series of stock prices using past information. Therefore the only way to achieve abnormal returns would be to take excessive risks, implying that the best achievable risk-adjusted return would be the market return. Thus, when the efficient market hypothesis holds, there is no room for investment strategies like technical analysis to generate abnormal risk-adjusted returns. This distrust in technical analysis among academics is well expressed by Malkiel (1973), a strong proponent of the efficient market hypothesis:

Obviously, I am biased against the chartist. This is not only a personal predilection, but a professional one as well. Technical analysis is anathema to the academic world. We love to pick on it. Our bullying tactics are prompted by two considerations: (1) the method is patently false; and (2) it's easy to pick on. And while it may seem a bit unfair to pick on such a sorry target, just remember: it is your money we are trying to save.

This attitude of the academic world has changed over the last two decades. Computer power increased to produce more reliable trading systems, but maybe even more important it allowed for serious improvement in the statistical analysis of technical indicators and its proclaimed profitability. Brock et al. (1992) provide a pioneering modern type study to test technical indicators using advanced computerized techniques. They find strong support for the moving average based indicators, as well as for break-out rules. However past empirical research has not produced consistent robust evidence that is fully able to resolve this discrepancy.

The efficient market hypothesis does not seem to find as much support among traders as it does among academics. Traders remain fascinated by technical analysis and are intrigued by the numerous success stories circulating Wall Street. Amateur traders brag about the returns they made using fancy indicators and complex trading systems whilst hiding any tales of substantial losses. This popular and flamboyant image of technical analysis is spurred by popular books like Michael Covel's *Trend Following, how great traders make millions in up or down markets* (2004). This bestselling book simplifies technical analysis by setting clear rules such as '*cut your losses and let your profits run'* or '*the trend is your friend'.* The idea behind the investment philosophy is to spot trends in the market and ride them out until the trend reverses. In order to spot these trends the book uses several trading systems based on a range of simple technical trading rules, also known as indicators. These indicators generate buy or sell signals according to the direction and timing of the trend.

This paper addresses the discrepancy of whether or not it is possible to beat the market using simple technical indicators. The purpose of this study is to test the profitability of the most popular technical indicators used in Michael Covel's *Trend Following, how great traders make millions in up or down markets* (2004). These popular indicators will be replicated and backtested using Matlab R2011a. The indicators in question are the Dual Exponential Moving Average (DEMA), Moving Average Convergence Divergence (MACD) and the Relative Strength Index (RSI). The DEMA and MACD are moving average based indicators that generate trading signals when the fast exponential moving average crosses the slow exponential moving average. These two indicators are known as lagging indicators because they follow the price of the security. The RSI on the other hand is a leading indicator, designed to lead price movements. The RSI generates trading signals when the traded security is thought to be overbought or oversold. Finding abnormal risk-adjusted returns for these indicators would be in conflict with the efficient market hypothesis and thus would be considered a market anomaly.

The reason why these three indicators need to be investigated is that they are among the most popular used indicators in the field of technical analysis (Brown & Ebrary, 1999; Lui & Mole, 1998; Taylor & Allen, 1992). Furthermore Covel provides evidence of trading systems that generate exceptional risk-adjusted returns using these three indicators. Since the indicators are used to generate the buy and sell signals for the trading system they are the foundation to the system itself. I want to test the indicators individually to see if they are able to provide abnormal risk-adjusted returns, after deducting a reasonable amount of transaction costs. I use the following main hypothesis to test the results,

Any of the three indicators on its own outperform the benchmark, after deducting reasonable transaction costs, using Jensen's Alpha as performance measure.

The interpretation of the three indicators used by Covel contains a high degree of freedom. This is to be expected because traders are reluctant to give up the secret to their winning trading system. In order to replicate the indicators I will first use the default settings, as described by their creators, for the three indicators. I compare the results to the AEX Index which is used as the benchmark to test the indicators. Second I propose a refined version of the indicators to see if these refined indicators can improve the risk-adjusted returns of the default indicators and generate positive Jensen's Alpha, therefore attempting to mimic the indicators used in *Trend Following's* trading systems.

In order to address the hypotheses this thesis is constructed as follows. First a detailed theoretical background to technical analysis is provided along with a revision of empirical studies in line with this thesis. After providing this theoretical background to technical analysis I form several hypotheses to test the results. The hypotheses are tested using a backtest procedure described in the data and methodology section. I test the profitability of the indicators based on Jensen's Alpha to see if the indicators are able to generate positive abnormal returns. I attempt to find an explanation for the results using several explanatory factors, including the momentum factor which I expect to be most influential. I finish this thesis with a detailed conclusion summarizing the results in order to answer the stated hypotheses. The conclusion is accompanied by the limitations of this thesis and recommendations are given for further studies on this topic.

2. Literature Review

2.1 Introducing Technical Analysis

Contrary to fundamental analysts, technical analysts believe that changes in supply and demand can be detected by looking at past prices. Technical analysts trade based on signals given by technical trading rules, also known as indicators, which focus on detecting recurrent and predictable patterns in security prices. There are many different types of technical indicators but the most popular are the moving average based indicators (Lui & Mole, 1998; Taylor & Allen, 1992). The moving average based indicators are used to spot trends in the market, being indifferent to either upward or downward trends.

Technical analysis can take two distinct forms of analysis; either objective or subjective. Subjective analysis depends on the person observing the information, for example a price chart. The interpretation of the information depends on the subjective view of the person studying the information. An often used subjective technical trading observation is the head shoulder pattern. The head and shoulders pattern is generally regarded as a reversal pattern and it is most often seen in uptrends. This pattern, plotted on a price chart in appendix A, looks like a head and two shoulders, marking the beginning of a downtrend. Objective information is not prone to this subjective issue, it cannot be interpreted differently. Objective technical analysis is more factual and often contains fixed numbers such as price, volume or more mathematical information like moving averages. Formulas for objective technical analysis, like the ones used in the DEMA, MACD or RSI indicator, are scientifically proved and agreed upon by investors and academics[1], therefore no difference in interpretation between technical analysts should exist.

Technical analysts try to outperform the market, forecasting prices based on historical prices, volume and/or open interest, often using algorithmic programs to decide on their next trade. They are often referred to as ‘chartists’ because they believe that changes in supply and demand can be extracted from price charts. It is important to notice that technical analysis has various assumptions instrumental to any technical indicator:

- Market action discounts everything
- Prices move in trends
- History repeats itself

The first assumption implies that all information - historic, current and even expected - is discounted into the markets and incorporated into the prices of currently traded securities. This means that the current price is of no importance to the chartist, he just needs to know whether the price is rising or falling.

The second assumption suggests that prices move in trends. This implies that, ceteris paribus, a lower closing price today is more likely to result in a lower closing price tomorrow and conversely a higher price today will lead to a higher price tomorrow. Technical analysts generally believe in Newton’s first law of

[1] This goes for mathematical justification only, this does not imply any statements about the profitability of these indicators.

motion: a trend in motion is more likely to continue than to reverse. The job of the trader is to spot these trends in time and act on them accordingly, therefore technical traders are often referred to as trend followers. The Dow Theory (1922)[2] states that three levels of market trends exist: primary, secondary and tertiary trends. The primary trends are the long-term trends, expressed in years, secondary trends are of intermediate duration ranging from a month to a year and finally tertiary trends are the short-term or intraday fluctuations.

The third and final assumption implies that the market is prone to repetition and repeats itself over time. It is therefore of utmost importance to the trader to understand the past in order to being able to predict the future. In this evolution of technical analysis many indicators have emerged, by studying human psychology, or behavioral factors, which are believed to be useful throughout time. It is believed that the patterns that have been spotted and have performed well in the past will also perform well in the future.

2.2 Trend Following Indicators

In his book *Trend Following,* Covel elaborates on trading systems that attempt to spot trends in the market. These trend following systems use moving average based indicators which are the most popular indicators among technical analysts (Lui & Mole, 1998; Taylor & Allen, 1992). This versatile indicator is used in different types of markets mostly due to its simplicity and evidence in support of the usefulness of the buy and sell signals it produces (Park & Irwin, 2004). Two moving average based systems elaborated on in *Trend Following* are the Dual Exponential Moving Average indicator (DEMA) and the moving average convergence-divergence indicator (MACD). In addition to these two moving average based indicators the Relative Strength Index (RSI) is added. The RSI is often used in trend following systems because it attempts to spot periods of overbought and oversold conditions of the traded security. However Covel does not provide exact definitions of the indicators and the parameters used in these indicators. Therefore a large degree of freedom on the exact definition of these indicators persists and an exact replication of the indicators used by Covel is difficult. In order to replicate the indicators I will use the default settings for the three indicators, which will be refined further on using a band system. These settings will be discussed briefly in this literature review and will be elaborated upon in section 4.

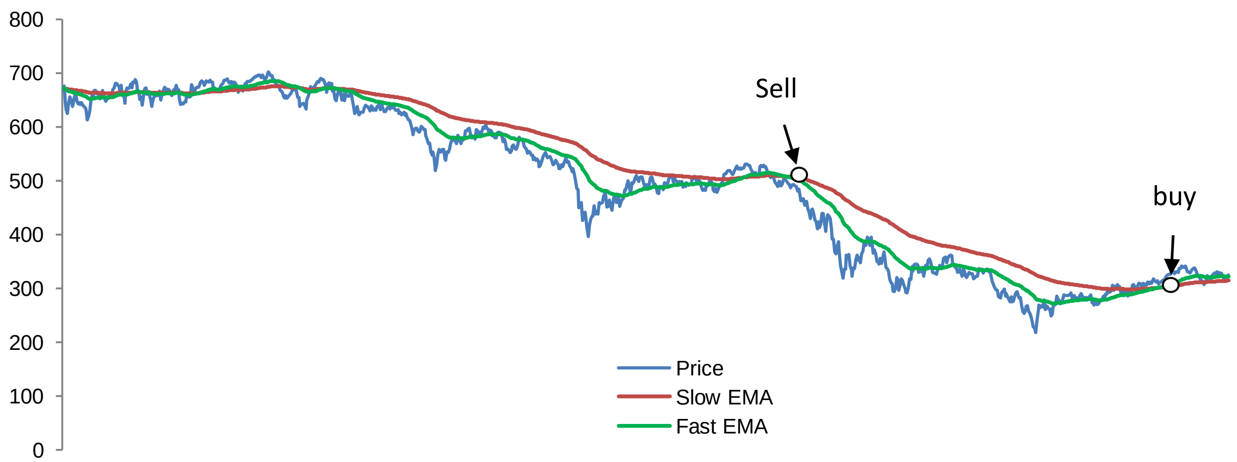
The DEMA indicator was first introduced by Patrick Mulloy in his article "Smoothing Data with Faster Moving Averages" (1994). The DEMA is an impovement to the Dual Moving Average Crossover (DMAC) Indicator which uses weighted average moving averages. The DEMA improves upon the DMAC by using exponential moving averages in order to provide a solution to a well known problem of moving averages. Moving Averages have a serious lag compared to the underlying security. This lag is partially offset by calculating a faster averaging methodology; the exponential moving average. The DEMA indicator is very simple to apply in a trading strategy. According to this moving average based indicator, trading signals are generated by two moving averages of the traded security. A buy signal is emmitted when a short-

[2] The Dow Theory is seen as the oldest form of technical analysis and is discussed in section 2.4.

period moving average rises above the long period moving average. Contrary to the MACD and the RSI there are no clear settings which officially pass as default parameters. However there is a widespread parameter setting as used in Brock et al. (1992). This conforms to a 2-day-Exponential Moving Average (EMA) for the short period and a 150-day-EMA for the long period. Therefore the 2-day-EMA, or fast EMA, and 150-day-EMA, or slow EMA, are used as default settings by this thesis. The concept behind this DEMA indicator is to smooth out an otherwise volatile security which allows the trader to spot trends in the securities price. The DEMA system relies on momentum factors to be present in the traded security and is therefore often named a momentum oscillerator. Momentum states that a price that is moving up in period T will continue to move upwards in period T+1 (the upward trend), and conversely when a price is dropping during time T it will likely continue to drop in period T+1 (the downward trend).

Figure 2.1 DEMA indicator

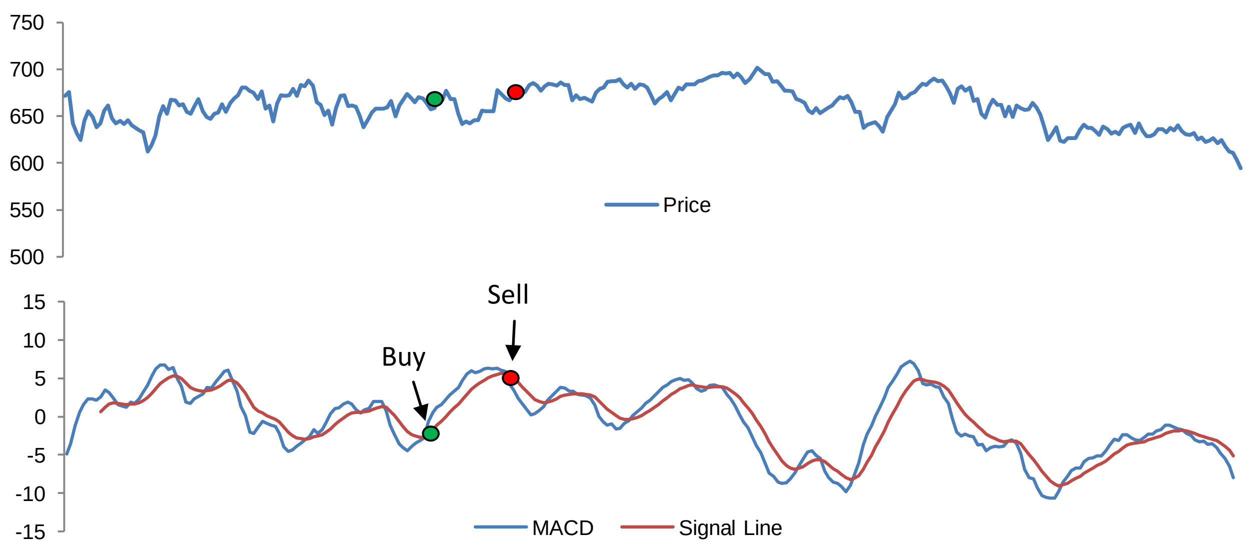
This figure shows a fast exponential moving average and a slow exponential moving average. An example of a buy and sell signal is provided at two randomly chosen crossover points between the two exponential moving averages. This figure is for illustrative purposes only.



The second momentum oscillator is the MACD indicator, first developed by Gerald Appel, a well known and respected technical analyst. In 1974 Gerald Appel created the moving average convergence-divergence trading method, also known as the MACD. The concept of the MACD is very similar to that of the DEMA but differs in the sense that it uses three exponential moving averages. First, the MACD line is computed by a 26-day exponential moving average (EMA) from a 12-day EMA. Second, the signal line is computed by calculating the 9-days EMA of the MACD line. The points of intersection between the two exponential moving averages indicate the buy and sell signals. EMAs highlight recent changes in a securities price. By comparing EMAs of different lengths, the MACD allows the trader to make a judgment on changes in the trend of a stock. A positive MACD indicates that the 12-day EMA is greater than the 26-day EMA, vice versa a negative MACD value indicates that the 12-day EMA value is smaller than the 26-day EMA value. When the MACD is on a rising move and crosses above the signal line it is interpreted as a bullish signal. A bearish signal occurs when the MACD decreases and crosses below the signal line. A graphical presentation as in figure 1 clarifies matters.

Figure 2.2 MACD indicator

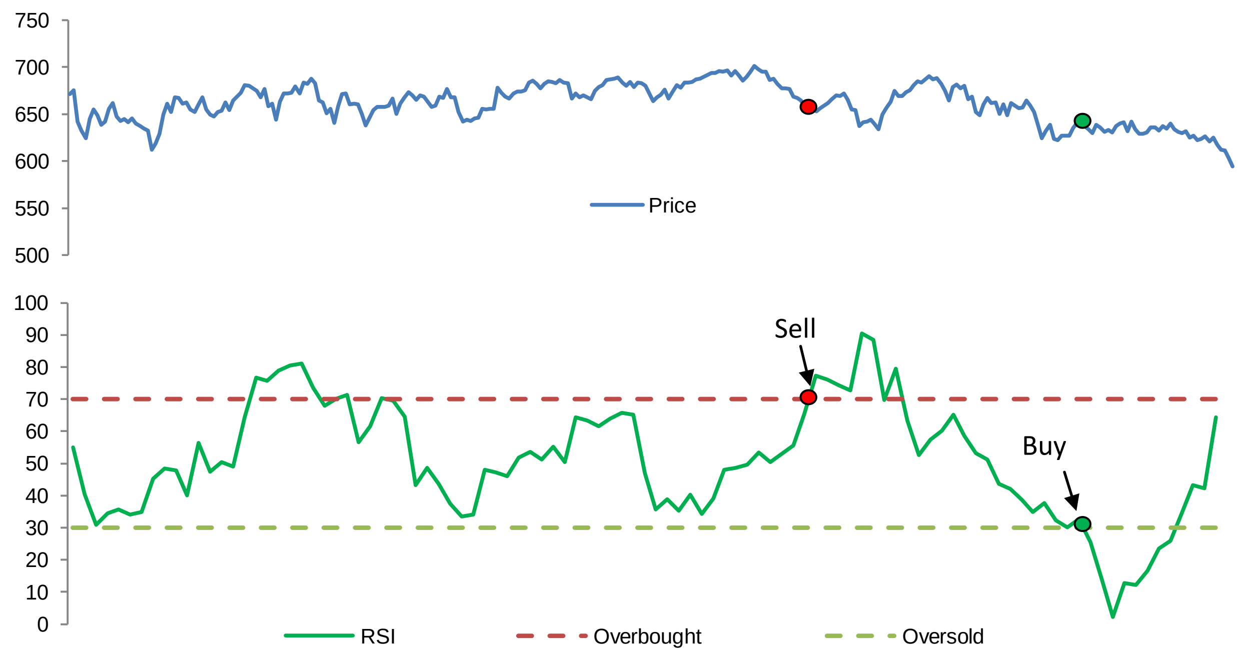
The top chart shows the securities price and the bottom chart shows the MACD and Signal line. An example of a buy and sell signal is provided at two randomly chosen crossover points between the MACD and Signal Line. This figure is for illustrative purposes only.



The third momentum oscillator is the Relative Strength Index (RSI) indicator, developed by J. Welles Wilder (1978), an American mechanical engineer. The RSI is often used to complement the MACD indicator because the RSI is a leading indicator as opposed to the lagging indicators MACD and DEMA. Leading indicators predict trends whereas lagging indicators, since they lag the underlying security, merely confirm trends. The RSI indicator attempts to measure the speed and direction of the trend by computing momentum as the ratio of higher closes to lower closes. This implies that higher (lower) RSI values for prices have historically had more or stronger positive (negative) changes. The RSI can take any value between 0 and 100. The default RSI indicator is set to a 14-day period as suggested by Wilder. It is assumed by Wilder that tops are indicated by a RSI level above 70 and bottoms are indicated by a drop of the RSI below 30. Therefore a security is believed to be overbought at a RSI above 70 and oversold at a RSI below 30, ceteris paribus. Again, Plotting the RSI simplifies matters.

Figure 2.3 RSI indicator

The top chart shows the securities price and the bottom chart shows the RSI. An example of a buy and sell signal is provided at two randomly chosen crossover points between the RSI and the thresholds. This figure is for illustrative purposes only.



Although these technical indicators differ in the computation and implementation they share one important feature with all other technical indicators. This feature is the key to success of any indicator and summarizes the art of technical analysis: identify a trend change at an early stage and stay with this trend until there is sufficient indication of a trend reversal. This may seem very simple but it demands much effort by the trader whom is intertwined in psychological biases. The most important bias that affects this trader is well described by Kahneman and Tversky in their prospect theory (1979). The Prospect Theory states that people value gains and losses differently and therefore act irrational. The trader will direct value to gains and losses rather than to the total return. An example clarifies matters; consider a choice between two equal options, one expressed in terms of possible gains and the other in possible losses, generally people would choose the last. This is also known as loss aversion. It is the traders' job to act rational and avoid such biases. He should adhere to the most sacred of rules among technical analysts:

"cut your losses and let your profits run"

2.3 Efficient Market Hypothesis

Before starting to evaluate the literature on the profitability of technical analysis it is important to discuss the Efficient Market Hypothesis (EMH). The Efficient Market Hypothesis (EMH) plays a crucial role in the financial lexicon, with its use widespread in the study of the behavior of stock prices. The Efficient Market Hypothesis evolved in the 1960s from Eugene Fama's Ph.D. dissertation. The EMH assumes markets to be efficient which can be interpreted by Fama's (1970) textbook definition: 'A market in which prices always "fully reflect" available information is called efficient'. Another well known academic, Jensen (1978), describes the concept of efficient markets in more detail: 'A market is efficient with respect to an information set $\emptyset_t$ if it is impossible to make economic profits by trading on the basis of information set $\emptyset_t$'. Jensen goes on to split the EMH into three forms of efficiency. The weak form efficiency claims that all past prices of a stock are reflected in today's stock price. This implies that only fundamental analysis can be used to identify stocks that are undervalued and overvalued. Therefore the only way for investors to spot profitable companies is by researching financial statements as opposed to technical analysis. The semi-strong form efficiency implies that all public information is incorporated into a securities current price. This means that neither fundamental nor technical analysis can be used to return abnormal profits. Finally the strong-form efficiency, the most extreme form of market efficiency, states that all information, whether it is public or private, is reflected in a securities price. This implies that not only technical analysis and fundamental analysis are useless, even insider information proves unprofitable.

The Random Walk Hypothesis (RWH) is closely related to the EMH. Bachelier (1900) first described the RWH in his book *Théory de la Spéculation,* where he asserted that fluctuations in stock prices can be explained by a random walk model. Although his work was not widely recognized the RWH became well known due to succeeding studies by various authors such as Alexander (1961) and Osborne (1959). The Random walk model is defined by:

$$x_t - x_{t-1} = \varepsilon_t$$

The left side of the equation describes the variable generated by the random-walk process, where ε_t is a sequence of random and independent values for time T. The successive price changes between the two periods are independent and have a zero mean where the variance is proportional to the interval between the successive periods. This implies that the annual variance is 250 times the variance of the daily changes, assuming a year with 250 trading days.

During the last two decades the EMH and RWH have been heavily criticized finding little support among practitioners, who criticize the two relating theories for being inapplicable in practice. George Soros (1994), a successful trader who became famous for his profitable investments during the 1992 Black Wednesday UK currency crisis, comments on the notion of efficient markets:

"This interpretation of the way financial markets operate is severely distorted.., it may seem strange that a patently false theory should gain such a widespread acceptance."

This motivates investors to try and outperform the market by turning to fundamental or technical analysis, or a combination of both as proposed by Bettman (2009). These investment styles share the objective of outperforming the market but differ in their methods of selecting their investments.

A myriad of empirical research has been done into the concept of efficient markets with opponents suggesting that evidence exists of predictability in equity returns from past return series (Chopra, Lakonishok and Ritter 1992, Fama & French 1986). One of the most popular studies testing the notion of efficient markets is the Capital Asset Pricing Model (CAPM). This asset pricing model was first developed by Sharpe (1964), Lintner (1965) and Black (1974) and has been a standard equilibrium model in the modern day financial lexicon. The following formula summarizes the CAPM:

$$r_i = r_f + \beta(r_m - r_f)$$

Where r_i is the expected rate of return, r_f the risk free rate, β the beta and r_m the market return. The CAPM implies that the expected returns on stock prices are positively linearly correlated to the market risk. This market risk is referred to as beta and is calculated by measuring the covariance of the asset and the market with the total variance of the market, where a high beta implies a high volatility compared to the market. Thus, according to the CAPM, the volatility is the main risk factor explaining the variations in stock price movements. The three-factor model, developed by Fama and French (1993), builds upon the CAPM and adds two additional explanatory factors. The first factor is the size factor which captures the fact that small cap stocks tend to outperform large cap stocks, also known as the Small Minus Low factor (SML). The second factor in this three factor model is the value factor that addresses the Price-to-Earnings anomaly. Companies with low Price-to-Earnings (value stocks) values tend to outperform companies with high Price-to-Earnings (growth stocks). This factor is known as the High Minus Low factor (HML). In summary the three-factor model can be described as:

$$r_i = r_f + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \alpha$$

Once the factors SMB and HML are defined the corresponding coefficients or beta's β, are estimated by means of regression. However the CAPM is based on a number of assumptions about the distribution of stock price returns and volatility. One assumption that could collide with the nature of this thesis is the fact that the CAPM assumes that stock price returns are normally distributed with the variance remaining constant over time. Lukac and Brorsen (1990) provide a comprehensive study into the return distributions of speculative markets and find that these markets are not normally distributed and have time-varying variance. Bollerslev et al. (1988) propose a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model of the CAPM (CAPM-GARCH). This model is better suited for empirical research into stock returns because the CAPM-GARCH allows variances of returns to vary over time and therefore avoids problems linked to heteroscedasticity. Using the CAPM-GARCH means that beta values are also allowed to vary over time, therefore reducing the degree of biasness in the estimators. Morelli (2003) performed a comparison study of the original, or conditional, CAPM and the CAPM - GARCH for the UK stock market for the period 1980 – 1999. The main objective was to see if the GARCH beta's differ from the unconditional beta's. Morelli found that the GARCH and the unconditional beta's are correlated at 0.475 or 0.575 depending on the method used. Using the conditional CAPM market premiums were found to be positive. However when unconditional betas were used the average market premium is negative and not statistically significant. Furthermore Morelli found that, when using the unconditional beta's, some individual years show a positive statistically significant risk premium. These individual years appear to correspond to periods of high volatility in stock market volatile which would implicate that the model has value during periods of relatively high volatility.

Other studies that find evidence against the notion of efficient markets include Lo and MacKinlay (1988), who publicized an empirical study rejecting the Random Walk Hypothesis for weekly U.S. stock indexes and show that historical prices can be a predictor for future returns to some degree, a fact which all technical analysts take for granted. Supporting studies find that various economic variables such as inflation (Fama & Schwert, 1977) and the term structure (Campbell, 1987) are able to forecast stock returns due to the time-varying risk premiums. Economists like Shiller (2000) find that there is consistent short-run momentum in the distribution of stock prices, a fact assumed by the random walk theory to be impossible. Shiller describes the rise in the US stock markets during the late 1990s as the consequence of psychological contagion. These findings are in line with the findings provided by behavioral economists such as Kahneman and Tversky (1981), founders of the Prospect Theory.

2.4 Empirical Studies on Technical Analysis

Technical analysis dates back to the 1800s and is often considered to be the original form of investment analysis. Technical analysis remains popular among investors today, even though it does not enjoy the following it once had. The oldest form of technical analysis comes from the Dow Theory (1922), often falsely attributed to Charles Dow, the founder of The Wall Street Journal. Most of what we know of the Dow Theory actually comes from Charles Dow's successor, William Peter Hamilton. The Dow Theory was developed during a series of *Wall Street Journal* editorials written by Hamilton in a period between 1902 and 1929. Hamilton used Charles Dow's theory of stock market movements as a ground stone for his methodology. A keystone of the theory is that financial markets are assumed to move in persistent 'bull' and 'bear' trends, hampered by short term deviations. These trends arise due to the human nature of investors. Investors exert irrational behavior, like herding, which reinforce past price movements and allow bull and bear trends to arise.

Technical analysis use is widespread, especially in speculative markets. Smidt (1965) studied the use of technical analysis among amateur traders in US commodity futures and finds that more than 50% of the survey's respondents use technical analysis either as sole indicator or as part of a bigger system. Billingsley and Chan (1996) find that nearly 60% of trading advisors in commodity markets rely heavily on technical trading systems. Fung and Hsieh (1997) elaborate on this finding, stating that the dominant strategy for commodity trading advisors is trend-following. Finally there is evidence that technical analysis is widely used in foreign exchange markets (Gehrig & Menkhoff, 2006; Menkhoff & Taylor, 2007; Neely & Weller, 2003; Taylor & Allen, 1992). Although it appears that technical analysis is widely used in speculative markets, academics are definitely not convinced that this trading strategy provides positive excess returns. This skepticism can be derived from the general acceptance of the EMH among these skeptics. This controversy has led to a spur in volume of academic literature on this topic. Empirical studies on technical analysis can be divided into early studies and modern studies. Early studies start from Donchian (1960) and run up to 1987. Donchian is one of the earliest authors known to study technical analysis and therefore Donchian is often known as the father of trend following. Other early studies are similar to Donchian (1960) in the sense that several limitations in the testing procedures exist. Modern studies (1988 – 2012) are assumed to commence with Lukac et al. (1988), providing a more comprehensive analysis and in doing so overcoming many limitations found in the early studies.

2.4.1 Early Studies

Studies on filter rules are most voluminous among early studies. Alexander (1961) first developed filter rules which generate trading signals when to buy or sell a security. The trading signals are based on percentage changes in prices from previous lows and highs, with one of the most popular filter rules being the RSI, discussed in section 1. Fama and Blume (1966) perform extensive tests on the filter rules introduced by Alexander and find that only three small filter rules (0.5%, 1%, 1.5%) generate excess returns compared to the buy-and-hold strategy, using 30 individual stocks in the Dow Jones Industrial Average over the period 1956–1962. Other indicators that were extensively researched are the moving average based trading systems. Van Horn and Parker (1967, 1968) conclude that a buy and hold strategy outperforms a simple moving average trading system using 30 NYSE securities during the period 1960 - 1966. James (1968) and Jensen and Benington (1970) come to the same conclusion dismissing the profitability of simple moving average based trading system. However numerous studies on foreign exchange markets and future markets find excess returns for simple technical trading strategies. Smidt (1965) and Stevenson (1970) find that there is predictability of soybean and corn prices through technical trading systems. Sweeney (1986) studies ten foreign exchange rates using filter rules and finds three filters (0.5%, 1% and 2%) to generate positive risk-adjusted excess returns.

These results on the profitability of technical indicators appear to show that technical indicators are more frequently used in commodity and foreign exchange markets than in stock markets in the period before the 1980s. This could be due to commodity and foreign exchange markets showing better trading patterns, such as clear trends, resulting from less efficiency in these markets. However these early studies possess several limitations in their study methods. First of all these early studies tend to either exclude tests of significance and therefore it might be premature to draw such conclusions. Furthermore early studies do not always use risk-adjusted return measurements as means of testing profitability. For example Leuthold (1972) reports an annual net return of 115.8% when testing a filter rule, which appears very appealing. However an investor also considers the risk he is involved with when pursuing the trading strategy, which Leuthold does not report in the study. Leuthold could have applied a CAPM regression in order to provide the beta of the trading strategy so that the investor knows what the risk of the trading strategy is compared to the benchmark. Finally early studies do not always consider data snooping biases. This gives rise to curve fitting, resulting in profits that are due to luck. This data snooping bias can be easily avoided by using a proper backtest procedure. This backtest procedure should test the indicators on one period and then validate the trading performance a different period.

2.4.2 Modern Studies

Modern studies commence with Lukac et al. (1988) and provide improved empirical analytics to overcome limitations of the earlier studies by using more rigorous tests and econometric methodologies. The fast growing computer power of the last two decades has enabled researchers to apply more advanced technologies necessary to improve the statistical analysis. This improvement in research has led to a number of different types of studies that provide improvements to early studies. First there are the studies that use parameter optimization in order to provide optimized results for the indicators. These optimized results are then verified using out-of-sample datasets. This type of modern study is referred to by Park (2007) as standard studies. An example of such a standard study is Lukac et al's (1988) study which simulates 12 technical trading systems on commodity futures using optimization methods. Lukac et al. (1988) test the results using Jensen's alpha providing tests on significance, assuming that the CAPM holds. Lukac et al. (1988) test for normal identically distributed returns using the Kolmogorov-Smrinov test for normality and finds that normality is not rejected. This test of normality is of great importance as research has shown that many security prices are not normally distributed but in fact leptokurtic implying more observations near the mean and in the extreme tails than originally assumed by the normal distribution. The study finds that four indicators, including the dual moving average crossover indicator, prove profitable after testing for significance and deducting trading costs. Lukac et al. (1988) thus provide many useful implications in testing the profitability of technical indicators, alleviating data snooping problems using out-of sample datasets for means of verification and conducting parameter optimization.

A second type of modern study indentified by Park (2007) is the Model-based bootstrap study. Possibly the most influential and most cited modern study is Brock et al. (1992), who were among the first to implement the bootstrap methodology on technical trading profitability. The bootstrap methodology is a resampling technique that allows for estimation of statistics. Bootstrap-based studies apply a bootstrap methodology to overcome problems linked to leptokurtic, autocorrelated, conditionally heteroskedastic, and time varying returns. A second advantage of the bootstrap methodology is that this test can develop a joint test of significance for a set of indicators, avoiding issues of complex dependencies when dealing with indicators individually. Another interesting pioneering feature of this study is the introduction of a band to the indicators. This band is added to the default technical indicators showing significant improvements in the profitability. The band improves profitability by reducing the number of trades generated by the indicator. Any ‘whiplash’ trades are omitted, which arise when the indicator generates too many trading signals in a short period of time. Whiplash trades mostly occur when a security price moves sideways instead of moving in clear trends. The indicator then falsely indicates that trends are forming and generates buy and sell signals accordingly.

A more recent trend in literature that has been targeting technical analysis is the focus on the transaction costs incurred by technical analysis, which are especially present in high frequency trading strategies, like intraday trading. Neely (2003) finds that when taking both transaction costs and trading hours into account there is no evidence of excess returns to the indicators derived using a generic program and an optimized linear forecasting model. Many studies that claimed to prove that technical analysis gave rise to excess returns are undermined by the fact that they do not sufficiently incorporate transaction costs. Examples of such studies include studies like Brock et al. (1992) and Bessembinder & Chan (1998). Furthermore recent literature shows that it is important to carefully consider the time frame used to backtest the indicators. Sullivan et al. (1999) utilize White’s Reality Check Bootstrap Methodology to evaluate simple technical indicators as in Brock et al. (1992), while quantifying the data snooping bias and adjusting for this effect. They find that the profitability of technical analysis has declined over time, which is confirmed by Bajgrowicz et al. (2008). This could imply that speculative markets have become more efficient since the 1980s. Therefore it would make little sense to include a long historical sample period when investigating simple technical indicators. Academics and investment professionals are more likely to be interested in recent period datasets than long data sample periods that start before the 1980s since this could give false expectations on technical indicators.

This study carefully considers the implications described by the modern literature. These implications will improve the statistical robustness of this study. In addition to the implementation of these existing implications this thesis will contribute to existing literature by applying some unique features to the analysis. First of all I will test the indicators on the AEX Index therefore evaluating the profitability of indicators in the Dutch stock market. Second I use a timeframe that includes exceptional economic periods such as the Dotcom Bubble and the Global Financial Crisis. Third I attempt to find the sources of any possible positive alpha by looking at the factors Size, Value and Momentum. I estimate these factors using the CAPM-GARCH, therefore attempting to overcome estimator biases present in the traditional CAPM estimation process.

3. Hypotheses

This thesis provides a thorough investigation into the basics of technical analysis. Three basic technical indicators, Dual Exponential Moving Averages, Moving Average Convergence Divergence and Relative Strength Index indicators are tested on their profitability. These three technical indicators are used by Covel in his best-selling trading book *Trend Following, how great traders make millions in up or down markets* (2004). Covel elaborates on trend following systems that use these indicators to provide the buy and sell signals. According to Covel these trend following systems are well able to generate abnormal risk-adjusted returns. Since these three indicators provide the foundation to the trend following strategies used by Covel, I want to test if these indicators are in fact able to provide abnormal risk-adjusted returns individually. Therefore I propose several hypotheses to perform a thorough backtest procedure of the three technical indicators. Since this book provides no clear backtest results of these indicators themselves there is no dataset to use as reference. However this should have no effect on the conclusion of this thesis since I introduce the AEX Index as the benchmark. I form my hypotheses in such a way that it will become clear whether these indicators provide abnormal risk-adjusted returns.

1) Any of the three indicators on its own outperform the benchmark, after deducting reasonable transaction costs, using Jensen's Alpha as performance measure.

The first hypothesis appears fragile as it will require all three the indicators to outperform the benchmark using merely default parameters. However since the benchmark is the AEX Index which did not perform well in the last decade due to economic turmoil, I expect the default indicators to outperform the benchmark showing positive alpha.

The refined indicators differ from the default indicators by addition of a band. The band reduces the number of trades by setting a minimum band of 2% between the price today and the price at the time of the previous trade. This means that a trade signal will only be generated if the price today is at least 2% lower or 2% higher than the price at the previous trade.

2) Refined indicators that use a band in addition to the default settings improve Jensen's Alpha compared to the default indicators.

I expect these refined indicators to show higher alpha than the default indicators. Furthermore I expect that the positive alpha can be explained by the Size, Value or Momentum factor.

3) Traditional Asset Pricing Models along with a momentum factor are able to explain the alpha of the three indicators.

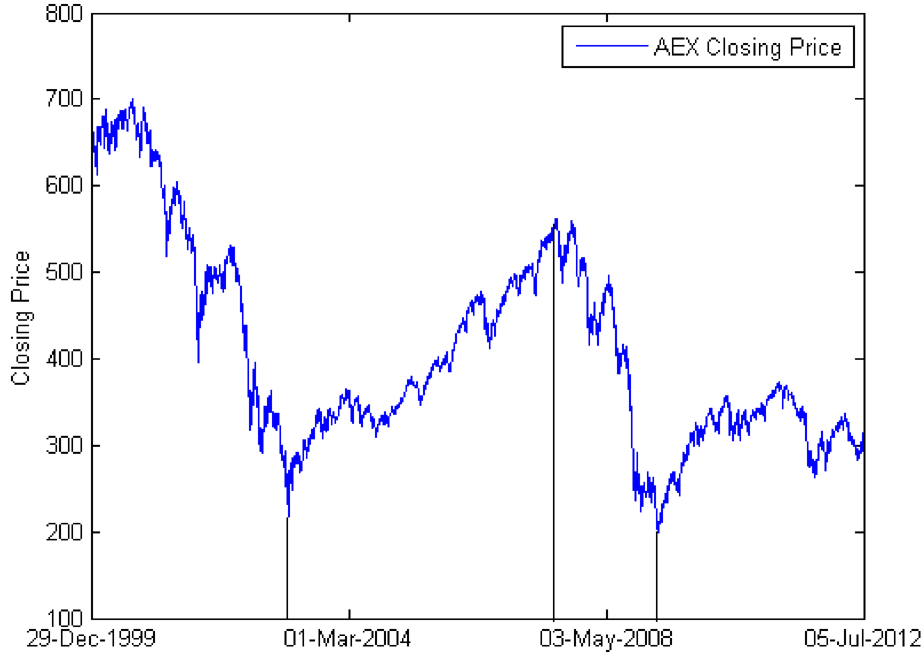
4 Data and methodology

This section provides a detailed overview of the data and methodology providing the foundation to this thesis. First a description of the dataset is provided. Second a mathematical description is provided describing the indicators in question, thereby complementing the introduction to technical analysis in section 1. Finally the backtest procedure and the method of testing the results are described in the methodology section.

4.1 Data

The Datastream database is consulted to download both the in-sample and out-of-sample dataset. The in-sample data series used in this study includes the Amsterdam Stock Exchange (AEX) closing prices from January 2000 to July 2012, capturing some of the most interesting periods in financial history. The out-of-sample dataset includes the Dow Jones Index, CAC 40, DAX 30, FTSE 100, EUR/USD currency rate and Gold US troy per ounce from January 2000 to July 2012. The out-of sample dataset should give some additional insights into the characteristics of the different indicators, constructed using different types of financial markets. In addition to the full sample, the dataset is split into four sub periods:

Figure 4.1



- Sub period 1: 31/Dec/1999 – 12/Mar/2003
- Sub period 2: 13/Mar/2003 – 16/Jul/2007
- Sub period 3: 17/Jul/2007 - 09/Mar/2009
- Sub period 4: 10/Mar/2009 - 03/Jul/2012

Sub period 1 shows a down-trend, marking the end of the Dotcom euphoria. The Internet bubble peaked at September 2000 causing a bear market until the recovery started in March 2003. The second sub period shows an up-trend caused by the bull market following the Dotcom crisis. The third period enters the beginning of a downtrend that was spurred by the subprime crises. The final sub period shows some recovery from the Global Financial Crisis, although not very convincing up to this date.

4.2 Indicators

One of the difficulties faced by technical analysts is the inability to customize their trading systems, since many programs offer trading models wrapped in a black box. Backtesting the indicators requires a software program that allows the user to customize the trading model in order to test the indicator at the traders' preferences. Matlab R2011a is perfectly suited for this task because it supports algorithm computation and allows the user to vary any input necessary. Furthermore Matlab R2011a provides several toolboxes which are perfectly suited for backtesting, such as the Financial and Optimization Toolboxes. This thesis therefore uses Matlab R2011a to write a model that is able to backtest the indicators in various settings. The first indicator to be tested is the DEMA indicator. The n-day exponential moving average is given by:

$$EMA_t = \frac{C_1 + (1-\alpha)C_2 + (1-\alpha)^2 C_2 + \ldots + (1-\alpha)^{t-1} C_t}{1 + (1-\alpha) + (1-\alpha)^2 + \ldots + (1-\alpha)^{t-1}}$$

With EMA_t being the exponential moving average (EMA) at period t and C_t the closing price for period i. Recall from section 1 that a buy signal is emitted when the short period EMA crosses over the long period EMA. Although there is no official default setting for the DEMA as is the case for the MACD indicator, there is a widespread parameter setting as used in Brock et al. (1992). This conforms to a 2-day-EMA for the short period and a 150-day-EMA for the long period.

The second indicator to be tested is the MACD indicator. Recall that the MACD uses 3 exponential moving averages:

- MACD = EMA[ClosingPrices,12] – EMA[ClosingPrices,26]
- Signal Line = EMA[MACD,9]

Recall that when the MACD crosses over the signal line a buy signal is generated. Conversely when the MACD crosses below the signal line a sell signal is generated. Note that the mathematical representation presented above uses the default parameter settings provided by its creator, Gerald Appel.

The final indicator is the RSI indicator which is different from the two moving average indicators because it is a leading indicator. This implies that the RSI indicator leads the security price whereas the DEMA and MACD lag the security price. The RSI is therefore often used as a complementary indicator for these two moving average based indicators because it can confirm the trading signals. Every period an upward change (U) or downward change (D) is measured:

$$U = Close_T - Close_{T-1} \quad \mathrm{D} = Close_{T-1} - Close_T \quad \text{with period T}$$

The average of these UPs and DOWNs is then calculated using an exponential moving average.
The ratio of these averages is the relative strength (RS):

$$RS = \frac{EMA\ (U)}{EMA\ (D)}$$

To convert the RS into an index, or the RSI, the following formula is used:

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

Recall that the default RSI indicator is set to a 14-day period as suggested by Wilder. It is assumed by Wilder that tops are indicated by an RSI level above 70 and bottoms are indicated by a drop of the RSI below 30. Therefore a security is believed to be overbought at a RSI above 70 and oversold at a RSI below 30, ceteris paribus.

4.2 Backtest Procedure

In order to examine the profitability of these indicators a backtest procedure is constructed. Special focus is attended to any problems relating to curve-fitting. Curve-fitting in general is the process of constructing a mathematical function which best fits a given dataset. Curve-fitting is a very effective way of drawing conclusions from experimental data. However curve-fitting is not appropriate when applied to trading strategies as this method produces over-optimized, over-optimistic results in the context of backtesting trading systems. Nearly every trading system has some “magic” combination of indicators and parameters that show excessive returns. However this magic combination is most likely the result of luck rather than skill and would be different for every dataset. This means that when this ‘magic’ combination is used on a different dataset, results probably will be very different to the returns generated with the full benefit of hindsight. This study tries avoids any possibilities of curve-fitting by applying a lag between the generation of the trading rule and the actual trading itself. Returns are therefore calculated using a 1-day lag between the emission of the trading signal and the computation of the return. A few assumptions are made functioning as input for the system. First it is assumed that the trading account is not necessarily closed at the end of the period. This is accounted for in the profit and loss account since this account is computed by adding the daily profit with the locked in profits from previous trades. Furthermore transaction costs are included and amount to 0.25% of the closing price per actual trade. The risk free rate is based on Dutch T-Bills and amounts to 3.79%. Finally it is assumed that a year consists of 250 trading days. The profit & loss accounts are calculated using compounded returns.

4.2 Methodology

This thesis uses a different approach to similar other studies. The bigger part of comparable empirical research on technical indicators is done using the Bootstrap Methodology as described by Brock et al (1992). This thesis chooses to use Jensen's alpha to test the indicators on abnormal returns using AEX Index as the benchmark, i.e. a Buy & Hold strategy. The reason for this different approach is to allow for a more straightforward approach to include Fama's 3 factors and an additional momentum factor, which I expect to explain any positive alpha present in the results.

4.2.1 Conditional CAPM

The conditional Capital Asset Pricing Model (CAPM) explains the relative variation in returns of a trading portfolio, or indicator, to the variation of the market. The CAPM calculates the expected rate of return, $E(R_i)$, of the trading portfolio using the following formula:

$$E(R_i) = R_f + \beta[E(R_m) - R_f]$$

The CAPM states that an investor needs to be compensates for both time and risk. The time value of money is represented by the risk free rate and compensates the investor for investing in some security over a period of time. The risk taken by the investor is represented by the risk measure beta (β) that compares the return of the security to the market risk premium ($R_m - R_f$). Jensen (1968) applies a modification to the conditional CAPM model by using the following regression:

$$R_i - R_f = \alpha + \beta\left(R_m - R_f\right) + \varepsilon_t$$

Jensen's Alpha (α) tests the outperformance relative to the market performance. Jensen's Alpha is used because it considers the market risk-adjusted excess returns and not just stand-alone risk. In order to give value to the estimators an Ordinary Least Squares (OLS) regression is used. However the estimators found using the OLS regression could be biased since this regression is based on the assumption of normal identically distributed returns with a constant variance. As discussed in section 2 Lukac and Brorsen (1990) find that speculative markets are not normally distributed and have time-varying variance. Therefore I Introduce a GARCH term, inspired by Bollerslev (1986).

4.2.2 GARCH

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is a generalized version of the Autoregressive Conditional Heteroskedasticity (ARCH) model, first developed by Engel (1982). The ARCH model states that conditional volatility increases with large (positive or negative) return shocks. Engel received the Nobel Prize for these findings.

$$e_t = \sqrt{h_t} u_t \qquad u_t \sim N(0,1)$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i e_{t-1}^2 \quad \omega, \alpha_i \geq 0$$

The estimate for today's variance, h_t, is an estimate of the long-run variance factor ,ω, and a summation of squared returns, e_t^2 assigned with a weight α_i.

Bollerslev (1986), a former PhD student of Engle, generalized the ARCH model to compute the GARCH model. The major improvement of the GARCH model is that it adds a mean reversion factor.

$$e_t = \sqrt{h_t} u_t \qquad u_t \sim N(0,1)$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i e_{t-p}^2 + \sum_{i=1}^{p} \beta_i h_{t-q}$$

Which is typically simplified to:

$$h_t = \omega + \alpha_i e_{t-1}^2 + \beta h_{t-i}$$

The omega, ω, is now a product of weight gamma, multiplied by the long-run variance. Furthermore GARCH adds a factor, βh_{t-i}, to the ARCH which is a mean reversion factor with, β, the assigned weight, multiplied by the lagged variance. It is generally considered sufficient to choose p=q=1 for the lagged variance equation, which is referred to as the GARCH (1,1).

4.2.3 CAPM-GARCH (1,1)

Now that the limitations of the CAPM model are clear and improvements have been suggested by means of the GARCH model a conditional CAPM is applied to test the profitability of the indicators:

$$R_i - R_f = \alpha + \beta\left(R_m - R_f\right) + \varepsilon_t \quad \varepsilon_t \sim N(0, h_t)$$

$$h_t = \omega + \alpha_i e_{t-1}^2 + \beta h_{t-i}$$

This model is better suited for empirical research into stock returns because the CAPM-GARCH allows variances of returns to vary over time and therefore avoids problems linked to heteroscedasticity. Using the CAPM-GARCH means that beta values are also allowed to vary over time, therefore reducing the degree of biasness in the estimators. After testing Jensen's alpha, α, and expecting to see positive values for certain trading strategies several factors are included in the regression in an attempt to explain any positive alpha. Following the Fama-French (1992) three factor model, the Small minus Big (SMB) factor is included in order to account for variations in returns for company size. Furthermore the High minus Low factor is included in an attempt to explain variation in Book-to-Market values. I expect the Momentum factor (MOM), first introduced by Chan et al. (1996), to be the explanatory factor of greatest significance. Recall from section 1 that Momentum states that a price that is moving up in period T will continue to move upwards in period T+1 (the upward trend), and conversely when a price is dropping at time T it will likely continue to drop in period T+1 (the downward trend). The following formula shows the regression.

$$R_{it} - R_f = \alpha_{it} + \beta_{it}\left(R_{mt} - R_f\right) + s_{it}(SMB) + \mathrm{h}_{it}(HML) + m_{it}(MOM) + \varepsilon_t \qquad \varepsilon_t \sim N(0, h_t)$$

$$h_t = \omega + \alpha_i e_{t-1}^2 + \beta h_{t-i}$$

5 Empirical Results

5.1 Return Distributions

Now that the trading system is functional, as constructed in the Data section, we can evaluate the results to test the hypotheses. Table 5.1 contains summary statistics for the AEX Index full sample and the accompanying sub-samples. Returns are calculated as the log differences of the corresponding AEX daily closing prices.

Table 5.1 Sample statistics benchmark

Results are presented for the full sample and for the four non-overlapping sub periods of the AEX Index. Results are measured on an annual basis, except for the number of observations (N). A full year consists of 250 trading days.

	FULL	00 - 03	03 - 07	07 - 09	09 -12
N	3263	834	1133	430	866
Mean	-5,84%	-33,66%	18,75%	-60,16%	1,48%
Std. Dev.	24,80%	28,99%	16,47%	36,19%	21,39%
Min	-32,18%	-32,18%	1,29%	-29,42%	-21,61%
Max	27,65%	-6,99%	27,65%	9,65%	13,63%
Skewness	-0,0623	-0,0565	0,0654	0,0413	-0,0519
Kurtosis	8,7993	5,1641	9,0507	7,5897	4,7863

The exceptional situation occurs where the mean of the full sample is negative. This occurs due to the timeframe of the dataset capturing both the burst of the Internet bubble as well as the full impact of the Global Financial Crisis. Volatility in the AEX Index is largest for periods 2000 – 2003 and 2007 – 2009, both periods of economic turmoil after which the succeeding periods show decreasing volatilities. The full sample shows negative skewness whereas the sub samples show both positive and negative signs of skewness. The returns appear to be leptokurtic, indicated by the positive values of the kurtosis. A Kolmogorov-Smirnov (KS) test is used to test for normality of the daily return series.

Table 5.2 Kolmogorov-Smirnov test

Smaller group	D	P-value	Corrected
AEX daily:	0.1513	0	
Cumulative:	-0.0564	0	
Combined K-S:	0.1513	0	0

Since the P-value is smaller than 0.05 the null hypothesis is rejected and it is thus assumed that the return distribution of the AEX Index is not normally distributed. This result is according to expectations since non-normal distributions are very common in financial return series (Lukac and Brorsen, 1990).

Figure 5.1 Daily returns AEX Index

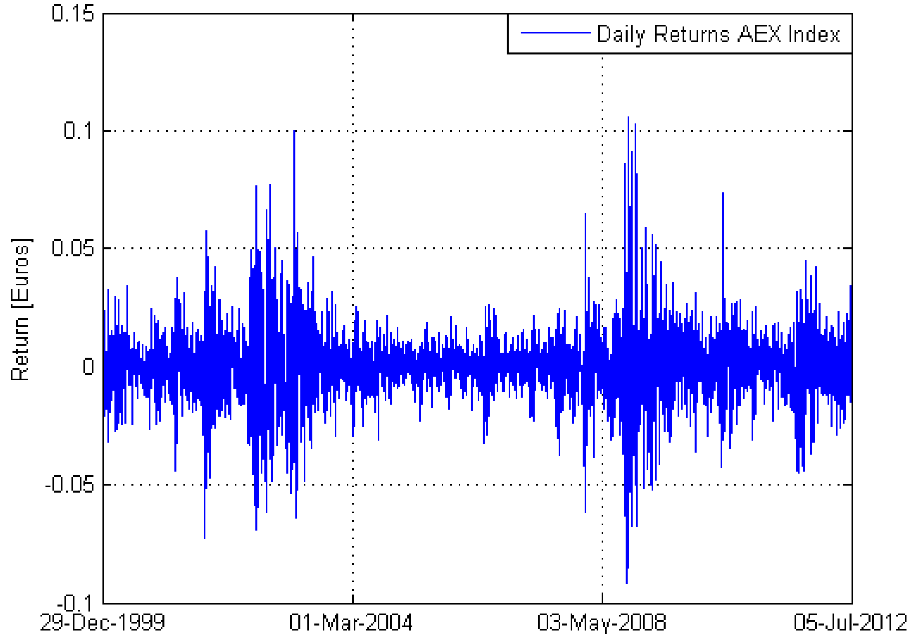


Figure 5.1 shows the daily returns of the benchmark. Absolute daily returns tend to be clustered during the crises periods, with a clustering of returns around the Dotcom bubble and extreme negative and positive returns clustered around the Global Financial Crisis. The traditional CAPM model assumes a constant relationship between risk and return. However financial time series often show volatility clustering with periods of higher volatility during crisis times. This volatility clustering is known as heteroskedastcity and can be tested by looking for significant autocorrelation in the squared returns. Table 5.3 shows a correlogram providing a test of autocorrelation.

Table 5.3 Autocorrelation of squared AEX closing prices log returns

LAG	AC	PAC	Q	Prob>Q
1	0.2144	0.2144	150.07	0
2	0.2969	0.2631	438.13	0
3	0.318	0.2417	768.52	0
4	0.2251	0.0913	934.2	0
5	0.3968	0.2734	1449.1	0
6	0.2627	0.0991	1674.8	0
7	0.2553	0.0545	1888.1	0
8	0.2267	-0.0073	2056.3	0
9	0.2392	0.0511	2243.6	0
10	0.324	0.1288	2587.4	0
11	0.221	0.0203	2747.4	0
12	0.2661	0.0595	2979.4	0
13	0.2849	0.1047	3245.4	0
14	0.1922	-0.0172	3366.5	0
15	0.2346	-0.0259	3547.1	0

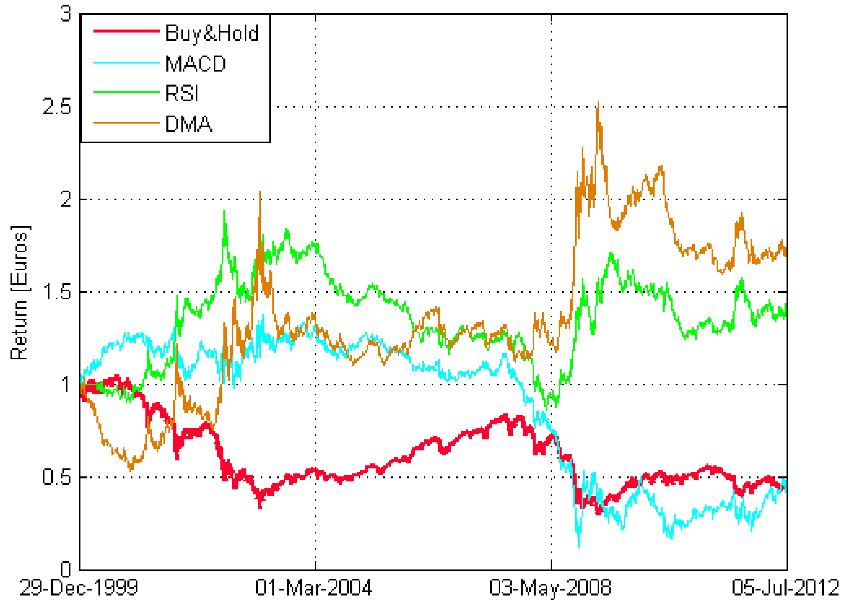
Table 5.3 shows that all the Q-statistics are significant since the p-values for all lags in the table are less than 0.05, therefore rejecting the null hypothesis of no serial autocorrelations. It can therefore be concluded that ARCH effects are present in the return series distribution.

5.1 In-Sample Analysis

Now that the distribution is described and it is clear that non-normality is the case a closer look is taken at the indicators itself. Figure 5.2 shows the returns of the indicators for illustrative purposes.

Figure 5.2

Plotted are the compounded returns of the various indicators and the benchmark.



Overall the indicators seem to outperform the benchmark, except for the MACD indicator. The detailed results for the full sample and the sub-samples are presented in table 5.4. Panel A shows the results for the full sample and panel B shows results for the sub-periods. The Sharpe (1994) ratio has been included as a measure of comparison. The Sharpe ratio is calculated using the following formula:

$$\text{Sharpe} = \frac{\bar{r}_i - \bar{r}_f}{\sigma_i}$$

A high Sharpe ratio indicates that the indicator yields high returns compared to the level of risk taken. No Sharpe ratios have been calculated for negative returns in order to adhere to the standard interpretation of the Sharpe ratio.

Table 5.4 Sample statistics default Indicators

Results are presented for the full sample and for the four non-overlapping sub periods. The first two columns show the number of trades executed. Total return is calculated using compounded daily returns. Excess returns are based on a risk free rate of 3.97%. Results for the sub-samples are given in panel B.

Period	Test	#buy	#sell	SUM	Total return	Annual Return	Total Annual Excess Return	Annual SD	Annualize Sharpe
Panel A: Full Sample									
2000-2012	Buy&Hold	1	1	2	-53.35%	-3.7%	-7.67%	4.73%	-
	MACD	133	133	266	-58.39%	-3.91%	-7.88%	6.40%	-
	RSI	121	89	210	43.38%	3.05%	-0.92%	8.32%	-
	DEMA	74	74	148	126.75%	7.06%	3.09%	8.94%	0.35
Panel B: Sub Periods									
1999-2003	Buy&Hold	1	1	2	-67.47%	-25.75%	-29.54%	7.03%	-
	MACD	38	37	75	14.13%	6.55%	2.76%	3.75%	0.73
	RSI	29	20	49	-51.23%	-27.32%	-31.11%	7.92%	-
	DEMA	14	15	29	76.46%	28.71%	24.92%	11.85%	2.10
2003-2007	Buy&Hold	1	1	2	133.88%	21.66%	17.87%	9.17%	1.95
	MACD	47	47	94	-0.24%	-0.06%	-3.85%	3.75%	-
	RSI	18	51	69	-20.50%	-5.16%	-8.95%	3.75%	-
	DEMA	17	17	34	21.86%	4.67%	0.88%	3.31%	0.27
2007-2009	Buy&Hold	1	1	2	-64.47%	-34.79%	-38.58%	9.98%	-
	MACD	9	9	18	-72.19%	-38.55%	-42.34%	12.18%	-
	RSI	17	15	32	-48.93%	-33.18%	-36.97%	11.51%	-
	DEMA	6	6	12	87.07%	45.61%	41.82%	16.01%	2.61
2009-2012	Buy&Hold	1	1	2	48.84%	12.67%	8.88%	11.26%	0.79
	MACD	40	41	81	14.61%	4.63%	0.84%	4.64%	0.18
	RSI	23	35	58	9.73%	2.82%	-0.97%	7.24%	-
	DEMA	15	14	29	37.17%	9.95%	6.16%	7.47%	0.82

Results from table 5.4 show the excess returns compared to the annual risk-free rate of 3.97% based on Dutch treasury bills. Some observations can be drawn by looking at these results, which will be properly tested later by means of robust statistical analysis. Comparing the indicator returns to the benchmark, two out of three indicators are able to beat this benchmark, based on total annual excess returns. However when the Sharpe ratio is computed and the indicators are compared to the risk-free rate only the DEMA indicator is able to prove profitable.

In order to properly test the results of the three default indicators, table 5.4 will not suffice since it shows merely observations. A proper statistical analysis as discussed in section 4 is performed guided by the first hypothesis.

1) Any of the three indicators on its own outperform the benchmark, after deducting reasonable transaction costs, using Jensen's Alpha as performance measure.

Table 5.5 Regression output default indicators

Results are presented for the full samples using daily returns. p-values are presented, shown below the estimate. Jensen's alpha (α) is annualized in order to simplify observations drawn from the results. Trading volume is measured as the sum of both buy and sell signals.

	DEMA	MACD	RSI
α	-0.0270	0.0420	0.0347
	0.381	0.306	0.436
β	0.012066	0.441456	0.036037
	0.124	0.000	0.008
ARCH	0.155544	0.113508	0.100135
	0.000	0.000	0.000
GARCH	0.868291	0.879266	0.893567
	0.000	0.000	0.000
Trading Volume	266	210	148

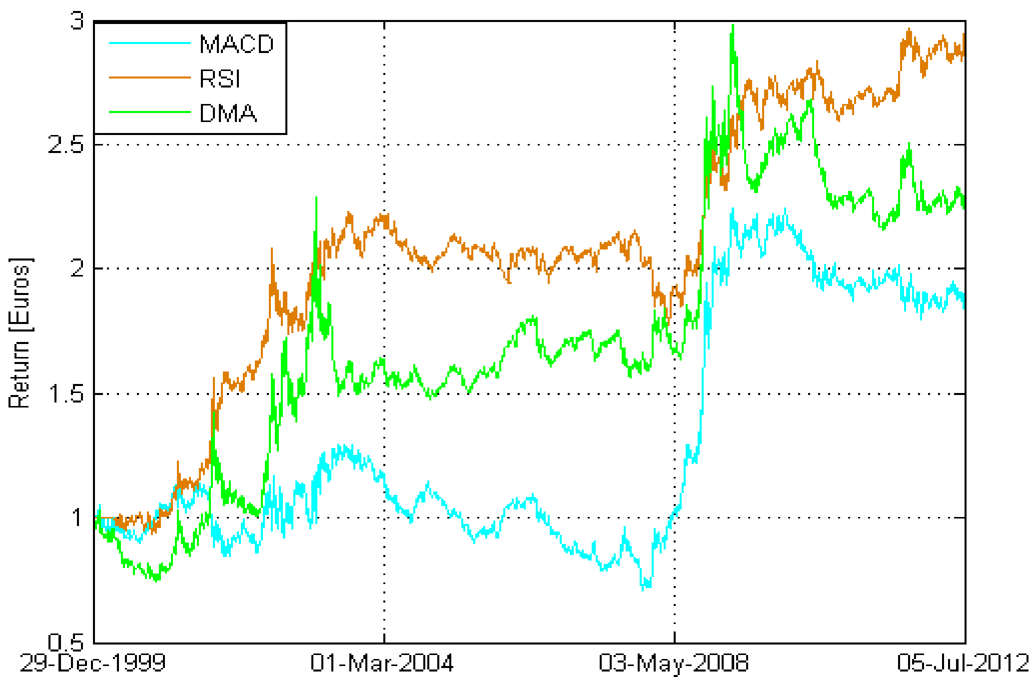
It immediately becomes clear from the regression results that all three alpha's are highly insignificant, therefore hypothesis 1 is instantly rejected. Despite the fact that all alpha's are highly insignificant these results can still provide useful insight into the default indicators by observing the beta's. The beta's are all highly significant, except for the DEMA indicator. A beta close to 1 implies that the indicator behaves similar to the market, therefore not exhibiting higher amounts of risk relative to the market. Table 5.5 shows that the beta for the MACD indicator is positive at a value of 0.44. Therefore the MACD appears to be slightly correlated to the changes in market returns. However the beta for the RSI is very close to zero which means that the returns of the indicator moves almost independent to the changes in the market returns. This is plausible since the indicator is indifferent to either upward or downward movements in the market and can profit from both movements. The market returns, which are measured by a buy-and-hold strategy, are long-only and therefore unable to profit from downward movements in the market. The ARCH estimator is significantly positive for all periods implying that the variance is going to be predicted higher in the next period following a high absolute return in this period. The GARCH estimator is significantly positive for all periods. When the GARCH approaches 1, next period's variance will be close to today's variance.

In order to attempt to improve the returns of the indicators and obtain positive alpha, refined versions of the default indicators are introduced. Inspired by Brock et al. (1992) and Gunter et al. (2001) I introduce a band that refines the default indicators.

The three default indicators that are tested in this study all contain one similar weakness. The indicators appear to work optimal in a setting of clear trends in the market. However when the market moves sideways, numerous 'whiplash' trades reduce profitability. These whiplash trades occur due to a sequence of signals occurring too close to each other in a short period of time. In order to filter out these whiplash trades I introduce a 'band' to the indicators. This band reduces the number of signals generated by refining the signals to a certain range. If the trade generated at time T occurs at a price too close to the price at the previous trade, time T-1, the signal is cancelled. Using Matlab optimization I define the band to 2%. For illustrative purposes the results of the refined indicators are shown in figure 5.3.

Figure 5.3

Plotted are the compounded returns of the indicators in combination with a 2% band.



It appears as if the returns have improved for all the three indicators. To provide a better comparison the detailed results are presented in table 5.5. For means of comparison the default indicator returns are also included. The refined indicators are shown with the band percentage in brackets.

Table 5.6 Sample statistics Indicators

Results are presented for the full sample and for the four non-overlapping sub periods. The first two columns show the number of trades executed. Total return is calculated using compounded daily returns. Refined indicators are accompanied by their band, shown in brackets. Excess returns are based on a risk free rate of 3.97%. Results for the sub-samples are given in panel B.

Period	Test	#buy	#sell	SUM	Total return	Annual Return	Annual Excess Return	Annual SD	Annual Sharpe
				Panel A: Full Sample					
2000-2012	Buy&Hold	1	1	2	-53.35%	-3.63%	-7.60%	4.73%	-
	DEMA	74	74	148	69.32%	4.49%	0.52%	10.72%	0.05
	DEMA (0.02)	35	29	64	125.37%	7.01%	3.04%	9.98%	0.30
	MACD	133	133	266	-58.39%	-3.91%	-7.88%	6.40%	-
	MACD (0.02)	56	71	127	84.00%	5.21%	1.24%	8.34%	0.15
	RSI	121	89	210	43.38%	3.05%	-0.92%	8.32%	-
	RSI (0.02)	85	88	173	194.37%	9.41%	5.44%	8.49%	0.64
				Panel B: Sub Periods					
1999-2003	Buy&Hold	1	1	2	-67.47%	-25.75%	-29.72%	7.03%	-
	DEMA	14	15	29	76.46%	28.71%	24.74%	11.85%	2.09
	DEMA (0.02)	5	6	11	128.83%	44.47%	40.50%	16.26%	2.49
	MACD	38	37	75	14.13%	6.05%	2.08%	3.75%	0.55
	MACD (0.02)	18	22	40	-2.17%	-0.96%	-4.93%	6.85%	-
	RSI	29	20	49	-51.23%	-20.18%	-24.15%	7.92%	-
	RSI (0.02)	7	20	27	121.56%	42.41%	38.44%	11.96%	3.21
2003-2007	Buy&Hold	1	1	2	133.88%	21.66%	17.69%	9.17%	1.93
	DEMA	17	17	34	21.86%	4.67%	0.70%	3.31%	0.21
	DEMA (0.02)	9	6	15	15.99%	3.48%	-0.49%	4.56%	-
	MACD	47	47	94	-0.24%	-0.06%	-4.03%	3.75%	-
	MACD (0.02)	16	20	36	-45.53%	-13.08%	-17.05%	5.49%	-
	RSI	18	51	69	-20.50%	-5.16%	-9.13%	3.75%	-
	RSI (0.02)	16	15	31	8.55%	1.91%	-2.06%	3.75%	-
2007-2009	Buy&Hold	1	1	2	-64.47%	-34.79%	-38.76%	9.98%	-
	DEMA	6	6	12	87.07%	45.61%	41.64%	16.01%	2.60
	DEMA (0.02)	2	1	3	141.54%	69.74%	65.77%	23.29%	2.82
	MACD	9	9	18	-72.19%	-38.55%	-42.52%	12.18%	-
	MACD (0.02)	4	7	11	140.54%	69.32%	65.35%	23.86%	2.74
	RSI	17	15	32	-48.93%	-33.18%	-37.15%	11.51%	-
	RSI (0.02)	5	13	18	56.53%	30.84%	26.87%	15.58%	1.72
2009-2012	Buy&Hold	1	1	2	48.84%	12.67%	8.70%	11.26%	0.77
	DEMA	15	14	29	37.17%	9.95%	5.98%	7.47%	0.80
	DEMA (0.02)	12	9	21	9.22%	2.68%	-1.29%	11.06%	-
	MACD	40	41	81	14.61%	4.18%	0.21%	4.64%	0.04
	MACD (0.02)	16	23	39	-28.71%	-7.87%	-11.84%	5.28%	-
	RSI	23	35	58	9.73%	2.82%	-1.15%	7.24%	-
	RSI (0.02)	20	18	38	33.29%	9.00%	5.03%	6.60%	0.76

Looking at the results of the full sample it is observed that the refined indicators prove to be more profitable. This is partly due to the lesser amount of transaction costs. Per year the MACD generates the most trades with an annual average of 22 trades. This is seen as a low amount of trades, therefore I conclude that it is not the decrease in transaction costs that increase returns but the decrease in unprofitable trades that increase returns. The three indicators show positive Sharpe ratios, implying that they are now all able to outperform the risk-free rate as well as the benchmark. The band seems to work well with the number of trades decreasing for all three indicators. The greatest improvement is shown by the refined MACD indicator which improves annual excess returns by 9.12% to 1.24%. The best performing indicator appears to be the RSI indicator which shows an annual excess return of 5.44%. Again these are observed results and should be properly tested on significance using Jensen's Alpha. Hypothesis 2 is used to guide the statistical analysis,

2) Refined indicators that use a band in addition to the default settings improve Jensen's Alpha compared to the default indicators.

Table 5.7 Regression output refined indicators

Results are presented for the full samples using daily returns. p-values are presented, shown below the estimate. Jensen's alpha (α) is annualized in order to simplify observations drawn from the results. Trading volume is measured as the sum of both buy and sell signals.

	DEMA	MACD	RSI
α	-0.1150	0.0400	-0.0155
	0.753	0.371	0.724
β	0.023123	0.013406	-0.096375
	0.060	0.352	0.000
ARCH	0.130467	0.103837	0.109465
	0.000	0.000	0.000
GARCH	0.880082	0.890168	0.884611
	0.000	0.000	0.000
Trading Volume	64	127	173

Again the alpha's for the indicators are highly insignificant and therefore hypothesis 2 is rejected. Turning to the beta's it now appears that the beta for the DEMA is significant at the 10% level. It is very close to zero and therefore moves indifferent to the return changes in the market. The MACD's beta is insignificant and therefore lacks useful insights. The beta for the RSI is highly significant and again close to zero. Comparing the default and refined indicators I cannot draw any conclusions concerning Jensen's Alpha. However the beta's are generally close to zero for both the default and refined indicators therefore it appears that the indicators move indifferent to the return changes in the market. The ARCH en GARCH terms again are highly significant. The ARCH and GARCH terms do not appear to be very different from the default indicators.

In order to provide further insights into the performance I extend the analysis to the sub-periods. To save space I will only present the results for the refined indicators since they are preferred due to the lesser amount of whiplash trades.

Table 5.8 Refined DEMA indicator - sub-sample analysis

Results are presented for the full sample and for the four non-overlapping sub periods using daily returns. p-values are presented, shown below the estimate. Jensen's alpha (α) is annualized in order to simplify observations drawn from the results. Trading volume is measured as the sum of both buy and sell signals.

	Full sample	1999-2003	2003 -2007	2007 - 2009	2009 - 2012
α	-0.1150	0.2617	0.1257	-0.0480	0.06025
	0.753	0.001	0.019	0.144	0.266
β	0.023123	-0.950822	-0.028828	-0.960228	0.824535
	0.060	0.000	0.182	0.000	0.000
ARCH	0.130467	0.622590	0.114284	1.907440	0.801664
	0.000	0.000	0.000	0.000	0.000
GARCH	0.880082	0.568009	0.850904	0.257378	0.497361
	0.000	0.000	0.000	0.000	0.000
Trading Volume	64	11	15	3	21

For means of comparison the full sample is included in the regression output. All sub-samples show lower p-values, therefore improving on significance. The 1999-2003 period alpha of 26.17% is highly significant. Most investors would be delighted to see such result, even more so considering this was a period of economic turmoil. Other sub-periods show insignificant alpha's. The beta for the 1999-2003 and 2007-2009 period are highly significant and close to -1. This implies that the indicators move in the exact opposite direction compared to the changes in market returns. This is plausible since both periods contain few trades. Since the indicators are indifferent to up or down swing in the market it is possible for them to move opposite to the market in such a short period of time. Periods 1999-2003, 2007-2009 and 2009-2012 show high ARCH values implying that the next period variance is expected to be considerably higher compared to the current period. These ARCH values are accompanied by low GARCH values, which is to be expected since this implies that next period variance is expected to be different from the current period variance.

Table 5.9 Refined MACD indicator - sub-sample analysis

Results are presented for the full sample and for the four non-overlapping sub periods using daily returns. p-values are presented, shown below the estimate. Jensen's alpha (α) is annualized in order to simplify observations drawn from the results. Trading volume is measured as the sum of both buy and sell signals.

	Full sample	1999-2003	2003 -2007	2007 - 2009	2009 - 2012
α	0.0400	-0.1257	-0.0843	0.0852	-0.1237
	0.371	0.000	0.163	0.000	0.000
β	0.013406	-0.807425	0.0667149	-0.984089	-0.965766
	0.352	0.000	0.000	0.000	0.000
ARCH	0.103837	0.300770	0.0792722	2.933849	20.540550
	0.000	0.000	0.000	0.000	0.000
GARCH	0.890168	0.851506	0.882698	0.320560	0.072552
	0.000	0.000	0.000	0.000	0.000
Trading Volume	127	40	36	11	39

Observing the results for the sub periods of the refined MACD indicator it becomes clear that merely the 2003-2007 period is insignificant and all other sub-periods are significant at the 1% level. It is only during the 2007-2009 period that the MACD shows positive alpha amounting to 8.52%. This is also the period with the least amount of trades. Looking at the beta's it is striking that all sub-periods show highly significant beta's whilst the full sample beta is insignificant. The MACD indicator moves indifferent to the changes in the market returns, except for the 2003-2007 period which has a beta close to zero. Again all ARCH terms are significantly positive with a strikingly high ARCH value for the periods 2007-2009 and 2009-2012. This could imply that the global financial crisis has a considerable effect on the predictability of the volatility of the MACD indicator.

Table 5.10 Refined RSI indicator - sub-sample analysis

Results are presented for the full sample and for the four non-overlapping sub periods using daily returns. p-values are presented, shown below the estimate. Jensen's alpha (α) is annualized in order to simplify observations drawn from the results. Trading volume is measured as the sum of both buy and sell signals.

	Full sample	1999-2003	2003 -2007	2007 - 2009	2009 - 2012
α	-0.0155	0.1122	-0.0360	0.09	0.0222
	0.724	0.000	0.519	0.159	0.070
β	-0.096375	-0.940667	0.009555	-0.994791	0.860666
	0.000	0.000	0.701	0.000	0.000
ARCH	0.109465	3.816940	0.115775	1.430647	1.173559
	0.000	0.000	0.000	0.000	0.000
GARCH	0.884611	0.211623	0.848040	0.305739	0.514412
	0.000	0.000	0.000	0.000	0.000
Trading Volume	173	27	31	18	38

For the RSI indicator the periods 1999-2003 and 2009-2012 are significant at the 10% level, whereas the other periods are insignificant. The RSI indicator performs very well at the 1999-2003 period with a positive alpha of 11.22%. It appears that the RSI indicator is well able to be at the right end of the Dotcom crash. Again extremely negative beta values are observed for the 1999-2003 and 2007-2009 periods, just as was the case for the MACD indicator. The ARCH and GARCH terms are all positive with considerably higher ARCH term for the 1999-2003 period.

Now that the three indicators have been thoroughly tested for the in-sample sub-periods, some observations can be drawn to complement the first and second hypotheses. Although the full sample results show consistent insignificant alpha's the sub-periods do show various cases of significant alpha's. This could imply that the indicators work better on short term horizons. There is no sub period for which the three indicators are all able to generate positive alpha. Looking at the beta there is more consistency to be found throughout the three indicators. All three indicators show beta's close to -1 for the 1999-2003 and the 2007-2009 period. Both these periods are characterized by extreme negative market returns. This shows that the indicators are able to move against the market when uncertainty and panic hits the Dutch financial markets.

It is interesting to see if the alpha's that were significant can be explained by using the Small Minus Big (SMB), High Minus Low (HML) and the Momentum (MOM) factors. A regression is used including these 3 factors in order to comment on hypothesis 4,

3) Traditional Asset Pricing Models along with a momentum factor are able to explain the alpha of the three indicators.

Table 5.11 Refined indicators - factor analysis

Results are presented for the full sample and for the four non-overlapping sub periods using daily returns. p-values are presented, shown below the estimate. Jensen's alpha (α) is annualized in order to simplify observations drawn from the results. Trading volume is measured as the sum of both buy and sell signals.

	DEMA	MACD			RSI	
	1999-2003	1999-2003	2007 - 2009	2009 - 2012	1999-2003	2009 - 2012
α_1	0.2617	-0.1257	-0.0843	-0.1237	-0.1122	0.0222
	0.001	0.000	0.000	0.000	0.000	0.070
β	-0.95082	-0.80742	-0.98408	-0.96576	-0.94066	0.86066
	0.000	0.000	0.000	0.000	0.000	0.000
SMB	0.00152	-0.000707	-0.00012	0.00005	-0.00028	0.00023
	0.000	0.000	0.004	0.000	0.000	0.000
HML	0.00071	0.00012	0.00000	0.00007	-0.00041	-0.00017
	0.000	0.000	0.152	0.000	0.000	0.000
MOM	0.00020	0.00041	0.00004	-0.00004	0.00037	0.00013
	0.000	0.000	0.118	0.000	0.000	0.000
ARCH	2.47787	7.89420	3.04091	28.84264	6.56203	11.9179
	0.000	0.000	0.000	0.000	0.000	0.000
GARCH	0.39180	0.25721	0.30318	0.05467	0.14711	0.06220
	0.000	0.000	0.000	0.000	0.000	0.000
α_2	0.38482	-0.17912	-0.08430	-0.10137	-0.16917	-0.04537
	0.000	0.000	0.000	0.000	0.000	0.000
∆α	-0.12310	0.05337	-0.00097	-0.02242	-0.04320	0.06760

The value of importance here is α_2 , the alpha after including the factors Beta, SMB, HML and MOM. The alpha remains different from zero for each sample. I therefore reject hypothesis 4 since the factors are not able to explain the entire alpha. However the factors do show significance overall, therefore they are able to explain part of the alpha. I expected the momentum factor to explain most of the variation in alpha, however this is not the case. The SMB factor shows most significance throughout the different samples.

5.2 Out-of Sample Analysis

In order to observe the characteristics of the indicators I study the indicators on an out-of sample dataset. As discussed in the data section several different types of markets are included in this dataset in order to study the characteristics of the indicators in a range of different speculative markets. All results are presented in appendix B in order to save space.

Table 5.12 shows the summary statistics for the 2000-2012 periods concerning the out-of sample dataset. The default DEMA indicator appears to be the best performing indicator amongst the default settings. However its refined version is not able to notably improve the results, with 3 instances of the default settings outperforming the refined settings based on Sharpe ratios. The MACD indicator performs very poorly throughout the dataset, with only the refined MACD indicator on the EUR/USD exchange rate generating positive Sharpe ratio. The default RSI indicator performs very poorly showing only positive Sharpe ratio for the FTSE. However the refined RSI appears to improve results, showing an impressive average annual return of 9.6% over all out-of sample markets. This improvement is confirmed by the positive Sharpe ratios for every indicator except the NASDAQ. Since the refined RSI indicator appears to perform consistently well, especially in comparison with the other indicators, I use a regression similar to the in-sample analysis in order to find out if this indicator is able to generate positive alpha. Table 5.13 in appendix B shows the results. The alpha's are significant at the 5% level except for the Dow Jones Index. Since the alpha's are not consistently positive I conclude that this indicator is unable to generate reliable risk-adjusted returns. The beta's are all strikingly close to 1 whereas the in-sample beta for this indicator is close to zero. It therefore appears that the refined RSI indicator moves in line with the change in market returns. A factor analysis is included in the regression output. In line with the in-sample results it appears that the factors are not consistently able to explain any positive alpha present.

6. Conclusion

The main purpose of this thesis was to test the three simple technical trading indicators as described by Covel in his bestselling book *Trend Following, how great traders make millions in up or down markets* (2004). Covel describes three indicators that provide the foundation to the profitable trading systems found in his book. In order to test these three indicators an extensive backtest procedure is set up to test the indicators individually on the AEX Index for the period 2000 - 2012. Performance is measured based on Jensen's Alpha and it is concluded that none of the three indicators are able to provide positive alpha. However since there is a large degree of freedom concerning the interpretation of the indicators by Covel I refine these indicators by introducing a band system that is able to filter out whiplash trades in order to improve profitability. The refined DEMA indicator generates 7.01% annual return, the refined MACD indicator generates 5.21% annual return and the refined RSI indicator tops with a 9.41% annual return. In order to include the amount of risk implicit in these indicators I perform an extensive regression analysis to study Jensen's Alpha. Since the returns of the AEX Index exhibit autocorrelation and heteroskedasticity I apply the CAPM-GARCH(1,1) model in order to overcome estimator biases in search of alpha. None of the refined indicators are able to provide significant positive alpha when regressed on the full sample using the CAPM GARCH(1,1). Conversely I find that the indicators are able to provide significant alpha when tested on certain sub-samples. For example the refined RSI indicator shows an annual significant alpha of 11.22% for the 1999-2003 period. It could be that the trading systems pictured by *Trend Following* are able to use these sub-period returns to make up for other losses. A trader that cuts his losses and lets his profits run is likely to find many of his trades unprofitable because he closes the trades after a certain loss percentage. However since this trader will let his profitable trades run he might be able to make up for these losses with certain very profitable trades, such as the 1999-2003 trade guided by the refined RSI indicator. In this way it could be possible that his trading system provides positive alpha even though the majority of his trades are unprofitable. In order to reject or validate such findings further research is needed that applies a "cut-loss system". However I do expect such a system to improve alpha due to some very high alpha's found in the sub-samples. In order to explain the positive alpha's for these sub-samples I add the factors Small Minus Big, High Minus Low and include a Momentum factor. None of these factors are fully able to explain the positive sub-sample alpha's. Furthermore there is little consistency throughout the factors therefore it is difficult to say which factor is able to explain most of the variation. Additionally I find that three indicators show beta's close to -1 for the 1999-2003 and the 2007-2009 period. Both these periods are characterized by extreme negative market returns. This shows that the indicators are able to move against the market when uncertainty and panic hits the Dutch financial markets.

An out-of sample analysis is used to give further insights into the characteristics of the indicators. This out-of sample dataset contains different types of financial markets in order to see how the indicators perform throughout different types of speculative markets. It is observed that the refined RSI indicator generates the most consistent results when applied to this out-of sample dataset. This is explained by the fact that the RSI indicator leads the price movements in the market whereas the two moving average-based indicators lag the price movements in the market.

In conclusion the three technical indicators depicted in *Trend following* do not seem to provide consistent significant positive alpha when tested individually. However this does not imply that the trading systems used by *Trend Following* are necessarily useless. Certain trading rules such as “cut your losses and let your profits run” could improve the alpha of the trading system when applied properly.

7. Limitations and Recommendations

This thesis tests the three simple technical trading indicators as described by Covel in his bestselling book *Trend Following, how great traders make millions in up or down markets* (2004). However it is difficult to replicate these trading rules since the trading systems that use these indicators do not provide exact definitions of the settings and parameters used for these indicators. For example it is unclear what time input is used for the fast and slow exponential moving average for the DEMA indicator. Also it is unclear to which extend the trading systems adhere to the golden rule; cut your losses and let your profits run. Further research is needed to find an optimal trading system that applies this golden rule. For example it could be that a trader should close his trades when they exceed a 1% loss of total portfolio value. This would amount to a large number of unprofitable trades but that could be compensated by building on the profitable trades.

Another limitation of this study is the use of closing prices. Since I apply a one day lag in order to overcome curve-fitting problems there is a serious lag between the generation of the trade and the actual trade itself. This lag could amount to a complete trading day. This is especially relevant when the indicators are used on a short term trading strategy. Intraday data is able to seriously reduce this lag and therefore capture possible profits that arise in between the generation of the trade and the trade itself.

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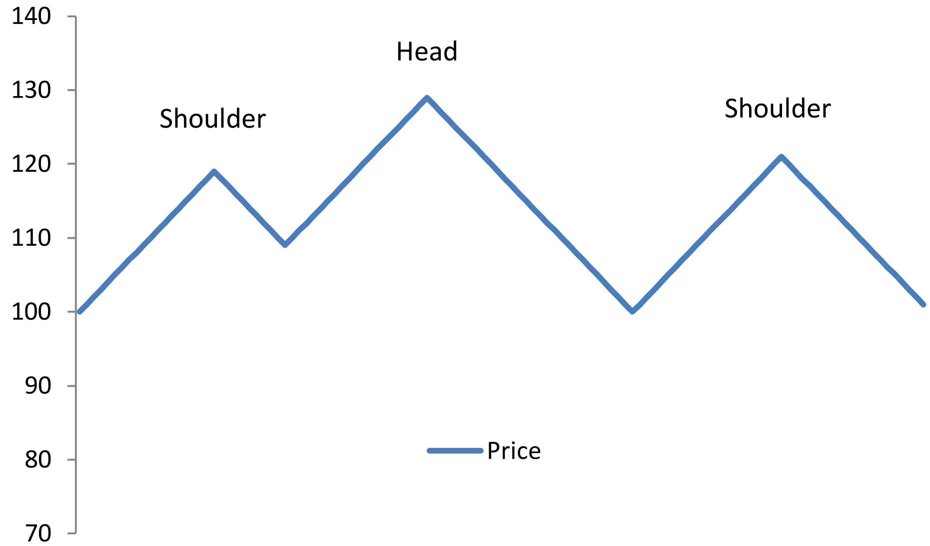
Appendix A

Figure A1 - Head Shoulder pattern

The Head and Shoulder pattern is most commonly observed in Bull markets, marking the end of an uptrend. The pattern can also be observed in Bear markets but is then reversed, therefore looking like the letter W.



Appendix B

Table 5.12 Out-of sample summary statistics

Results are presented for the periods showing significant alpha, using daily returns. p-values are presented, shown below the estimate. Trading volume is measured as the sum of both buy and sell signals.

Period	Test	#buy	#sell	SUM	Total return	Annual Return	Annual Excess Return	Annual SD	Annualized Sharpe
CAC40	Buy&Hold	1	1	2	-45.38%	-3.17%	-7.14%	5.41%	-
	DEMA	58	57	115	106.31%	6.22%	2.25%	8.77%	0.26
	DEMA (0.02)	60	50	110	72.08%	4.63%	0.66%	7.02%	0.09
	MACD	142	143	285	19.66%	1.51%	-2.46%	6.15%	-
	MACD (0.02)	70	72	142	52.68%	3.59%	-0.38%	7.71%	-
	RSI	117	88	205	55.80%	3.76%	-0.21%	7.95%	-
	RSI (0.02)	87	72	159	170.86%	8.66%	4.69%	7.85%	0.60
DAX	Buy&Hold	1	1	2	-6.64%	-0.54%	-4.51%	6.78%	-
	DEMA	69	68	137	85.49%	5.28%	1.31%	11.17%	0.12
	DEMA (0.02)	60	64	124	116.77%	6.66%	2.69%	9.11%	0.30
	MACD	131	132	263	-81.29%	-5.08%	-9.05%	7.05%	-
	MACD (0.02)	64	64	128	-80.17%	-5.03%	-9.00%	7.00%	-
	RSI	137	89	226	-10.11%	-0.81%	-4.78%	9.50%	-
	RSI (0.02)	96	78	174	165.71%	8.48%	4.51%	9.10%	0.50
FTSE	Buy&Hold	1	1	2	-36.65%	-2.64%	-6.61%	4.05%	-
	DEMA	76	75	151	64.20%	4.22%	0.25%	8.60%	0.03
	DEMA (0.02)	38	45	83	53.10%	3.61%	-0.36%	6.14%	-
	MACD	140	141	281	17.83%	1.38%	-2.59%	5.57%	-
	MACD (0.02)	57	48	105	58.56%	3.92%	-0.05%	6.14%	-
	RSI	106	75	181	74.19%	4.73%	0.76%	6.76%	0.11
	RSI (0.02)	75	58	133	167.59%	8.55%	4.58%	6.14%	0.75
DJI	Buy&Hold	1	1	2	9.75%	0.78%	-3.19%	6.03%	-
	DEMA	103	102	205	-42.54%	-3.00%	-6.97%	7.92%	-
	DEMA (0.02)	63	56	119	-42.27%	-2.98%	-6.95%	5.99%	-
	MACD	129	130	259	-72.38%	-4.64%	-8.61%	5.53%	-
	MACD (0.02)	61	55	116	35.30%	2.55%	-1.42%	6.07%	-
	RSI	117	79	196	-8.73%	-0.70%	-4.67%	7.02%	-
	RSI (0.02)	77	63	140	121.12%	6.84%	2.87%	6.24%	0.46
NASDAQ	Buy&Hold	1	1	2	-42.08%	-2.97%	-6.94%	4.61%	-
	DEMA	93	93	186	17.34%	1.34%	-2.63%	11.05%	-
	DEMA (0.02)	72	74	146	59.60%	3.97%	0.00%	8.02%	-
	MACD	133	133	266	20.65%	1.58%	-2.39%	7.36%	-
	MACD (0.02)	68	72	140	15.99%	1.24%	-2.73%	8.28%	-
	RSI	113	82	195	33.68%	2.45%	-1.52%	9.35%	-
	RSI (0.02)	77	67	144	26.82%	2.00%	-1.97%	9.62%	-
GOLD	Buy&Hold	1	1	2	336.85%	13.07%	9.10%	13.04%	0.70
	DEMA	104	103	207	-59.61%	-3.97%	-7.94%	6.99%	-
	DEMA (0.02)	33	40	73	81.43%	5.09%	1.12%	5.43%	0.21
	MACD	126	126	252	-96.53%	-5.79%	-9.76%	5.15%	-
	MACD (0.02)	44	53	97	-90.74%	-5.53%	-9.50%	5.39%	-
	RSI	117	76	193	-30.02%	-2.21%	-6.18%	5.54%	-
	RSI (0.02)	88	49	137	82.31%	5.13%	1.16%	5.21%	0.22
EUR/USD	Buy&Hold	1	1	2	25.76%	1.93%	-2.04%	5.02%	-
	DEMA	71	72	143	7.32%	0.59%	-3.38%	4.25%	-
	DEMA (0.02)	21	18	39	117.98%	6.71%	2.74%	3.53%	0.78
	MACD	128	128	256	-64.35%	-4.23%	-8.20%	3.54%	-
	MACD (0.02)	35	32	67	80.94%	5.07%	1.10%	4.40%	0.25
	RSI	105	89	194	-14.45%	-1.13%	-5.10%	3.12%	-
	RSI (0.02)	64	55	119	72.75%	4.66%	0.69%	2.94%	0.23

Table 5.13 Refined RSI indicator

Results are presented for the full sample using daily returns. p-values are presented, shown below the estimate. Jensen's alpha (α) is annualized in order to simplify observations drawn from the results.

Refined RSI	CAC	DAX	FTSE	DJI	NASDAQ	GOLD	EUR/USD
α	-0.0194	-0.0303	0.009175	-0.007025	0.0106	0.084125	-0.0543
	0.044	0.000	0.054	0.196	0.050	0.000	0.000
β	0.863440	0.908049	0.881720	0.902889	0.900340	0.953073	0.913264
	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SMB	0.000211	0.000647	0.000024	-0.00014	-0.00042	0.000203	7.92E-05
	0.007	0.000	0.396	0.000	0.000	0.000	0.000
HML	-0.00017	0.00057	-0.000417	-0.00015	-0.00151	0.00032	-6.9E-05
	0.001	0.000	0.000	0.001	0.000	0.000	0.000
MOM	-0.0001	-0.00098	0.000168	7.92E-05	0.000393	-8.5E-05	-1.6E-05
	0.011	0.000	0.000	0.000	0.000	0.000	0.000
ARCH	1.167277	1.582225	1.090010	1.657192	1.195731	2.521675	1.237817
	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GARCH	0.478279	0.407261	0.503793	0.392332	0.469392	0.311704	0.457800
	0.000	0.000	0.000	0.000	0.000	0.000	0.000
α	-0.00755	-0.0209	0.01145	-0.007375	0.0004125	0.084325	-0.0514
	0.426	0.000	0.058	0.188	0.944	0.000	0.000
∆α	-0.445400	-0.030300	-0.048825	-0.195025	-0.933400	0.084125	-0.054300