Lunds Universitet
Ekonomihögskolan

Title: **Above average? – A study of moving average technical trading rules**
Course: Master thesis (NEKM01) 15 ECTS

Name: Lenny Erlesand
Philip Örn

Supervisor: Erik Norrman

Date: 29th of August 2010
Spring term 2010

Abstract

The thesis investigates whether moving average technical trading rules can be applied profitably to ETFs of a wide range of commodities and indices, as well as directly to these underlying assets. It concludes that moving average strategies are not profitable in general, yet there are a few which can achieve excess profits for certain assets. The results were statistically tested using the bootstrap method, which showed that most trading results were statistically significant. It is observed that a moving average strategy can no longer be applied profitably to emerging markets, which in previous research have been shown to be very receptive to technical trading.

Content

1 Introduction and purpose

This section presents the background and the purpose of the thesis, as well as it explains the order by which the sections follow.

1.1 Introduction

The predictive proficiency, as well as the profitability, of technical analysis is a hotly debated topic. While efforts to interpret historical price patterns date back hundreds of years and enjoy widespread popularity to this day, they are disdained to say the least by most academics in the field of finance. The success of trading strategies, based on technical analysis, in delivering excess profits beyond those of the markets would disqualify even the weakest form of the efficient market hypothesis, also called the EMH. According to the EMH, market participants will quickly distinguish any profitable trading methods or strategies, as well as any relevant information, and trade until prices adjust so that no excess profit is to be had. Needless to say, the EMH can be considered quite a broad target, and to any student of economics with a contrarian streak, an appealing such. It has a certain winner-take-all character, and the downside involved is limited. Either a trading strategy is excessively profitable, in which case an authoritative theory is proven wrong, or it is not, in which case countless academics and even Nobel Laureates are correct.[1]

This thesis applies eleven different moving average strategies, each in four varieties, on twenty-one different securities, of which four are natural resources, nine are ETFs, and eight are indices. By including assets from very diverse classes and parts of the world, an attempt has been made to employ a wide range of data which can result in broadly applicable results. The selection of several ETFs as focal points for the analysis is motivated by the authors' desire to study strategies which are sure to be practically applicable using broadly available investment products. All too often trading strategies are presented which are nearly impossible for any broader audience of investors to replicate, either due to excessive transaction costs or limited market access. This shall not be the case with this thesis.

[1] Paul Samuelson, who won the Nobel Memorial Prize in Economic Sciences in 1970, published proof for a type of the EMH in his 1965 article "*Proof That Properly Anticipated Prices Fluctuate Randomly*", Industrial Management Review, Vol. 6, No. 2, pp. 41-50.

1.2 Purpose

The purpose of this thesis is to determine whether trading strategies based on the moving average indicator can be applied with excessive profits on an extensive array of securities. Furthermore, it shall be concluded which choice of length, with which modifications, will deliver the very highest profits, and whether these are excessive in respect to a simple buy and hold strategy. A third inquiry to be resolved is whether moving average strategies fare better than a buy and hold strategy during generally bear markets. Obviously such an analysis would also investigate whether the weak form of the efficient market hypothesis holds for the assets and markets under consideration.

1.3 Outline

Section	Contents
2	**Exchange Traded Funds** - Provides a factual backdrop to ETFs
3	**Theory** - Describes theories and concepts which are central to the subject for the thesis, as well as for a thorough understanding of the investigation conducted
4	**Previous Research** - Consists of a comprehensive and detailed account of previous research done on the application of technical analysis strategies, as well as of articles which are of value for the full appreciation of the study
5	**Data** – Provides some information about how the data has been collected and problems that might arise in the study.
6	**Methodology** - The methods of analysis of the time series are thoroughly portrayed
7	**Results** - The results attained in the study are presented
8	**Analysis** – The analysis of the strategies is conducted.
9	**Conclusion** - Contains a concise conclusion of the results and of the analysis carried out.
10	**Future Research** – Suggestions for future research.

2 Exchange Traded Funds

This section provides a detailed overview of exchange-traded funds by thoroughly explaining their structure and accounting for the overall development of the ETF industry. Furthermore, using data and figures for the U.S., provided by the Investment Company Insitute, an explicit representation is given of the current status of the industry in its largest market, the U.S..

Exchange-traded funds, usually abbreviated ETFs, are usually organized as mutual funds which they also have similarities to, except that shares in ETFs are freely traded on stock exchanges just like regular stocks (*Securities and Exchange Commission, 2008, p.14619*). Another aspect which distinguishes ETFs from regular mutual funds is that the supply and demand of the marketplace determines the price of each share, meaning that it can fluctuate both above and below its net asset value (NAV). Departures from the funds' intrinsic values are however quite transitory as authorized participants, the institutions assigned the task of assembling the securities which ETF shares consist of, can cash in their shares in exchange for their net asset values at the end of every trading day. There are also arbitrage mechanisms which keep share prices close or equal to their net asset values. If for example a share is trading above its NAV, authorized participants may buy the basket of securities constituting the ETF, in exchange for shares in the ETF which then are sold on the market (*Investment Company Institute, 2010a, pp.43-44*).

Since the very first ETF was created in 1993, a fund trailing the Standard & Poor 500 Index, the number of funds has grown to 839 merely in the United States, with a combined 805.364 billion dollars under management. As a side note, it can be mentioned that the original 1993 fund, *Standard and Poor's Depositary Receipts*, which is included in this study, is still traded as well as it is the single biggest ETF with total net assets amounting to 73.395 billion dollars.[2] In the twelve months up until March 2010, assets under management in U.S. ETFs grew by 67.1%, or 323.35 billion dollars. Solely during the month of March 2010, net issuance of ETF shares was 21.323 billion dollars (*Investment Company Institute, 2010b*).[3] The recent subprime crisis did not seem to discourage investors significantly from investing in ETFs, as the net issuance in the U.S. of ETF shares during 2007 was 151 billion dollars. For

[2] As of May 10th 2010. Fund overview for SPDR S&P 500 ETF (SPY) provided by State Street Global Advisors.
[3] Investment Company Institute (2010)b. Data on Exchange-Traded Fund Assets, March 2010.

2008 it was 177 billion dollars and for 2009 the same figure was 116 billion dollars. These numbers clearly indicate that ETFs are experiencing a rising popularity. Not only among institutional investors using them to profit from broad market movements, but also among retail investors as ETFs comprised 6% of total assets under management by investment companies in the U.S. at the end of 2009 (*Investment Company Institute, 2010a, p.45*). While the stock market slump did not decrease investor interest in ETFs as an investment product, demand for broad U.S. equity ETFs shrank somewhat, evident in the 12 billion dollar net negative share issuance in such ETFs (*Investment Company Institute, 2010a, pp.46-47*).

When initiating ETFs, fund companies first choose an objective for the fund, that is what its investment profile should be. More often than not, ETFs track a particular index, asset class, commodity or broad industry portfolio. Yet, there are also actively managed ETFs, 22 in the U.S. at year-end 2009, which function similarly to mutual funds, except for the instant transferability of shares. Secondly, a method of tracking the target asset is picked. Either the fund constructs a portfolio consisting of all the securities which are to be tracked, or it only holds a smaller sample of securities which suffice in delivering the replicated return (*Investment Company Institute, 2010a, p.42*).

Regarding the fauna of ETFs available, growing investor demand has brought a greater selection of profiles. However, in the U.S. at the end of 2009, U.S. large cap equity ETFs were still the biggest and most common investment profile with 191 billion dollars under management. Emerging markets were the runner up with 109 billion dollars, amounting to 14% of assets under management at year-end 2009, closely followed by bond and hybrid funds which accounted for 107 billion dollars (*Investment Company Institute, 2010a, pp.46-47*). ETFs do however offer a much broader span of products and investment opportunities. In recent years ETFs focusing on certain sectors (e.g. technology, auto, finance or real estate), as well as on more specific industries and commodities have been launched. Looking solely at commodity and sector ETFs in the U.S. at the end of 2009, commodity funds only make up 21% of actual funds yet account for 48%, or 75 billion dollars, of all assets under management (*Investment Company Institute, 2010a, pp.47-49*).

The popularity of more distinct and specific funds such as those focusing solely on certain precious metals (approximately 67% of commodity funds trailed either gold or silver spot prices), or bond niches such as corporate loans with specific lengths, point towards that investors are embracing simpler ways of investing in previously hard to reach and illiquid assets (*Investment Company Institute, 2010a, p.47*). The simplicity of investing as well as the instant transferability of shares are arguably the key advantages of ETFs. They are especially liberating to the broad category of retail investors which previously were shunned to broad market indices. They can now, with an ease and broad appeal not offered by mutual funds or futures, include specific assets in their portfolios without incurring deterring transaction costs and management fees. When looking at the big picture, ETFs are inadvertently contributing in making markets more efficient and prices adjust quicker by bringing in more participants.

3 Theory

This section consists of a detailed portrayal of theories and notions which are at the very core of the thesis. First off, technical analysis as a concept is described. The main focus is on moving averages, of which several different types are dealt with comprehensively. The second part of the section is about the efficient market hypothesis, where its cornerstones, as well criticism against it, are presented.

3.1 Technical analysis

Technical analysis, or charting theory as it is also known, is a collective term for a wide assortment of trading rules which in some way are based on securities' historical data (*Brock et al, 1992, p.1731*). It is the method by which forecasts are attempted to be made on the basis of past observations and prices, i.e. price history (*Griffioen, 2003, p.4*). Chartists, which appliers of technical analysis are called, consider historical patterns in the price movements of securities to be a depiction of investors' decisions, which they believe will be made again given the same circumstances, resulting in reoccurring price movements. When utilizing technical analysis the assumption which inevitably is made, is that historical security prices contain information which determine, or at least influence, the behaviour of future security prices (*Fama, 1965, p.34*). Even though technical analysis was applied as early as in the 18th century in Japan, then in the form of candlestick charts, modern technical analysis can be said to have its origins in the works of Charles Dow (*Nison, 2001, pp.15-18*). Around the turn of the 20th century he wrote a number of editorials in *The Wall Street Journal* where he discussed the behaviour of the stock markets, as well as presented a number of ideas and theories on how to profitably trade stocks. These editorials were compiled in a book in 1902, in which they were given the name *The Dow Theory* (*Murphy, 1998, pp.23-24*).

The substance to be found in technical analysis is widely disputed. Burton Malkiel called it the *anathema to the academic world*, as well as *patently false* and *easy to pick on* (*Malkiel, 2007*). Nevertheless, according to a 1992 study by Mark P. Taylor and Helen Allen, 90% of chief foreign exchange dealers in London utilized it in some way (*Taylor and Allen, 1992, pp.311-312*). This fact, together with the exposure which technical analysis is receiving both in academic and popular literature, in newspapers, magazines, on television as well as in newsletters by brokerage firms and banks, suggests that it enjoys widespread popularity and interest (*Brock et al, 1992, p.1732*).

3.1.1 In comparison to fundamental analysis

While technical analysis utilizes historical price data, fundamental analysis is the practice of analyzing the state of companies by considering financial, managerial as well as general business conditions. In effect it is the normative determination of what a company's prospects are, made on the basis of information about it. Comparatively, technical analysts can thus be said to give more weight to investors sentiment and psychology than fundamental analysts do. While the former analysts look at the financial state of a company which might be unchanged even though the market sentiment has changed, the latter keeps a close eye on price movements, which are immediately affected by any change in outlooks and attitudes (*Shefrin, 2002, p.54*).

3.1.2 Moving Averages

Moving averages are what are called finite impulse response filters which use a predetermined number of inputs to establish average values for segments of larger comprehensive data sets. Suppose that a full data set consists of a total of 1000 observations with varying values, with new observations being added continuously. Moving averages can then be calculated for different numbers of observations. For example, a moving average of 200 data observations were the last observation is the most recent one, will yield the average of the last 200 data points. As new observations are made and new data consequently is added to the full sample, the moving average will inch forward replacing the 200^{th} observations with the very newest observation, i.e. the 1^{st}, possibly changing the average value if the newest and oldest observation differ. What the moving averages offer are smoother plots of observation values, which become ever smoother as the number of inputs are increased, as temporary fluctuations are essentially given less impact on the final product.

Sometimes going under the name of moving average oscillators, the moving averages are often considered one of the most popular technical indicators among investors, lauded for their simplicity, straightforwardness and adaptability (*Brock et al, 1992, p.1733*). When applied to financial data such as stock prices and index values, moving averages are the calculated average prices of securities over certain time periods, which of course may be given any desired length. The price data used in the computations are usually daily closing prices. Nevertheless, the price time series may be modified to consist of high, low, closing or opening prices, as well as the data collection frequency may be altered to any increment, for example secondly or minutely data when calculating intraday averages (*Achelis, 2001, p.203*).

3.1.2.1 Lengths

The length chosen for the moving average is one of the most significant modifications of the indicator. A short length will naturally be more responsive than a longer one, which on the other will be better at signalling long term trends. Reasonably, the choice of length should correspond to the length of the price cycles in the underlying security. Steven B. Achelis has presented the following equation to determine the ideal moving average length:

$$Ideal\ moving\ average\ length = \frac{\text{Cycle length}}{2} + 1$$

Where *Cycle length* denotes the length between two peaks, or two troughs (*Achelis, 2001, p.204*).

When applied to stocks, the most commonly used lengths are 10, 20, 50 and 200 days, of which the 200-day moving average can be considered the most popular (*see Brock et al (1992, p.1735), Achelis (2001, p.204), Renz (2003), pp.83-84*). Lengths up to 25 days are regarded as short term, 25 to 100 days are intermediate, while 100 to 200 days are suitable for longer terms. Of course the lengths of the moving averages depend on the type security it is to be applied on. While 10, 20, 50 and 200 days are both popular and suitable when applied to stocks, moving average lengths for commodities are usually shorter than 40 days, an indication of their volatile nature. When it comes to futures, lengths are often even shorter than that, reflected in the popularity of a moving average combination of 4, 9 and 18 days (*Murphy, 1998, p.14*).

3.1.2.2 Bands

Moving averages can also be modified by introducing a so called band which encloses the longer moving average. The consequence of a band, commonly 1%, is that a buy or sell signal will not be given until the stock price or the shorter moving average has moved above or below this band. What a band aims to achieve is to eliminate or at least reduce the number of *whiplash* or *whipsaw signals*. That is, false signals which can occur frequently when prices are fluctuating, or whipsawing, in a narrow channel and the stock price, or short moving average, is quite close to the long moving average (*see Brock et all (1992, p.1735), Milionis and Papanagiotout (2008, p.184), Fong and Young (2005, p.48)*).

3.1.2.3 Signals

The moving average trading technique generates signals whenever the price of the security crosses the moving average. When the price crosses the average from beneath, i.e. rises above the average, a buy signal is given. Whenever the price moves downwards across the moving average, a sell signal is generated (*Achelis, 2001, p.203*). However, depending on the moving averages and lengths of these used, signals might be generated by the averages crossing each other. It is quite common that instead of using the actual price of the security, which actually can be considered the 1-day moving average, a 2- or 5-day moving average is used. In such a case a signal is generated when the shorter length moving average crosses the moving average with a longer time period (*Brock et al, 1992, p.1735*).

3.1.2.4 Weighting

Apart from variations in the type and frequency of the input data, modifications are usually made to the weight which is assigned to data observations. Different weighting determines whether old observations are given the same significance and impact on the full average. The predicaments concerning equal weighting are that it makes the moving average unresponsive to recent occurrences, as well as it results in that observations suddenly go from as important as the most recent one to meaningless when they are pushed out of the data series. Furthermore, equal weighting causes the averages to be susceptible to *ghost effects*. A small number of incredible and highly improbable observations, for example extremely high or low prices during a very small time period of high volatility, will have an unwarranted impact on the averages and disrupt their credibility until they are taken out of the data series (*Dowd, 2006, pp.92-93*).

There are several common types of moving averages, differing mainly in their application of various weights to observations; simple or arithmetic, exponential, time series, triangular, volume adjusted and weighted (*Achelis, 2001, p.203*).

3.1.2.5 Simple moving averages

The simple moving average assigns equal weights to all observations. It is created by adding price data for a certain number of time periods, i.e. the length of the moving average, and then dividing by the number of time periods (*Achelis, 2001, p.207*).

$$Simple\ moving\ average = \frac{\sum_{t}^{n} \mathrm{price}}{n}$$

Where *n* is the number of time periods, and *price* is the price of the security

.

3.1.2.6 Expontential moving averages

Exponential averages assign observations with weights that decrease exponentially, which gives recent observations more significance and a larger impact on the value of the average. The weighting factor is given a value between 0 and 1, where a higher value diminishes the importance of older observations more rapidly (*Achelis, 2001, pp.208-209*).

$$EMA_t = (w * p_t) + \left((1 - w) * EMA_{t-1}\right)$$

Where EMA_t is the value of today's exponentially weighted moving average, *w* is the weighting, p_t is today's security price and EMt_{t-1} is the value of yesterday's exponentially moving average (*Roberts, 1959, p.240*).

3.1.2.7 Time series moving averages

Also called a time series forecast, it calculates the trend, which is arrived at through a linear regression analysis, of a security's price over a certain time period. The time series average predicts and plots the next point of the linear regression by appending the slope of the linear regression to the actual value of the linear regression. It therefore gives a price which the security, from a purely statistical point of view, should achieve in the next period given that the present trend in the security's price development maintains itself (*Achelis, 2001, pp.210, 333-334*).

3.1.2.8 Triangular moving averages

Triangular moving averages are moving averages of moving averages, i.e. they are double smoothed moving averages. Most of the weight is assigned to observations in the middle of the data series (*Achelis, 2001, p.210*). The double smoothing makes the average more even and slightly less responsive to sudden and rapid price movements.

$$Triangular\ moving\ average = \frac{\sum_t^n Simple\ MA}{n}$$

Where *n* is the number of time periods, i.e. the length, used.

3.1.2.9 Volume adjusted moving averages

The volume adjusted moving average weights the data observations according to the trading volume at the time of the data recording. Thus, most of the weight in the average is assigned to observations made during the days of the data set with the largest trading turnover (*Achelis, 2001, p.212*). It is calculated by first computing the average volume of the time series. This figure is then given a certain volume increment value. Dick Arms who developed the method would assign the average volume a value of 1. Larger volumes would then be given corresponding multiples of the increment value, though rounded off upwards to the nearest integer. Say for example that the average daily volume was 10'000 shares. A day during which 12'000 shares were traded would be given an increment value of 2, as 1.2 is rounded off upwards. A volume of 23'000 would be given an increment value of 3, and so on. The increment value determines how many entries to the moving average the trading day is given. A 10 period moving average would compute the average of the ten most recent price entries (*Arms, 1996, pp.55-56*). The reasoning behind the volume adjusted moving average is that securities usually initiate new trends under heavy trading. Volume weighting will then assign turning points such as high volume tops and bottoms more importance, resulting in earlier signals (*Arms, 1996, pp.59-60*).

3.1.2.10 Weighted moving averages

The weighted moving averages places the majority of the weight on the most recent price observations. It is calculated by multiplying each observation with the number of time periods which have passed since the very first price recording, i.e. their weight factor. Thus, a 100-day average would allocate a 100 times more weight to the most recent observation than to the first one. The second most recent observation would then be multiplied by a weight factor of 99, and so on. The sum of these products would then be divided by the sum of all weight factors encompassed by the length of the moving average (*Achelis, 2001, pp.212-213*).

3.2 Efficient market hypothesis

The efficient market hypothesis states that market prices of securities reflect all available information. That is, that all information available to investors has been incorporated into the securities' price (*Fama, 1991, p.1575*). This statement implies that there are no excess profits to be made by trading on any information, since this information will already have been priced in (*Jensen, 1978, p.96*). This hypothesis will only be fully accurate in the case of zero information and zero transaction costs. Since there naturally are certain costs for both of these, the most extreme form of the efficient market hypothesis will probably not be fulfilled (*Elton et al, 2007, p.400*). The hypothesis is categorized into three subdivisions of varying degrees of market efficiency; weak form, semistrong form and strong form. Research performed on the hypothesis is consequently catalogued under these headings (*Fama, 1991, p.1576*).

Weak form market efficiency states that all information contained in historical prices is incorporated in current prices. I.e., that there is no predictability to be found in time series of past prices. Before the 1970s, weak form tests focused on investigating whether forecasts of future prices could be made solely on the basis of past prices. More recent research in the area of market efficiency tends to focus on the predictive abilities of financial ratios and variables such as interest rates (*Fama, 1991, pp.1577-1578*). Research on the predictive powers of technical indicators, and the profitability of technical analysis also fall under the category of weak form tests, as do studies of calendar effects.

Semistrong form tests concentrate on whether all publically available information is completely incorporated into security prices, and furthermore, on how quick this inclusion is achieved (*Elton et al, 2007, pp.400-401*). Fama calls such research, event studies, since oft analyzed topics include occurrences such as stock market reactions to dividend hikes or cuts, and price movements after new issues of stock (*Fama, 1991, p.1600*). A test of semistrong efficiency could consist of studying whether it would be profitable to buy stocks immediately after announcements of dividend increases are made (*Elton et all, 2007, p.402*).

Strong form tests, termed by Fama as tests for private information, are concerned with whether all information, available both publically and privately, are wholly reflected in market prices of securities (*Fama et al, 1991, p.1577*). Tests of strong form market efficiency often focus on analyzing whether certain investor groups are able to consistently achieve excess returns. It is often spoken of whether certain groups have an information monopoly which they can utilize to attain superior returns. Numerous studies have been performed on the performance persistence of fund managers, one of the few groups of investors for which data is readily available (*Elton et al, 2007, p.402*). The stance of the strong form market efficiency is that no investors have a superior ability, and thus that it is not possible to consistently beat the market. The theory of strong form market efficiency thus shakes the reason d'être of mutual funds, portfolio managers, equity analysts as well as the practice of fundamental analysis at its very core, as their proficiencies and merits are considered temporary at best. The strong form asserts that it is impossible to beat the market in any way, with any information, which would imply that insider trading is an unprofitable pastime. A viewpoint which many studies as well as legislation in most countries discredits (*Fama et al, 1991, pp.1603-1604*).

3.2.1 The random walk model

The random walk model states that stock price movements can be likened to a *random walk*, meaning that its development and progress is completely unpredictable. It is defined as that successive returns are independent, and that returns are identically distributed over time (*Elton et al, 2007, p.403*). By this it is meant that each individual price movement, i.e. return, is completely uncorrelated to other price movements, and that every price movement or return is equally likely to occur. The random walk model lends support to the efficient market hypothesis since the instantaneous adjustments to new information which the hypothesis asserts, occur in an independent and random manner. While the information still is new, investors will assess its impact differently and act upon their own individual opinions of its worth, that is in an independent and random way (*Fama, 1995, p.76*).

The implications for technical analysis, of the random walk model being a correct rendering of the financial markets, is that its application is completely useless. Since every price movement is random and fully unpredictable, there is no excess return to be found in analyzing historical patterns (*Fama, 1995, p.80*). Fama states that since the empirical evidence in favor of the random walk model is so overwhelming, it is up to chartists to provide evidence that they can consistently deliver excess returns using technical analysis (*Fama, 1995, p.80*).

3.2.2 Criticism of efficient market hypothesis

The efficient market hypothesis relies on three assumptions. The first is that investors are rational and value securities rationally. Secondly, it is assumed that trades by irrational investors are random and cancel each other out on average. The final assumption is that irrational investors are countered by arbitrageurs which bring securities to rational prices (*Schleifer, 2000, p.2*).

Concerning the first assumption it has been asserted that investors are hardly fully rational, as they do not only take fundamental aspects of securities into consideration when making investment and trading decisions. Examples of such less than rational influences and decisions would be taking advice from questionable financial experts, overweighting positions and failing to diversify, trading on hunches and sentiment, overreacting to news, trying to “pick” stocks and intentionally taking on losses for fiscal reasons (*Schleifer, 2000, p.10*).

When it comes to the second assumption, it has been shown that investors stray collectively from rationality, not randomly. There is a high correlation among trading by irrational investors. What worsens the problem is the inclination of people to listen to rumours, be affected by herd mentality, imitate each other, and trade on collective premonitions (*Schleifer, 2000, p.12*). Examples of this would be the tendency of fund managers, which as a group oversee the investment of much of the capital in the financial markets, to overweight in assets which follow their benchmark closely, for example by investing in index products. This is done in order to bolster the probability that performance at the very least is not worse than that of the benchmark. Furthermore, managers have been shown to be inclined to buy the same stocks as well as stocks in the same industries, in order to at least not perform worse than their peers. What this results in is in fact a high correlation among the actions of fund managers, implying that any action in effect is not just random, but followed by many more similar dealings (*Schleifer, 2000, pp.12-13*).

Pertaining to the third and final assumption, that arbitrage will keep irrational pricing in check, an essential component is the availability of close substitutes to the irrationally prices security which is to be arbitraged. Securities such as futures and options will of course have such appropriate substitutes, but for certain individual stocks there might not exist a substitute which offers traders a riskless arbitrage. This would imply that certain stocks which fall into a no-substitute category would remain irrationally priced, at least for a while (*Schleifer, 2000, pp.13-14*).

4 Previous research

The following section gives detailed accounts of 11 previous studies conducted on simple moving average technical trading rules, beginning with Brock et al. (1992) which set the standard for most subsequent research on the subject.

Simple Technical Trading Rules and the Stochastic Properties of Stock Returns
Authors: Brock, Lakonishok, LeBaron (1992)

The authors investigated what according to them was one of the simplest and most popular technical trading rules; the moving average-oscillator. The data used in the study encompassed daily closing prices for the Dow Jones Industrial Average for the years 1897 to 1986, yielding a total of 90 years of data. The lengths that were chosen for the moving average-oscillator were 1-50, 1-150, 5-150, 1-200 and 2-200. The choices of these lengths were explained by their popularity among investors, as the authors wished to examine the most popular variations of the moving average oscillator trading technique. Furthermore the paper introduces a 1% band around the moving averages, which reduces the number of whiplash signals arising when the moving average are very close to each other. This initiative is also explained by this particular modification's popularity. In sum, ten variations of the moving average-oscillator are formed. Three rules of the moving average trading technique were studied, the variable length moving average (VMA), the fixed length moving average (FMA) and the trading range break (TRB). The first two are very similar apart from the fact that the latter stipulates a specific holding period after a signal, after which the position is closed. The authors once again explain their choices of rules by referring to their simplicity and popularity.

It is concluded that the differences between daily returns of buy and sell signals given by the variable length moving average are all positive and statistically significant, which rejects the null hypothesis of equality, i.e. of the rule not being able to deliver any excess returns. The average one-day return given by buy-signals for all ten variations of the rule is 0.042%, or roughly 12% on a yearly basis. The results for all ten variations are statistically significant on the 5 percent level, although four only marginally so. The average one-day return of sell-signals is -0.025%, or -7% on an annual basis. These results are all firmly significant on the 5 percent level.

In addition to having used the data for the Dow Jones Industrial Average, the authors simulated additional data using the bootstrap methodology in order to be able to test statistical inferences. The returns delivered by buy and sell signals using the original Dow Jones data was compared to returns given by simulated series based on the null hypothesis that no excess return is possible. More specifically the models were: a random walk with a drift, AR(1), GARCH-M and EGARCH. None of the returns delivered by the Dow Jones data could be replicated by these models, as buy and sell signals always yielded better performance than the normal returns given by the simulated series. Taken together, the results supported the technical trading rules and indicated that the strategies had strong predictive capacities, although transaction costs could diminish potential returns.

The profitability of technical trading rules in the Asian stock markets

Authors: Bessembinder, Chan (1995)

Bessembinder and Chan investigate whether technical analysis, more specifically variations to the moving average technical trading rule, can be considered to have predictive capabilities in the financial markets of Hong Kong, Japan, Korea, Malaysia, Thailand and Taiwan. It is considered that if the stock markets are relatively inefficient the strategies will be successful, while efficient markets will hamper their application. The authors refer to Brock et al. (1992) in their choice of rules for the technical analysis strategy, stating that they wish to avoid data-snooping biases by applying the exact same rules as Brock et al. Apart from the VMA, the rules examined were the FMA and the TRB. The variations to these rules which were studied in the paper were the same as those applied by Brock et al.; lengths of 1-50, 1-150, 5-150, 1-200 and 2-200, all of which were evaluated with and without a 1% band.

In total there were sixty observations for the VMA rule as there are ten variations to the rule and six markets. Out of these, 53 observations demonstrated buy signal-returns which exceeded sell signal-returns. The last seven observations were all from Japan, possibly attributable to the efficiency of its financial markets. The average daily difference between buy signal and sell signal returns was 0.103%, or 29.2% on an annual basis. The average daily difference for Hong Kong, Japan and Korea was 0.037%, while it was 0.168% for Malaysia, Thailand and Taiwan, possibly reflecting the inefficiency in the latter's financial markets.

The authors followed the lead of Brock et al. and applied a bootstrap methodology in order to assess the results of the original data. The data series simulated using bootstrap produced p-values of 0.160, 0.334 and 0.038 for Hong Kong, Japan and Korea, and an average p-value of less than 0.001 for Malaysia, Thailand and Taiwan. These results once again suggested that the three former stock markets were more efficient than the three latter. The bootstrap simulations thus rejected the null hypothesis that the returns for buy signals and sell signals are equal concerning Malaysia, Thailand and Taiwan. The authors concluded that the technical trading rules had predictive powers in certain Asian stock markets, reflecting their information inefficiency during the sample period.

A note on the weak from efficiency of capital markets: The application of simple technical trading rules to UK stock prices – 1935 to 1994

Authors: Hudson, Dempsey, Keasey (1996)

The authors replicated the study of Brock et al. (1992) by investigating whether two technical trading rules, the moving average oscillator and the trading range break out, could be profitably applied on the Financial Times Industrial Ordinary Index. The data sample consisted of daily closing prices for the FT30 index, spanning from 1935 to 1994. The lengths used in computing the moving averages were 1-50, 1-150, 1-200, 5-150, as well 1-50 with a 1% band. The study did not include a bootstrap test of the statistical significance of the results, as standard statistical tests were considered sufficient. The average daily return for all moving average rules for buy signals was 0.058%, or around 16% on an annual basis. The sell signals had an average daily return of -0.021%, or roughly 6% on an annual basis. However, only two out of five buy signals, but four out of five sell signals, were actually statistically significant. The buy signal returns clearly exceeded the returns delivered by a buy and hold strategy, amounting to 0.0264% on a daily basis, or circa 7% on an annual basis.

The authors concluded that technical trading rules did have a predictive ability, given a long enough data sample. Although the fact that more sell signals than buy signals yielded significant returns, made them question whether the moving average rule was a sustainable strategy.

Technical Analysis and the London Stock Exchange: Testing Trading Rules Using the FT30 –
Author: Mills (1997)

The paper used data from 1935 to 1994 for the FT30 Index, a total 15003 observations, to study whether two technical trading rules, the moving average oscillator and the trading range breakout, had any predictive abilities. The authors explain their choice of trading rules by referring to Brock et al. (1992). The choice of lengths for the moving average strategy, 1-50, 1-150, 5-150, 1-200, 2-200, is also justified by explaining that the paper follows Brock et al., as is the authors decision to analyze all variations both with and without a 1% band.

For the full sixty year sample period, the moving average strategies yield a mean daily return for buy signals of 0.053%, or 15% on an annual basis, which can be put in relation to the market return of 0.022% on a daily basis. Statistically significant t-statistics on the 5% level, which reject the null hypothesis of no excess returns for the strategies, can only be observed for two out of ten variations, more specifically for 1-50 with and without a band. For the sell signals, the mean daily return amounts to -0.015%, or roughly 4% on an annual basis. For the sell signals all variations except for two display statistically significant t-statistics which reject the null hypothesis. For the first two subperiods of the study, 1935-1954 and 1955-1974 the moving average strategies displayed results which were quite similar to those attained for the full sample. In other words, the strategies yielded excess profits which were statistically significant more frequently for sell signals than for buy signals. For the third and last subperiod, 1975-1994, the strategies showed profits which were not dissimilar to those of the market, furthermore the results displayed little statistical significance.

Following the lead of Brock et al. (1992), the author applied bootstrap methodology on the three subperiod samples, in order to assess the results of the original sample. The AR-ARCH bootstrap simulations showed that for the first subperiod, only 4.2% of simulations delivered higher performances following buy signals. For the second subperiod the number was 0.6%.. In the third subperiod however, the results from the bootstrap simulations were inconclusive. Taken together the bootstrap simulations affirmed the results attained from the original sample, being that during the first two subperiods the moving average strategy had predictive capabilities, though not during the third period. The authors concluded these results by stating that the trading rules could predict the market up until the 1970s, after which the strategy's performance was uncertain.

Profits on technical trading rules and time-varying expected returns: Evidence from Pacific-Basin equity markets
Author: Ito (1999)

The study investigated whether the three technical trading rules used by Brock et al. (1992), the VMA, the FMA and the TRB, could achieve excess returns when applied to Japanese, U.S., Canadian, Indonesian, Mexican and Taiwanese indices. Japan was dually represented both through a wide Japan index and Nikkei 225 futures. As was the United States, through a broad U.S. index, as well as through the Dow Jones Industrial Average. The data used for the three developed markets spanned from January 1980 to December 1996, while the data span for the latter emerging markets ranged from April 1990 to December 1996 for Indonesia, January 1988 to December 1996 for Mexico and January 1988 to December 1996 for Taiwan. The author chose the lengths for the moving average oscillator by following the method of Brock et al. (1992); 1-50, 1-150, 1-200, 2-200, 5-150. Furthermore, in accordance with the study of Brock et al., the variations are investigated with as well as without a 1% band.

For Japan, returns for buy and sell signals were positive and negative respectively, as well as the buy – sell difference was significantly different from zero at the 1% level. For Japanese Nikkei futures, the U.S. index and the Dow Jones Index, returns after buy and sell signals as well as buy – sell differences were mixed and never statistically significant. However, when it came to Canada, also a developed market, buy signal returns were positive, sell signal returns negative, and the buy – sell difference was significantly different from zero at the 1% level. Indonesia, Mexico and Taiwan all had positive buy signal returns and buy – sell differences which were significantly different from zero at the 1% level.

By running a bootstrap simulation, it was reaffirmed that the moving average trading strategy had predictive abilities for indices in Japan, Canada, Indonesia, Mexico and Taiwan. In Japan for example, only 3.34% of random walk simulations could generate higher buy signal returns, while only 0.6% of simulations could simulate lower sell signal returns.

The author concluded that the moving average trading technique had significant predictive abilities for the Japan index, Canada, Indonesia, Mexico and Taiwan. A result which had strong statistical support by bootstrap simulations.

Tests of technical trading strategies in the emerging equity markets of Latin America and Asia
Author: Ratner, Leal (1999)

The paper investigated whether a variable length moving average technical trading rule could be applied profitably on stock markets in ten Latin American and Asian emerging markets. The data set encompassed daily closing prices from January 1982 to April 1995, of local indices in ten emerging markets; Argentina, Brazil, Chile, India, Korea, Malaysia, Mexico, the Philippines, Taiwan and Thailand. For comparative purposes the United States and Japan were also included in the study. The authors stated that in order to avoid data snooping bias, they would follow the trading rules laid out by Brock et al. (1992). Thus the lengths analyzed were 1-50, 1-150, 5-150, 1-200 and 2-200. Since the return distributions of the strategies were not normally distributed, the authors applied a bootstrap methodology in order to test the statistical significance of the buy – sell differences.

Five moving average rules tested for ten markets each make for a total sample of fifty tests. Out of these forty-six trading rules had buy signal returns which were larger than sell signal returns, indicating a certain predictive ability in the moving average rules. Although, only fourteen buy returns were significantly larger than sell returns. Nevertheless, the average moving average return was superior to a buy and hold return in every emerging market except Argentina and Brazil. Transaction costs narrowed the occurrence of returns, superior to market returns, down to Korea, Taiwan, Thailand and Mexico. In Taiwan the moving average strategy delivered a yearly return of 32.14% compared to the buy and hold return of 17.59%. In Thailand the equivalent figures were 25.05% and 15.36%, in Mexico they were 20.52% and 19.53%, and finally in Korea they were 9.78% and 8.63%.

The authors drew the conclusions that moving average trading rules only offered limited abilities to profitably forecast stock price movements after taking transaction costs into consideration. According to the authors, the moving average strategy did however have certain forecasting abilities in more or less every market studied.

Simple technical trading rules of stock returns: evidence from 1987 to 1998 in Chile

Author: Parisi, Vasquez (2000)

Focusing on the stock market of Chile, the authors investigated the performance of what they considered two of the simplest and most popular trading rules. The data used encompassed daily closing prices for the Indice de Precio Selectivo de Acciones of the Santiago Stock Exchange from January 1987 to September 1998, a total of 2916 observations. Following the study of Brock et al. (1992), the lengths for the moving average strategy were set to 1-50, 1-150, 5-150, 1-200, 2-200. Furthermore, just as Brock et al. did, all length variations were analyzed both with and without a 1% band.

The ten moving average variations displayed a mean daily return for buy signals of 0.1655%, while the same figure for sell signals was -0.0512%. These results are quite different from the average daily return for the Chilean stock market over the full sample, amounting to 0.127%. Five out of ten results for buy signals are statistically significant, rejecting the null hypothesis of zero excess returns. When it came to the sell signals, seven out of ten results were statistically significant and rejected the null hypothesis. The authors interpret this as an indication that the moving average strategy would be able to prevent losses. The authors concluded the study by stating that the moving average strategy had a *special ability* to avoid losses, and that the technical trading rules would deliver excess returns given low transaction costs.

Trading rules and stock returns: some preliminary short run evidence from the Hang Seng 1985 – 1997

Author: Coutts, Cheung (2000)

The paper investigated whether it was profitable to apply two technical trading rules, the moving average oscillator rule and the trading range break out rule, on the Hong Kong Stock Exchange. The lengths analyzed are also the same as in Brock et al.; 1-50, 1-150, 5-150, 1-200, 2-200, both with and without a 1% band. The authors mentioned that these are the same rules as Brock et al. (1992) used. The data used in the study consisted of daily closing prices for the Hang Seng Index from October 1985 to June 1997, a total of 3061 observations. For the full sample period, the buy signals of the moving average trading rules deliver an average one day return of 0.155%, while the sell signals yield an average one day return of -0.152%. These results were noticeably higher than the buy and hold strategy's average one day return of 0.074%. Furthermore, the results for both buy and sell signals, for all variations of the moving average rule are significant at the 5% confidence level, robustly rejecting the null hypothesis of zero excess returns beyond the market yield. Concerning the sub-periods of 1985 to 1991 and 1991 to 1997, the returns for buy signals are positive, while returns for sell signals were negative. However, only the results for sell signals and the buy & sell strategy were significant. The authors concluded that the returns of the moving average trading rule were superior to the buy and hold strategy and thus could have constituted a profitable trading strategy, but that the high transaction costs of trading on the Hang Seng Index could diminish, if not eliminate, such excess returns.

Testing for predictability in emerging equity markets

Author: Chang, Lima, Tabak (2004)

The authors used a moving average trading technique to determine whether technical analysis possessed forecasting abilities concerning price changes in a number of emerging stock markets. The choice of technical trading rule was explained by the authors by the fact that most studies use the moving average strategy, following Brock et al. (1992). The lengths applied to the moving average strategy were also adapted from Brock et al. as they were considered the most common lengths and also were utilized in most studies; 1-50, 1-150, 5-150, 1-200 and 2-200. The data set consisted of local indices in eleven emerging markets as well as two developed markets included for comparative purposes; Argentina, Brazil, Chile, India, Indonesia, Malaysia, Mexico, the Philippines, South Korea, Taiwan, Thailand, Japan and the U.S.. The analyzed time period spanned from January 1991 to January 2004.

Relying heavily on bootstrap methodology, it was observed that the moving average strategy performed quite poorly. On average the trading rules delivered annual excess returns of -3.35% for emerging markets. Nevertheless, the moving average technique did yield superior returns for certain markets, noticeably Malaysia and the Philippines.

The authors concluded that the results attained indicated that technical analysis possessed meagre forecasting powers, except for in certain markets. It was noted that evidence in favour of the profitability of technical analysis now had disappeared in Mexico, where it had been applied profitably not long before the study at hand. It was considered that as the trading method became more broadly known and consequently more widely utilized, its profitability diminished.

The profitability of the simple moving averages and trading range breakout in the Asian stock markets
Author: Ming-Ming, Siok-Hwa (2006)

This study scrutinized whether the application of a variable moving average trading strategy, following the study conducted by Brock et al. (1992), could be profitably applied to various Asian stock market indices. The data consisted of daily closing prices, for a maximum time span ranging from January 1988 to December 2003, for nine local indices in China, Thailand, Taiwan, Malaysia, Singapore, Hong Kong, Korea, Indonesia and Japan. The authors used ten variations to the moving average rule, namely: 1-20, 1-60, 1-120, 1-180 and 1-240, all both with and without a 1% band.

In the stock markets of Malaysia and Korea the strategy delivered mostly statistically significant returns for buy signals for all lengths, rejecting the null hypothesis of zero excess return beyond those of the passive buy and hold strategy. The highest returns were delivered by the length 1-20 with a 1% band. In Japan no returns were statistically significant, which the authors interpreted as an indication of that particular market's superior information efficiency, also longer length moving averages performed better. In the financial markets of Hong Kong, Taiwan and China, the moving average strategy delivered superior returns which were the highest and most significant for lengths of 20 and 60 days both with and without a 1% band. The results for the stock markets of Singapore, Thailand and Indonesia were both superior to a buy and hold strategy, as well as they were mostly significant.

The authors concluded that except for Japan, the technical trading rules had a large degree of predictability as well as they delivered superior profits to passive market returns when applied to the particular markets dealt with in the study. The highest forecasting powers were offered by relatively short length moving averages such as 1-20 and 1-60, both with and without a band, except in Japan's case were longer lengths were more successful. The authors interpreted Japan's divergence concerning the most profitable length as an indication of the generally longer investment horizon in that particular stock market.

Technical Trading Rules in Emerging Markets and the 1997 Asian Currency Crises

Author: McKenzie (2007)

The paper scrutinizes the predictive ability of three technical trading rules; the variable length moving average, the fixed length moving average and the trading range breakout. The author explained his choice of trading techniques by referring to their popularity and the possibilities for direct comparison with previous research. The data set consists of seventeen Latin American and Asian emerging markets, as well as an US index which used as a benchmark. The sample period is different for different countries, but spans at the most from January 1986 to September 2003. Referring to Brock et al. (1992), McKenzie investigated the following length variations of the moving average trading technique: -50, 1-150, 1-200, 2-200 and 5-150.

On average, the variable length moving average strategy delivered mean daily returns following a buy signal which for every variation and for every country were superior to the mean daily returns of the sample market. The statistical significance of the difference of these results from the mean sample return did however differ from country to country. While none of the buy signal results for Brazil and Mexico were significant, six out of ten moving average lengths in Argentina's case gave buy signal returns which were significantly different from the sample mean. Concerning the sell signal returns, the returns and the significance of their difference from the mean sample returns varied. Nine out of ten variations of the moving average length for Argentina and Chile delivered statistically significant sell signal returns, while the same figure for Brazil and Mexico was zero. For the United States, the benchmark to which the results for the emerging markets was to be compared, no moving average lengths delivered significant returns, neither for buy signals nor for sell signals.

Just as Brock et al. did, the author applied bootstrap methodology on the samples in order to once more test the significance of the trading returns. The bootstrap simulations produced returns after buy and sell signals which were statistically significant noticeably more often than the original sample had. The null hypothesis of no forecasting power was thus rejected more often in the bootstrap simulations, reinforcing the notion that the moving average trading technique does have predictive capabilities and is able to deliver returns superior to those of the market. The authors conclude that the performance of a moving average trading strategy is country specific, in consistency with previous research; performing better in developing markets than in developed.

5 Data

This section accounts for the time series data utilized in the study, their time span, the number of observations, as well as it presents an econometric analysis conducted of their composition.

5.1 Data set

In an effort to achieve a broad and extensive data sample for the moving average strategies, both commodities, and indices for different countries and regions around the world, have been utilized. In order to ensure that the trading strategies are easily applicable in practice, exchange-traded funds, which trail the indices of the selected countries and regions, have been chosen instead of actual indices. Regarding the commodities this has not been the case, instead we opted to apply the trading strategies on the actual spot prices. The rationale being that the price data for ETFs trailing certain natural resources did not span over nearly as many years as the trailed spot prices, meaning that the latter had the advantage of a much larger data sample.

Daily closing prices for the commodities, ETFs and indices were gathered using Datastream Advance.

Appendix A shows econometrical and descriptive statistics regarding the data used, the table below describes these using the commodity copper as an example. The econometrical tests are based on a general autoregressive model of order 1, including a trend term and intercept,

$$P_{Copper} = \beta_0 + \beta_1 * Trend + \rho P_{Copper_{t-1}}$$

(1) Class and

(2) Line chart of price change during the period.

(3) Name of asset

(4) Price at first trading day of the specific period.

(5) Closing price at the end of the period.

(6) Indicated whether the intercept term in the OLS regression is significant and displays the p-value.

(7) Trend, same as (6) but analyses whether a trend is applicable.

(8) The coefficient of the AR(1) term.

(9) Time-period the price data covers.

(10) Number of observations throughout the period.

(11) Return of the buy and hold passive strategy.

(12) Probability value of serial correlation LM test of order 2.

(13) P-value of Breusch-Pagan-Godfrey heteroskedasticity test

(1) **Commodity**: Copper

(2)

(3)	Name:	Copper spot	Period:	1993-07-05 – 2010-04-16	(9)
(4)	Initial price:	1932	Observations:	4380	(10)
(5)	Final price:	7728	B&H:	8,23% / yr	(11)
(6)	Intercept:	☒ 0,4131	Serial correlation:	☒ 0,0000	(12)
(7)	Trend:	☑ 0,0302	Heteroskedasticity:	☒ 0,0000	(13)
(8)	Unit root:	0,9987			

Worth nothing is that all of the series have very high Jarque-Bera values, indicating that the residual terms are not normally distributed and thus bootstrapping will be used to perform the inference testing of the returns. However, since this the probability value of all Jarque-Bera tests is 0.0000 it has not been included in the tables.

6 Methodology

The subsequent segment presents and describes the method used when conducting the econometric analysis of the time series data. It also explains bootstrapping as a concept and method of statistically testing inferences of technical trading rules.

6.1 Method

6.1.1 Econometrical Testing of Data

As mentioned in the previous section the econometrical tests are based on a autoregressive model of order one, AR(1) which is a very common model used when modelling stock prices; a classic sign of this is that the time series has a decaying autocorrelation function and a single spike at the first lag of the partial autocorrelation function (*Enders, 1995*).

Since the inference is relying on the results from the bootstrap, the econometrical analysis is only performed in order to try establishing whether there is a reason of why strategies work better than some time series than others does. Thus, only general tests are made and focus will be on the results of the different trading strategies.

The Perron (*1988*) unit root testing procedure starts with a unit root equation using all deterministic components, which is the reason why both a trend and a constant is included in the AR(1) model shown in the previous section.

The unit root tests looks at the unit root coefficient, ρ, and analyses whether this one is below one, indicating a stationary time series (*Verbeek, 2008, pp.269-299*). A stationary series would be a requisite for a trading strategy to work since otherwise the stock price would follow a random walk and trying to predict a future price would be purely based on luck (*Kennedy, 2009, pp.314-315*).

The Breusch-Pagan test checks for serial correlation of the residual terms and uses the null hypothesis of there being no correlation up the the p^{th} lag, where p equal to two is often sufficient (*Kennedy, 2008, pp.126-127*). Kennedy (*2008, p.127*) recommends using this method instead of Durbin-Watson (DW) when a autoregressive model is analysed since DW is not reliable in this case.

The test for heteroskedasticity, the Breusch-Pagan-Godfrey test, checks for heteroskedasticity in the linear regression and has homoskedasticity as the null hypothesis (*Kennedy, 2008, pp.116-117*).

6.1.2 Bootstrap

In order to avoid making assumptions concerning the statistical distribution of the returns of the stock market ETFs and indices, which can hardly be argued to be normally distributed, the bootstrapping method was utilized (*Brooks, 2002, p.585*). What it does is repeatedly draw observations in a random manner from the original sample, with which it creates a new bootstrapped sample. Every bootstrapped sample is then analyzed in order to arrive at a statistical distribution, which should be very close to the real distribution of the sample (*Barreto and Howland, 2006, pp.709-710*). It is often stated that 500 samples generated by bootstrapping are sufficient to attain a reliable distribution (*Brock, Lakonishok and LeBaron, 1992, p.1745*).

Bootstrapping has been suggested as a powerful tool for analyzing whether technical trading rules in fact have predictive abilities, or if they are products of data snooping and pure chance. The argument given for this is that data snooping usually results in only some profitable strategies being put forward, while they in fact only make up a small part of generally failing trading rules. Bootstrapping can then be used to determine the probability with which a particular strategy can be profitable (*Brooks, 2002, p.586-587*). Accordingly bootstrapping has been the preferred method for statistically testing trading rules in most previous research mentioned in this study.

Microsoft Excel and Visual Basic for Application (VBA) has been used in order to construct a bootstrap of the data. First of all a time series is selected and a number of stock prices are randomly drawn from it in order to generate a new sample. The different moving average strategies are then applied to the sample and the return based on it is calculated. This is repeated 1000 times for each of the 44 strategies and 21 different time series.

When a buy signal is generated the number 1 is shown in the spreadsheet of Excel, whilst a sell (or going short) signal is represented by -1. This method greatly improves the efficiency of the programming since one then can multiply these signals with the daily return in order to get the correct sign of the strategies' returns.

Once the 1000 returns have been simulated these can be used in order to calculate the probability value of the initial strategies' return being insignificant.

6.2 Data-snooping bias

Data snooping bias is the occurrence when models are applied to data, that patterns are discerned and mistaken for actual proof of for example a certain trading method, while they in fact are products of pure chance (*Sullivan, Timmerand and White, 1999, pp. 1647-1691*). A discussion of the possibility of data-snooping bias are essential to any study of the application of trading rules to time series, as the probability of there occurring a bias increases with the number of methods, strategies or variations of strategies applied. Brock et al. (*1992*) made a strong case for the avoidance of data-snooping bias in their now oft-replicated article. Later researchers studying the same technical trading rules as they did often mention their intention to avoid data-snooping biases by testing the exact same rules and variations to these rules. The idea is that if researchers study precisely the same rules, and the same moving average length or lengths seem to have predictive powers in each study, those results are probably not due to chance. If researchers began testing obscure lengths and modifications to the moving average rules, there is a probability that some of those would appear to predict profits, though the likelihood of those results being due to pure chance would be greater.

7 Results

This section straightforwardly presents the quantitative results attained from the analysis conducted of the time series data, as well as from the bootstrap applied to the data.

The table below shows the yearly return for the commodities, ETFs and indices used in the study. Most of them show a positive return, with the exception of five series. Worth noticing are the Nickel, Emerging markets, Latin 40 and Latin 40 series which show a yearly return in the excess of 10%.

		BUY & HOLD
COMMODITY	Copper	8,23%
	Nickel	10,23%
	Oil	7,65%
	Zinc	5,31%
ETF	Emerging	20,14%
	Europe 350	0,16%
	Germany	3,41%
	Japan	-2,45%
	Latin 40	22,02%
	Russell 3000	-0,62%
	S&P 500	5,71%
	S&P 500 Short	-8,53%
	Switzerland	4,28%
INDEX	Emerging	3,83%
	Europe 350	5,39%
	Germany	-0,48%
	Japan	-3,18%
	Latin 40	16,43%
	Russell 3000	6,45%
	S&P 500	6,12%
	Switzerland	7,38%

These returns will be used when comparing the turnouts of the different strategies in order to establish whether one or more of them show abnormal returns and beats a passive approach.

The next two pages show tables consisting of the yearly returns from eleven different moving average (MA) combinations. As mentioned previously each of the combinations is subject to three different restricted versions (a one percent band, a one-day lag and a mixture of both) and one unrestricted.

Most of the MA combinations have frequently been used in previous research, as previously mentioned, and for example “2 vs 50” indicates that signals are generated when the 2-days moving average crosses the 50-days MA.

7.1 Results of Technical Trading Rule

7.1.1 Raw results

The strategy used in this study produced buy signals when the shorter moving average crossed the longer moving average from below. Depending on whether the strategy was amended by certain modifications, e.g. a percentage band or a lag, a buy signal would be delayed until the shorter moving average had either moved beyond the band, or had been given for a set number of trading days. A sell signal would on the other hand be produced given the exact reverse conditions, i.e. that the shorter moving average crossed the longer one from above, and possibly satisfied certain additional criterions.

The moving average strategies tested, 44 in total, delivered widely diverging results over the various assets they were implemented on, see appendix B for the results. Metals proved to be remarkably receptive, in absolute terms, to a simple moving average strategy. Yearly returns would consistently land in the tens of percentages. Nickel in particular turned out to be a profitable target asset, delivering annual returns of as much as 16,57% for a 5 vs 50 days strategy with a band and lag restriction. 4 of the 44 strategies applied to nickel did however deliver negative returns, at most -8,41% for 1 vs. 200 with a 1-day lag restriction.

8 Analysis

This part consists of two sections, one which deals with the raw results attained from the application of the moving average strategy to the time series, and one pertaining to the results from the bootstrap. Both sections thoroughly describe, analyze and provide close scrutiny of the outcomes.

8.1 Analysis of Strategy Results

8.1.1 Analysis – Raw Results

In general, it can be said of metals that even though most strategies can be applied profitably, one must be somewhat careful with, and even go so far as to avoid, applying lags without a percentage band. When used in combination with a percentage band lags yield positive returns, yet generally much lower than for the 0 lag strategy variations. A possible explanation for this phenomena could be that when a signal is given in a metal, trades must be made immediately or passed over. Any delay will close the window for profit, or at least diminish it. Oil on the other hand does not provide room for any noticeable profits, most are in fact negligible or negative. There is however one starchly irregular profit of 18,7% for 1 vs 200 days with a lag restriction.

Concerning the equity markets, for which the 44 strategies were applied to 9 ETFs, as well as to their 8 underlying indices, strategies across the board were strikingly more profitable in absolute terms when applied to ETFs and indices of emerging or developing markets such as Latin America, than when applied to ETFs or indices focusing on highly developed markets such as Japan or Germany. Concerning the former, the majority of strategies applied achieved positive results. For the general emerging market ETF tested only ten trading rules delivered negative results, though most negative results were quite severe, their average being -11.18% on an annual basis. The 34 strategies yielding positive results achieved a respectable 8.15% average annual return. On average the strategies applied to the MSCI Emerging Markets ETF delivered annual returns of 3.75%, the second highest return for all ETFs, superseded only by the Latin America ETF.

For the Latin America ETF the average negative annual result reached -18.58%. The same figure for the 39 positive strategies was 16.2%. This implied a 12.25% average annual return for all strategies. Looking at the trading return of the strategies when applied to the MSCI Latin America index, i.e. the ETF's underlying asset, Latin America's pole position among equity assets on which the trading strategies performed favourably was reaffirmed once again. Only one strategy had negative returns, while the average for the other 43 was a remarkable 13.99%.

Looking at ETFs and indices of developed markets, which for reasons such as greater volumes, greater liquidity and easier access should be more efficient, the strategy results are more often than not negative or negligible. Strategies applied to the Eurostoxx 350 ETF had an average return of -0.65%, delivered negative results in 25 out of 44 cases, averaging -5.32%. Positive results were attained in 19 out of 44 cases, averaging 5.49%. Not a great track record.

For the Japan ETF the average return was -2.59%. Negative results were attained by 28 of 44 strategies, on average amounting to -5.01%. The positive results in the remaining 16 cases, averaged 2.74%. For the MSCI Japan Index the average trading return was -1.17%. Trading rules applied to the Switzerland ETF delivered negative results in 27 cases, averaging -6.18%, and positive returns in 17 cases, on average 8.48%. This amounts to a -0.51% average return.

The lowest average trading return by far for ETFs was achieved for the Russell 3000, where a strategy implemented would deliver an annual average yield of -8.34%. A trading loss occurred in 36 out of 44 cases, on average amounting to -11,77%. Positive returns were achieved by only four strategies, though these yielded a respectable 14.13% average annual return. The remaining four strategies delivered on average a zero percent return. As the Russell 3000 index is composed of a large number of small cap stocks, and is very liquid, it can be argued that the market is highly efficient which renders any technical trading rules obsolete. A comparison of the strategy returns of the ETF to those of the Russell 3000 index itself, only fortifies this viewpoint as the average annual return delivered was a meagre 1.72%.

The only developed equity markets which have been able to consistently resist moving average strategies and not allowing them to achieve neither significant absolute, nor excess returns, have been the Russell 3000 Index and the S&P 500. While the Russell ETF was outperformed in 9/44 cases, and the S&P 500 ETF in 2/44 cases, their underlying indices were both outperformed by only 2/44 strategies.

Possible explanations for these somewhat confusing results are increasingly efficient markets where prices do in fact contain more information. As the countries with so called emerging capital markets have experienced economic development, their financial markets have followed suit. The previously so evident red tape has been removed by increasingly liberal regulation which has opened these markets up to international capital flows, which have made it easier for global investors to take advantage of opportunities on short notice. As the liquidity and number of groups partaking in the markets have increased, information is analyzed and traded upon more rapidly.

Another more plausible explanation that is not contradicted by the seeming success of the strategies in some of the most efficient markets in the world, is investor learning. As numerous studies have been conducted on specifically moving average technical trading rules, and these studies have almost unanimously shown that emerging, inefficient markets are the most profit-likely target assets, investors have increasingly applied these rules and thereby traded away any potential excess profits. The most likely explanation for the failure of the strategy to apply profitably to emerging markets is probably a combination of the two. Investors have noticed the profitability of moving average trading rules, and have subsequently taken advantage of the improved availability of emerging capital markets to employ these trading strategies. This application has then removed its application.

The slight evidence pointing towards that the strategies have applied somewhat well to developed capital markets can be explained by it being very weak, not very convincing and barely discernable.

8.1.2 Comparison with Buy and Hold

Appendix D shows the difference in yearly return between the buy and hold (B&H) and the different technical trading strategies. This gives a good indication of whether a specific strategy offers the opportunity of abnormal returns.

Firstly a comparison between the different classes (commodities, ETF and index funds) and the returns is made, as shown below, where e.g. 25 percent indicates that for the specific class the technical trading rule outperforms the B&H in one out of four attempts.

	1 vs. 20				1 vs. 50				1 vs. 100				1 vs. 150			
	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Com.	25%	25%	50%	75%	75%	25%	75%	100%	75%	25%	50%	0%	50%	25%	75%	50%
ETF	33%	44%	33%	33%	11%	11%	22%	11%	11%	0%	33%	33%	33%	33%	44%	33%
Index	38%	25%	13%	25%	63%	38%	50%	38%	75%	25%	75%	50%	75%	13%	75%	63%

	1 vs. 200				2 vs. 50				2 vs. 100				2 vs. 200			
	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Com.	50%	50%	50%	25%	50%	0%	50%	50%	50%	0%	50%	25%	50%	0%	50%	50%
ETF	33%	33%	56%	44%	22%	33%	11%	22%	33%	44%	11%	11%	56%	56%	44%	33%
Index	63%	38%	88%	63%	50%	50%	38%	50%	63%	13%	63%	75%	100%	25%	75%	50%

	5 vs. 50				5 vs. 150				5 vs. 200			
	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Com.	50%	0%	75%	75%	75%	0%	75%	75%	25%	25%	50%	50%
ETF	11%	44%	22%	22%	56%	33%	44%	56%	44%	33%	56%	56%
Index	50%	25%	38%	50%	75%	25%	75%	63%	50%	13%	50%	75%

A few strategies seem promising for at least two classes:

- With no restrictions: 1 vs. 100, 2 vs. 200 and 5 vs. 150
- With a band: None
- With a lag: 1 vs. 150, 1 vs. 200 and 5 vs. 150
- Both band and lag: 5 vs. 150 and 5 vs. 200

Secondly it will be analysed whether a certain strategy seems to produce abnormal returns for several different funds.

		1 20				1 50				1 100				1 150				1 200				2 50			
		None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Commodity	Copper	-	-	1	1	1	-	1	1	1	-	1	-	-	-	1	-	-	-	-	-	1	-	1	-
	Nickel	1	1	1	1	1	1	1	1	1	-	1	-	1	1	1	1	1	1	1	-	1	-	1	1
	Oil	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-
	Zinc	-	-	-	1	1	-	1	1	1	1	-	-	1	-	1	1	1	-	1	1	-	-	-	1
ETF	Emerging	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Europe 350	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Germany	1	-	-	-	-	-	1	-	-	-	-	-	-	-	1	-	1	-	1	1	-	-	-	-
	Japan	-	1	1	1	1	-	1	-	-	-	1	-	1	-	1	1	-	-	1	1	1	1	1	1
	Latin 40	1	1	1	1	-	-	-	-	-	-	-	1	1	1	-	1	-	1	-	-	-	1	-	1
	Russell 3000	-	-	-	-	-	-	-	-	-	-	-	1	-	1	-	-	1	-	1	1	-	-	-	-
	SP500	-	1	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-
	SP500 Short	-	-	-	-	-	1	-	-	1	-	1	-	-	-	-	-	-	-	1	-	-	-	-	-
	Switzerland	1	-	-	1	-	-	-	-	-	-	-	1	1	1	1	1	1	1	1	1	-	1	-	-
Index Fund	Emerging	-	1	-	-	-	-	-	1	-	-	1	-	-	-	1	-	-	-	-	-	1	-	-	-
	Europe 350	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Germany	1	-	1	1	1	-	1	1	1	-	1	-	1	-	1	1	1	-	1	1	1	1	1	1
	Japan	-	-	-	-	-	1	-	1	1	-	1	1	1	-	1	1	1	-	1	1	-	-	-	1
	Latin 40	-	1	-	1	1	-	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	-	-
	Russell 3000	1	1	-	-	1	1	1	-	1	1	1	1	1	-	1	1	-	1	-	1	1	1	1	1
	SP500	1	-	-	-	1	-	1	-	1	-	1	-	1	-	1	-	1	-	1	-	1	-	1	1
	Switzerland	-	-	-	-	1	1	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-
	Percentage	33%	33%	29%	38%	43%	24%	43%	38%	43%	14%	48%	29%	48%	24%	57%	43%	43%	33%	57%	43%	38%	29%	29%	38%

		2 100				2 200				5 50				5 150				5 200			
		None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Commodity	Copper	1	-	1	-	-	-	-	-	1	-	1	1	1	-	1	1	-	-	-	-
	Nickel	1	-	1	-	1	-	1	1	1	-	1	1	1	-	1	1	-	-	1	1
	Oil	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Zinc	-	-	-	1	1	-	1	1	-	-	1	1	1	-	1	1	1	1	1	1
ETF	Emerging	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Europe 350	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Germany	-	-	-	-	1	1	1	1	-	-	-	-	1	-	1	1	1	-	1	1
	Japan	1	-	1	1	-	1	1	1	1	1	1	1	1	-	1	1	1	-	1	1
	Latin 40	-	1	-	-	1	1	-	-	-	1	1	1	1	1	1	1	-	1	1	-
	Russell 3000	-	-	-	-	1	-	1	-	-	-	-	-	-	-	-	1	1	-	1	1
	SP500	-	1	-	-	-	1	-	-	-	1	-	-	-	1	-	-	-	1	-	-
	SP500 Short	1	-	-	-	1	1	-	-	-	-	-	-	-	-	-	-	-	-	-	1
	Switzerland	-	1	-	-	1	-	1	1	-	1	-	-	1	1	1	1	1	1	1	1
Index Fund	Emerging	1	1	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-
	Europe 350	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Germany	1	-	1	1	1	-	1	-	1	1	1	1	1	-	1	1	1	-	1	-
	Japan	1	-	1	1	1	-	1	1	-	-	-	1	1	-	1	1	1	-	1	1
	Latin 40	1	-	1	1	1	1	1	1	-	-	-	-	1	1	1	1	1	-	1	-
	Russell 3000	1	1	1	1	1	1	-	-	1	1	1	-	1	1	1	1	-	1	-	1
	SP500	-	-	1	1	1	-	-	1	1	-	1	1	1	-	1	-	-	-	-	1
	Switzerland	-	-	-	-	1	-	1	-	-	-	-	-	-	-	-	-	-	-	-	1
	Percentage	43%	24%	38%	33%	62%	33%	48%	38%	29%	29%	38%	38%	62%	24%	57%	57%	38%	24%	48%	52%

- No restrictions: 2 vs 200 (62%) and 5 vs. 150 (62%)
- Band: None
- Lag: 1 vs. 150 (57%), 1 vs. 200 (57%) and 5 vs. 150 (57%)
- Both band and lag: 5 vs. 150 (57%) and 5 vs. 200 (52%)

Worth noticing is that only a few strategies were successful at the "Emerging Markets" and none were successful for "Europe 350".

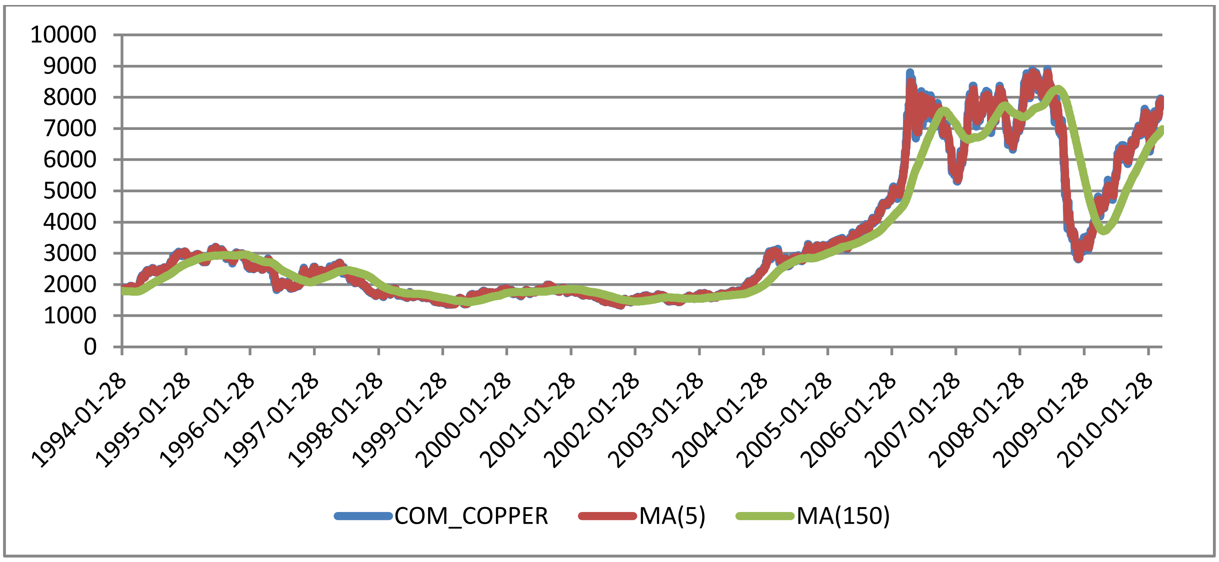
8.1.3 Analysing compared to Buy and Hold

In the previous section it was shown that a few different strategies seemed promising when they were applied to a specific family of assets, especially the 5 vs 150 trading strategy: without any restrictions, or using a lag restriction with or without a band/lag it gave a higher return in 68.75 percent of the situations.

A possible explanation of why a rather inert strategy seems promising in this case might be because three out of four commodities indicate that they have a significant trend component when using a critical level of five percent. Thus, over the long run these prices tend to climb upwards, as seen when applying the passive buy-and-hold strategy, which generated positive returns for all commodities.

However, for the commodities the 1 vs. 50 days moving average strategy also seems favourable compared to the buy-and-hold, but since there only are four commodities it seems rash to make such a statement. It is however worth keeping in mind.

The graph below shows how the two moving averages, based on the Copper spot price, interact and crosses each other throughout the relevant period. The two lines intersect each other quite infrequently during periods of high price fluctuations and one limits the risk associated with an active strategy, to buy at a high and sell at a low since it takes some time before the strategy reacts to changes in price.



As for the ETFs, only three of them have a trend component that is in the region of a 15 % critical level. If we are to follow or previous reasoning this would indicate that a strategy with a lower moving average period ought to be used. When looking at the results of the strategies, when they are compared with the passive buy-and-hold, it shows that the best strategies offer a better return only in 56 percent of the cases. Although this is slightly above half of the time it is a lot less than the 75 percent encountered with the commodities.

Finally, the index funds have about half of the trend components below 15 %. Fewer of them are thus following a trend compared to the commodities, but some ought to still be responsive to a strategy using a semi-high moving average. As touched upon previously, when it comes to the index funds the 1 vs 150, 1 vs 200, 2 vs 100 and 5 vs 150 days strategies are all outperforming the buy-and-hold, except in the case where a restriction of only a band is applied.

As mentioned in the previous section, none of the strategies were successful for the ETF's of the Emerging Markets or Europe 350, and very rarely in the case of the underlying indices. Why this is the case is hard to explain, possibly another moving average time span is worth considering, especially for the emerging market ETF since it has shown very good growth.

8.2 Analysis - Bootstrapped results

Appendix C shows the results from the bootstrapping. The tables contain the probability values of rejecting the null hypothesis of the return being insignificant. Below is a summary of how many results are insignificant using the different strategies and restrictions.

	1 vs. 20				1 vs. 50				1 vs. 100				1 vs. 150			
	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Com.	0%	0%	0%	25%	0%	0%	0%	0%	0%	25%	0%	25%	0%	0%	0%	0%
ETF	0%	0%	11%	44%	0%	0%	11%	56%	0%	0%	11%	56%	0%	0%	0%	44%
Index	0%	0%	25%	25%	0%	0%	13%	25%	0%	0%	13%	38%	0%	0%	0%	0%

	1 vs 200				2 vs 50				2 vs 100				2 vs 200			
	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Com.	0%	25%	0%	25%	0%	0%	0%	0%	0%	25%	0%	0%	0%	25%	0%	0%
ETF	0%	0%	0%	44%	11%	0%	11%	56%	11%	0%	22%	67%	0%	11%	0%	33%
Index	0%	13%	13%	0%	0%	0%	13%	50%	0%	0%	13%	13%	0%	13%	13%	13%

	5 vs 50				5 vs 150				5 vs 200			
	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Com.	0%	50%	0%	25%	0%	25%	0%	0%	0%	25%	0%	0%
ETF	11%	0%	22%	33%	0%	0%	11%	22%	0%	0%	11%	22%
Index	0%	13%	38%	25%	0%	0%	0%	0%	13%	0%	13%	25%

Based on these results many of the strategies' returns are significant. There seems to be some loss in efficiency when combining the two restrictions of a band and a one-day lag. A quick summary of which strategies provide more than 40 per cent insignificant results,

- No restrictions: None
- Band: 5 vs 50 (Commodities)
- Lag: None
- Band & Lag: 1 vs 20, 1 vs 50, 1 vs 10, 1 vs 150, 1 vs 200, 2 vs 50, 2 vs 100 (ETF)
  2 vs 50 (Index)

Looking across the board it can be seen that,

- the band and lag restriction produced 64 insignificant results
- only using a lag makes 22 returns insignificant compared to 12 using a band
- If no restrictions are applied only 4 returns are insignificant.

What effect does the different restrictions and moving average lengths have on the results of the bootstrap? The set of tables above show a clear pattern regarding the inference; as more restrictions are added, the weaker does the inference get. This pattern is even easier to see as one observes the short summary of the results at the end of the section. When both restrictions (band and lag) are applied 64 insignificant results obtained.

It is also worth mentioning that all but a couple of these insignificant returns are negative. As more restrictions are imposed, the harder it is to perform the inference, especially as we are dealing with negative returns. It does not seem to be a problem when the strategies are positive.

8.3 Results and Theory

As the reader might be aware of, the efficient market hypothesis states that it is impossible to constantly achieve excess returns over the return of the market, meaning the buy and hold return, as all available information is already included in all prices. Its weak form also states that it is impossible to achieve excess returns by using patterns of past prices. Generally the results are no better than a regular buy and hold strategy, this is completely in line with the efficient market hypothesis. There are a small number of cases where a certain variation of the moving average strategy delivers excess returns, which contradicts the efficient market hypothesis, yet as these occurrences make up such a small percentage of the total number, it must be concluded that the efficient market hypothesis is generally not threatened by the results attained in this thesis

8.4 Analysis compared with previous research

8.4.1 Raw results

In all previous studies covered in this thesis, researchers have arrived at the conclusion that moving average technical trading rules have some kind of predictive ability, although the strength of this ability differs among markets. The results attained in this study are not as evidently or overwhelmingly in favour of a general predictive ability, as for example those of Brock et al. (*1992*), Ito (*1999*) and Ratner et al. (*1999*). Rather, they point towards the method performing well with certain lengths for certain markets. The results are therefore more in line with those which were attained by Bessembinder (*1995*) and McKenzie (*2007*), which indicate that performance is specific to countries, as well as to certain lengths which match the general investment horizons in those particular markets.

The only indices which the 44 variations of the moving average strategy outperformed on an average annual base were the MSCI Germany and Japan indices. Only one ETF, the S&P500 Short, was outperformed on an average annual basis. When looking at the ratio of outperforming strategies to underperforming strategies for the ETFs and indices Japan and Germany are once again at the top of the list, albeit with company. The fact that Japan is one of the markets for which the moving average strategy performs well when applied on is somewhat surprising. Previous research, notably Bessembinder and Chan (*1995*) and Ming-Ming, Siok-Hwa (*2006*), have observed that technical trading rules tend not to function very well in Japan's case, which they considered a testament to Japan's efficient stock markets. Even more surprising is the fact the performance of moving average strategies have been mediocre when applied to Latin America. Ratner, Leal (*1999*), Parisi, Vasquez (*2000*) as well as McKenzie (*2007*) to some extent, have observed that moving average rule have certain forecasting abilities and can applied profitably given low transaction costs. The occurrence that moving average trading strategies perform better and have superior predictive abilities in markets which can be considered inefficient has been observed in numerous studies. Bessembinder and Chan concluded that if markets are somewhat inefficient, a moving average trading rule would be profitable. They pointed towards the fact that such a strategy was successful in emerging Asian markets, yet not in Japan. This phenomena is discernible in the results attained in this study as well, as 59.1% of all strategies applied to the MSCI Emerging Markets Index beat the market.

.

8.4.2 Bootstrap

First off, it should be stated that most results from the application of the moving average strategy have been shown to be significant by the bootstrap. Only in a small amount of cases did results turn out to be insignificant. These results are comparable to those of Brock et al. (1992), where all technical trading results were shown to be statistically significant on the 5% level. Bootstrap results which in a wide majority of cases point towards a statistical significance in strategy results are not very uncommon, both Mills (1997) and Parisi, Vasquez (2000) observed such outcomes.

Results were more prone to be statistically insignificant if the strategy included both lags and percentage bands, as well as if the asset was Japan or the US (either the S&P 500 and the Russell 3000). These observations are in certain aspects similar to those of Ito (1999), in which it was noted that while most strategy results were significant for their respective countries, they were always insignificant for Nikkei futures, though not for the Nikkei index proper, as well as for U.S. indices. The fact that Japanese assets seem slightly harder to achieve significance for when applying the moving average strategies has been quite common in the previous research studied for this thesis. Bessembinder, Chan (1995) and Ming-Ming, Shio-Hwa (2006) both also discovered this. The conclusion which may be drawn is that U.S. and Japanese stock markets are relatively more efficient and therefore more resistant to profitable technical trading.

It should be added that the bootstrap significances for emerging markets are in line with those of previous research. In the case of this thesis both the Emerging Market and Latin American ETF and their underlying indices displayed very high average levels of significance. This makes perfect sense as their presumably less efficient markets should be more receptive to technical trading. Such results have been arrived at by both Bessembinder, Chan (1995) and McKenzie (2007).

9 Conclusion

The following part provides the reader with a concise reiteration of the results attained, and the analyses carried out.

The results attained in the application of the simple moving average trading technique do generally not point towards the existence of a technical trading rule which can be applied broadly and profitably in stock markets. Contrary to previous research, where moving average trading rules have had superior performance when applied to emerging markets, the indices for which the moving average strategy performed best in this study were those of highly developed countries with capital markets which are considered extremely efficient. The strategies' best performances were racked up when applied to Europe, Germany and Japan.

The moving average strategies' weak performance may be due to a number of factors, the most plausible being increasingly efficient capital markets, especially among the emerging markets in the world, and investor learning. Most probably it is a combination of the two which has made the moving average strategy unprofitable in these previously so lucrative markets. The trading rules have however performed somewhat well in, surprisingly enough, developed and highly efficient markets. However, these occurrences are rare and in the authors opinion of insufficient weight to draw any conclusions from.

As the study arrives at the conclusion that moving average strategies do not provide any excess profits beyond that of a buy and hold strategy, the efficient market hypothesis is neither questioned nor threatened. The results support the notion of efficient market places were prices include available information, and where historical information about prices cannot be used to attain excess profits.

Based on the analysis on the strategies above it is worth pointing at a couple of things. First of all, if a specific asset seems to be following a trend, then it probably a good idea to use a long moving average combination. It was found that 5 vs 150 days was a good signal generator in the case with the four commodities.

The more restrictions one add, such as the price must be outside a 1% band, or the strategy must generate the same signal during two consecutive days, the harder it will be to interpret the results correctly as the inference gets worse.

To conclude, not all moving average strategies can be applied profitably to any tradable asset, in fact most cannot. However, certain lengths and variations applied to specific assets may deliver excess returns. These lengths and modifications differ, necessitating further research focused on certain assets to be able to draw more secure conclusions. Emerging markets, which previously have been so receptive to technical trading have become less so, quite possibly due to an increasing efficiency among these markets.

10 Further Research

This section provides some suggestion of how to continue with the research performed in the following thesis.

Risk-adjusted returns

In order to find out whether a simple moving average trading rule delivers excess returns on a risk-adjusted basis, the risk-adjusted returns, e.g. the Sharpe or Treynor ratio, could be compared to that of a buy and hold portfolio over the same time period. It would be interesting to see whether the simple moving average strategy in fact mitigates the volatility of a trading portfolio.

Applied to currencies

Applying moving average trading rules to currencies would shed light on assets which have not been studied as thoroughly as equity markets. Interesting aspects would be how the international flow of capital, as currency are much more liquid, and macroeconomic factors affect the profitability of such a strategy.

Applied to a diverse range of commodities

Once again, in order to broaden the range of assets on which moving average trading rules have been applied. It would be interesting to observe whether it is profitable to trade on the basis of a moving average strategy. The commodities available for trading are numerous, e.g. agricultural, metals, energy, making it possible to apply the strategy to an extremely diverse range of assets.

Compared to value investing

The direct opposite of technical trading rules is the investing in companies which after a thorough financial analysis display “value”, hence the name “value investing”. It would be interesting to see how these completely different ways of investing measure up. Naturally the value investing strategy to be applied must be decided on beforehand, probably in the form of certain financial ratios.

Modify the signal generating process

Create a method that generates a signal once you have been above the previously highest price during a predetermined period for a set number of days e.g. 15. As in the case with the EFT of Latin America, such a method would clearly generate abnormal returns, at least based on the price development previously.

Bibliography

Achelis, Steven B. (2001): *Technical Analysis from A to Z* (2nd edition, McGraw-Hill).

Arms, Richard W. Jr. (1996): *Trading without fear* (John Wiley & Sons, Inc.).

Barreto, Humberto and Howland, Frank M. (2006): *Introductory Econometrics* (Cambridge University Press)

Bessembinder, Hendrik and Chan, Kalok (1995): "*The profitability of technical trading rules in the Asian stock markets*", Pacific-Basin Finance Journal, Vol. 3, No. 2-3, pp. 257-284.

Brock, William and Lakonishok, Josef and LeBaron, Blake (1992): "*Simple Technical Trading Rules and the Stochastic Properties of Stock Returns*", The Journal of Finance, Vol. 47, No. 5, pp. 1731-1764.

Brooks, Chris (2002): *Introductory econometrics for finance* (Cambridge University Press

Chang, Eui Jung and Lima, José Araújo and Tabak, Benjamin Miranda (2004): "*Testing for predictability in emerging equity markets*", Emerging Markets Review, Vol. 5, No. 3, pp. 295-316.

Coutts, J. Andrew and Cheung, Kwong-C. (2000): "*Trading rules and stock returns: some preliminary short run evidence from the Hang Seng 1985 – 1997*", Applied Financial Economics, Vol. 10, No. 6, pp. 579-586.

Dowd, Kevin (2006): *Measuring Market Risk* (2nd edition, John Wiley & Sons, Ltd, Chichester).

Elton, Edwin J. and Gruber, Martin J. and Brown, Stephen J. and Goetzmann, William N. (2007): *Modern Portfolio Theory and Investment Analysis* (7th edition, John Wiley & Sons, Inc.).

Enders, Walter, (1995): *Applied Econometric Time Series* (Wiley)

Fama, Eugene F. (1965): "*The Behavior of Stock-Market Prices*", The Journal of Business, Vol. 38, No. 1, pp. 34-105.

Fama, Eugene F. (1991): "*Efficient Capital Markets: II*", The Journal of Finance, Vol. 46, No. 5, pp. 1575-1617.

Fama, Eugene F. (1995): "*Random Walks in Stock Market Prices*", Financial Analysts Journal, Vol. 51, No. 1, pp. 75-80.

Fong, Wai Mun and Yong, Lawrence H.M. (2005): "*Chasing trends: recursive moving average trading rules and internet stocks*", Journal of Empirical Finance, Vol. 12, No. 1, pp. 43-76.

Griffioen, Gerwin Alfred Wilhelm (2003): "*Technical Analysis in Financial Markets*", Ph.D. thesis, University of Amsterdam.

Hudson, Robert and Dempsey, Michael and Keasey, Kevin (1996): "*A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices – 1935 to 1994*", Journal of Banking & Finance, Vol. 20, No. 6, pp. 1121-1132.

Investment Company Institute (2010)a: *Investment Company Factbook – A Review of Trends and Activity in the Investment Company Industry* (50th edition).

Investment Company Institute (2010)b: Press release April 27th 2010 Washington D.C., *Fund- and market statistics for exchange traded funds*.

Ito, Akitoshi (1999): "*Profits on technical trading rules and time-varying expected returns: Evidence from Pacific-Basin equity markets*", Pacific-Basin Finance Journal, Vol. 7, No. 3-4, pp. 283-330.

Jensen, Michael A. (1978): "*Some anomalous evidence regarding market efficiency*", Journal of Financial Economics, Vol. 6, No. 2-3, pp. 95-101.

Kennedy, Peter (2009): *A Guide to Econometrics* (6th edition, Blackwell Publishing, Oxford)

Lydon, Tom (2010): *The ETF Trend Following Playbook* (FT Press, New Jersey).

Malkiel, Burton (2007): *A random walk down Wall Street: the time tested strategy for successful investing* (9th edition, W. W. Norton & Company, Inc., New York).

McKenzie, Michael D. (2007): "*Technical Trading Rules in Emerging Markets and the 1997 Asian Currency Crises*", Emerging Markets Finance and Trade, Vol. 43, No. 4, pp. 46-73.

Milionis, Alexandros E. and Papanagiotou, Evangelia (2008): "*Use of the Moving Average Trading Test for Weak Form Efficiency in Capital Markets*", Economic Notes by Banca Monte dei Paschi di Siena SpA, Vol. 37, No. 2, pp. 181-201.

Mills, Terence C. (1997): "*Technical Analysis and the London Stock Exchange: Testing Trading Rules Using the FT30*", International Journal of Finance & Economics, Vol. 2, No. 4, pp. 319-332.

Ming-Ming, Lai and Siok-Hwa, Lau (2006): "*The profitability of the simple moving averages and trading range breakout in the Asian stock markets*", Journal of Asian Economics, Vol. 17, No. 1, pp. 144-170.

Murphy, John J (1999): *Technical Analysis of the Financial Markets: A comprehensive guide to trading methods and applications* (New York Institute of Finance).

Nison, Steve (2001): *Japanese candlestick charting techniques: A contemporary guide to the ancient investment techniques of the Far East* (2nd edition, New York Institute of Finance).

Parisi, Franco and Vasquez, Alejandra (2000): "*Simple technical trading rules of stock returns: evidence from 1987 to 1998 in Chile*", Emerging Markets Review, Vol. 1, No. 2, pp. 152-164.

Perron, Pierre (1988): “*Trends and random walks in macroeconomic time series – Further evidence from a new approach*”, Journal of Economic Dynamics and Control, Vol. 12, pp. 297-332

Ratner, Mitchell and Leal, Ricardo P.C. (1999): “*Tests of technical trading strategies in the emerging equity markets of Latin America and Asia*”, Journal of Banking & Finance, Vol. 23, No. 12, pp. 1887-1906.

Renz, Curt (2003): *The Investor’s Guide to Technical Analysis* (McGraw-Hill).

Roberts, S. W. (1959): “*Control Chart Tests Based on Geometric Moving Average*”, Technometrics, Vol. 1, No. 3, pp. 239-250.

Samuelson Paul (1965): “*Proof That Properly Anticipated Prices Fluctuate Randomly*”, Industrial Management Review, Vol. 6, No. 2, pp. 41-50.

Schleifer, Andrei (2000): *Inefficient Markets* (Oxford University Press, Oxford).

Securities and Exchange Commission (2008): “*Exchange-Traded Funds; Proposed Rule*”, Federal Register, Vol. 73, No. 53, pp. 14618-14658.

Shefrin, Hersh (2002): *Beyond Greed and Fear* (Oxford University Press, Inc., New York).

Sullivan, Ryan and Timmermann, Alan and White, Halbert (1999): "*Data-Snooping, Technical Trading Rule Performance and the* Bootstrap" The Journal of Finance, Vol. 54, No. 5, pp. 1647-1691, p. 1647-1648)

Taylor, Mark P. and Allen, Helen (1992): “*The use of technical analysis in the foreign exchange market*”, Journal of International Money and Finance, Vol. 11, No. 3, pp. 304-314.

Verbeek, Marno (2008): *A Guide to Modern Econometrics* (3rd edition, John Wiley & Sons, Ltd)

Appendix A

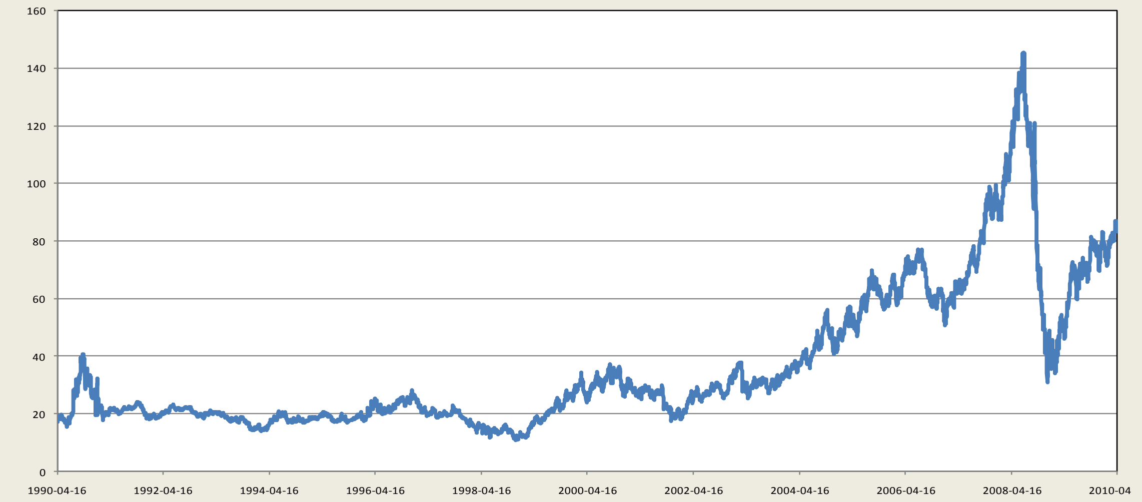
Commodity: Copper

Name:	Copper spot	Period:	1993-07-05 – 2010-04-16
Initial price:	1932	Observations:	4380
Final price:	7728	B&H:	8,23% / yr
Intercept:	☒ 0,4131	Serial correlation:	☒ 0,0000
Trend:	☑ 0,0302	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9987		

Commodity: Nickel

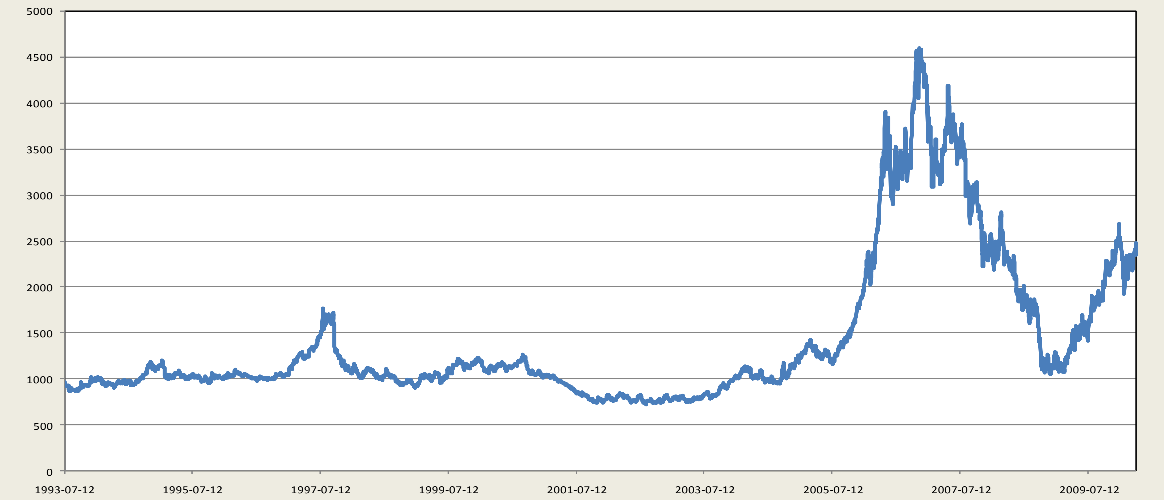
Name:	Nickel Spot	From:	1993-07-20
Initial price:	4858	Observations:	4369
Final price:	26645	B&H:	10,23% / yr
Intercept:	☒ 0,5314	Serial correlation:	☒ 0,0000
Trend:	☑ 0,0321	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9982		

Commodity: Oil



Name:	Oil Spot	From:	1990-04-16
Initial price:	17,9	Observations:	5220
Final price:	83,2	B&H:	7,65% / yr
Intercept:	☒ 0,7690	Serial correlation:	☒ 0,0000
Trend:	☑ 0,0003	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9975		

Commodity: Zinc

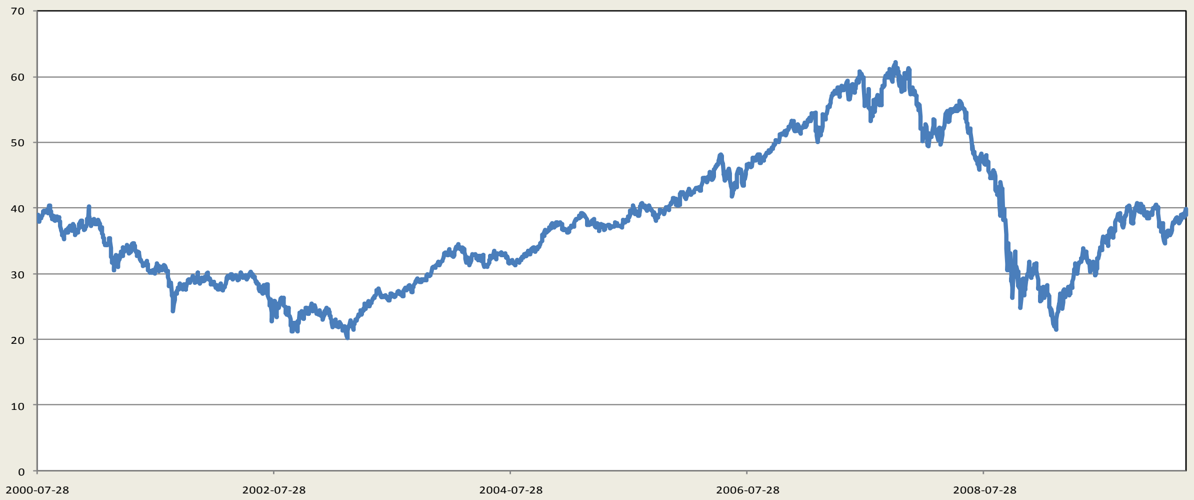


Name:	Zinc Spot	From:	1993-07-12
Initial price:	966	Observations:	4375
Final price:	2390	B&H:	5,31% / yr
Intercept:	☒ 0,9598	Serial correlation:	☒ 0,0000
Trend:	☒ 0,1048	Heteroskedasticity:	☒ 0,0419
Unit root:	0,9984		

ETF: Emerging

Name:	iShares MSCI Emergin Markets Index Fund	From:	2003-04-11
Initial price:	11,1	Observations:	1831
Final price:	42,5	B&H:	20,14% / yr
Intercept:	0,5460	Serial correlation:	0,0000
Trend:	0,0888	Heteroskedasticity:	0,0000
Unit root:	0,9954		

ETF: Europe

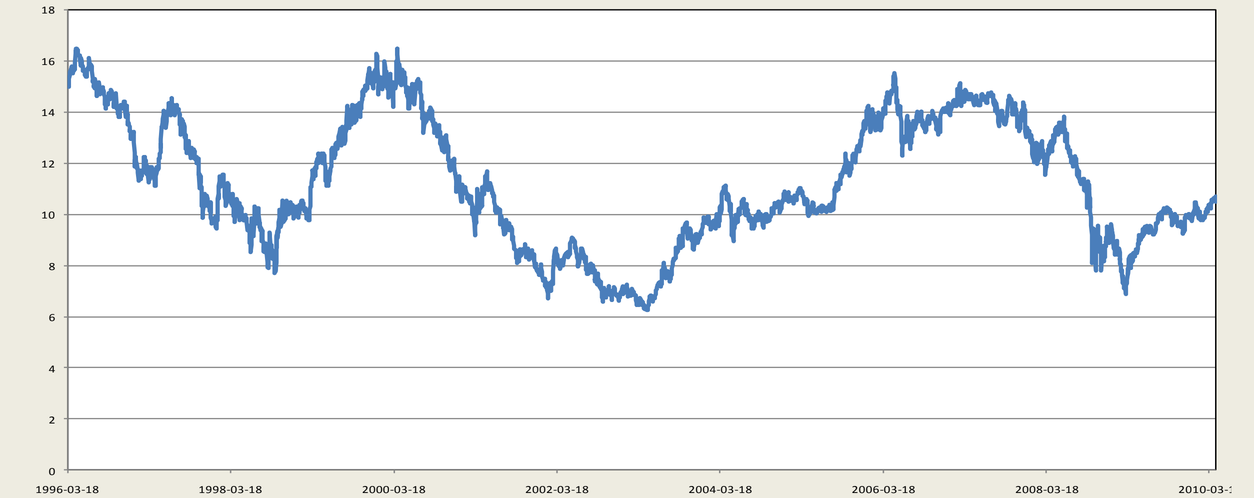


Name:	iShares S&P Europe 350 Index Fund	From:	2000-07-28
Initial price:	38,3	Observations:	2536
Final price:	38,9	B&H:	0,16% / yr
Intercept:	0,9191	Serial correlation:	0,0000
Trend:	0,2978	Heteroskedasticity:	0,0000
Unit root:	0,9980		

ETF: Germany

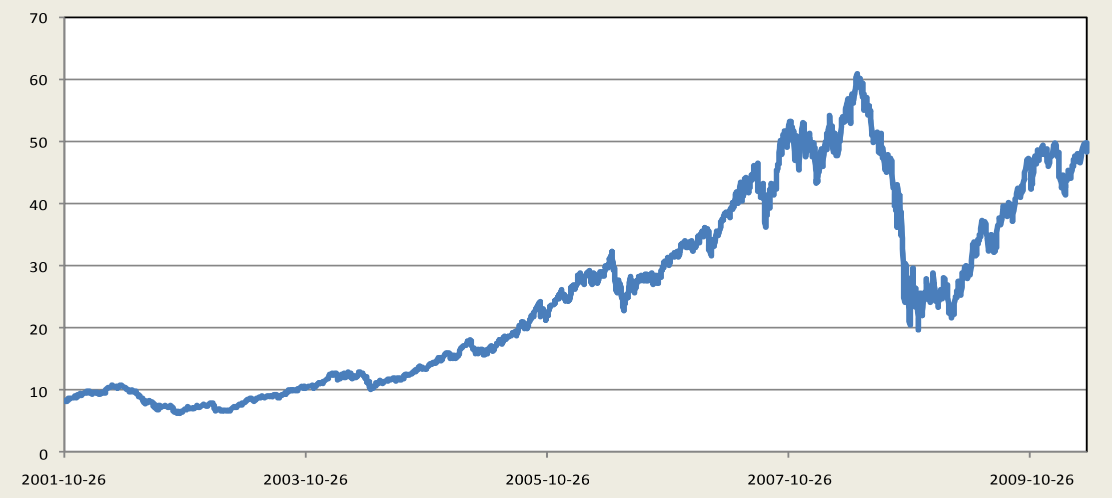
Name:	iShares MSCI Germany Index Fund	From:	1996-03-18
Initial price:	13,5	Observations:	3675
Final price:	22,1	B&H:	3,41% / yr
Intercept:	☒ 0,1693	Serial correlation:	☒ 0,0000
Trend:	☒ 0,6499	Heteroskedasticity:	☒ 0,0001
Unit root:	0,9981		

ETF: Japan



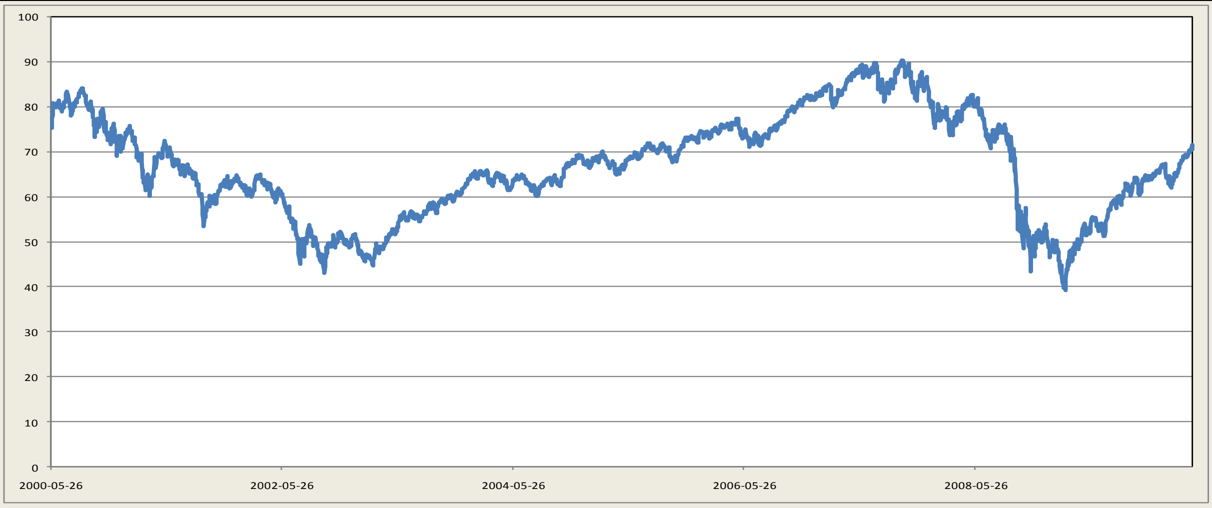
Name:	Shares MSCI Japan Index Fund	From:	1996-03-18
Initial price:	15,1	Observations:	3675
Final price:	10,5	B&H:	-2,45% / yr
Intercept:	☑ 0,0096	Serial correlation:	☒ 0,0038
Trend:	☒ 0,9003	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9972		

ETF: Latin



Name:	iShares S&P Latin America 40	From:	2001-10-26
Initial price:	8,32	Observations:	2111
Final price:	48,4	B&H:	22,02% / yr
Intercept:	☑ 0,0033	Serial correlation:	☒ 0,0000
Trend:	☑ 0,0000	Heteroskedasticity:	☒ 0,0001
Unit root:	0,9953		

ETF: Russell



Name:	iShares Russell 3000 Index Fund	From:	2000-05-26
Initial price:	75,3	Observations:	2581
Final price:	70,6	B&H:	-0,62% / yr
Intercept:	☒ 0,2203	Serial correlation:	☒ 0,0000
Trend:	☒ 0,4549	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9971		

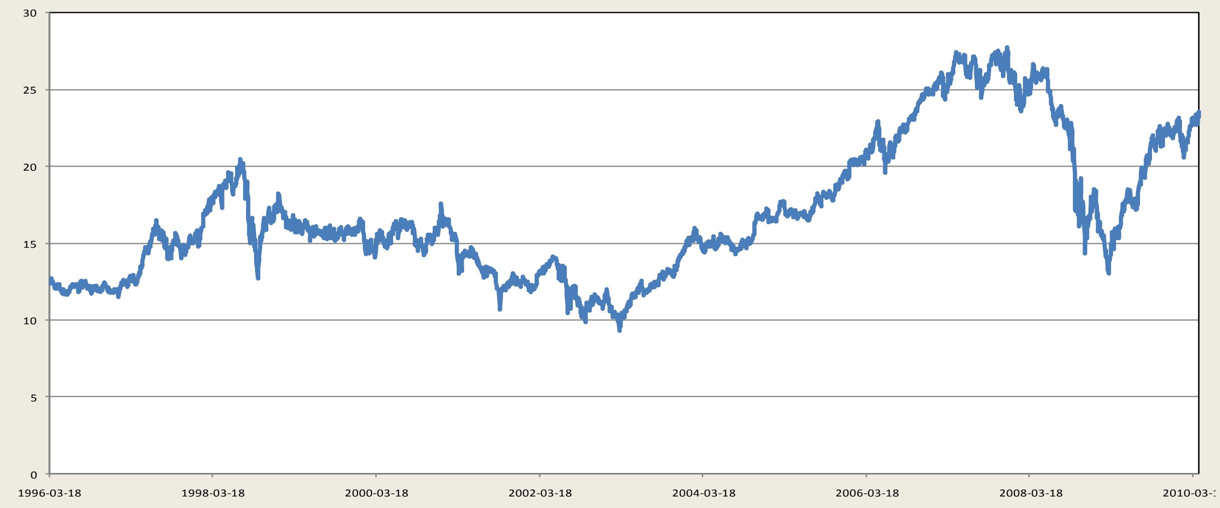
ETF:S&P 500

Name:	SPDR S&P 500	From:	1993-01-29
Initial price:	44	Observations:	4491
Final price:	119	B&H:	5,71% / yr
Intercept:	0,0551	Serial correlation:	0,0000
Trend:	0,4480	Heteroskedasticity:	0,0000
Unit root:	0,9985		

ETF: S&P 500 Short

Name:	ProShares Short S&P 500	From:	2006-06-21
Initial price:	69,2	Observations:	998
Final price:	48,5	B&H:	-8,53% / yr
Intercept:	0,1204	Serial correlation:	0,0037
Trend:	0,4841	Heteroskedasticity:	0,0000
Unit root:	0,9901		

ETF: Switzerland



Name:	iShares MSCI Switzerland Index Fund	From:	1996-03-18
Initial price:	12,5	Observations:	3675
Final price:	23,2	B&H:	4,28% / yr
Intercept:	☒ 0,2330	Serial correlation:	☒ 0,0000
Trend:	☑ 0,0461	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9974		

Index: Emerging

Name:	MSCI Emerging Markets Index	From:	1994-05-31
Initial price:	551	Observations:	4144
Final price:	1027	B&H:	3,83% / yr
Intercept:	☒ 0,6008	Serial correlation:	☒ 0,0000
Trend:	☒ 0,2483	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9994		

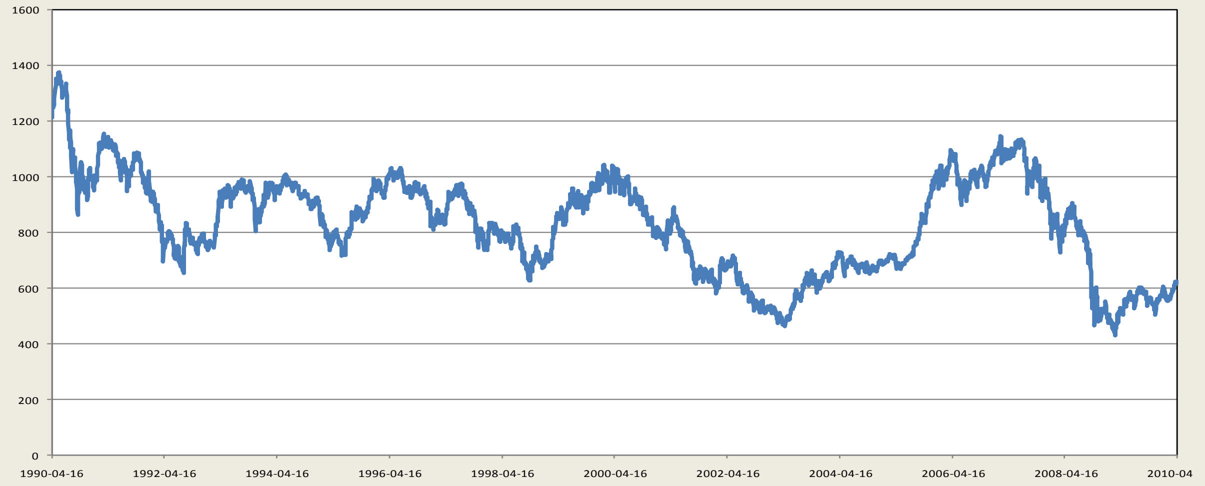
Index: Europe

Name:	S&P Europe 350	From:	1990-04-16
Initial price:	330	Observations:	5220
Final price:	988	B&H:	5,39% / yr
Intercept:	☒ 0,2191	Serial correlation:	☒ 0,0000
Trend:	☒ 0,5979	Heteroskedasticity:	☒ 0,0073
Unit root:	0,9992		

Index: Germany

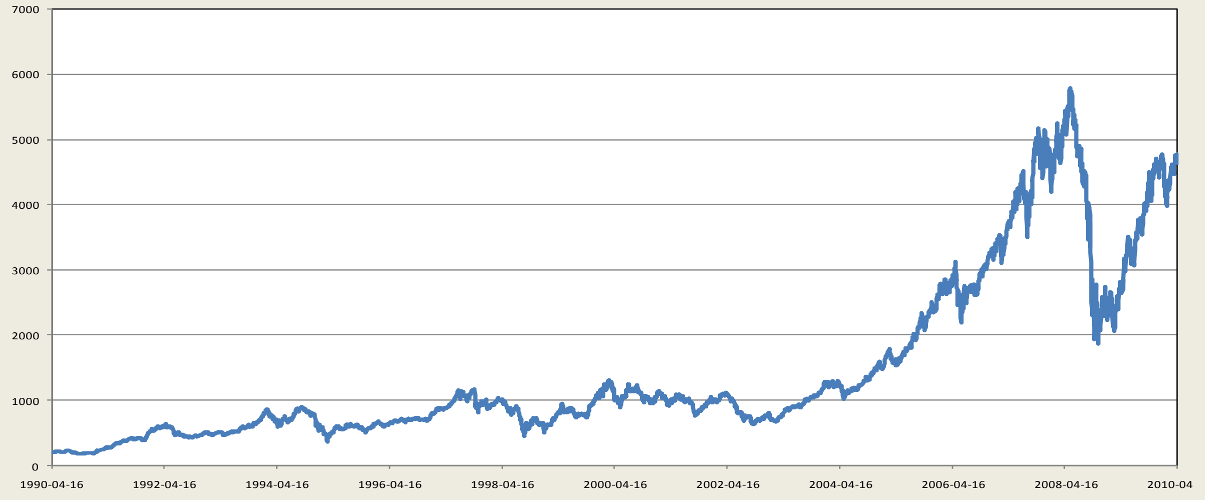
Name:	MSCI Germany Index	From:	1998-12-31
Initial price:	100	Observations:	2947
Final price:	94,4	B&H:	-0,48% / yr
Intercept:	☒ 0,1370	Serial correlation:	☒ 0,0000
Trend:	☒ 0,7744	Heteroskedasticity:	☑ 0,4156
Unit root:	0,99883		

Index: Japan



Name:	MSCI Japan Index	From:	1990-04-16
Initial price:	1212	Observations:	5220
Final price:	617	B&H:	-3,18% / yr
Intercept:	☑ 0,0000	Serial correlation:	☒ 0,0298
Trend:	☒ 0,3195	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9974		

Index: Latin 40



Name:	S&P Latin America 40	From:	1990-04-16
Initial price:	193	Observations:	5220
Final price:	4634	B&H:	16,43% / yr
Intercept:	☒ 0,3060	Serial correlation:	☒ 0,0000
Trend:	☑ 0,0036	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9986		

Index: Russell 3000

Name:	Russell 3000	From:	1990-04-16
Initial price:	191	Observations:	5220
Final price:	705	B&H:	6,45% / yr

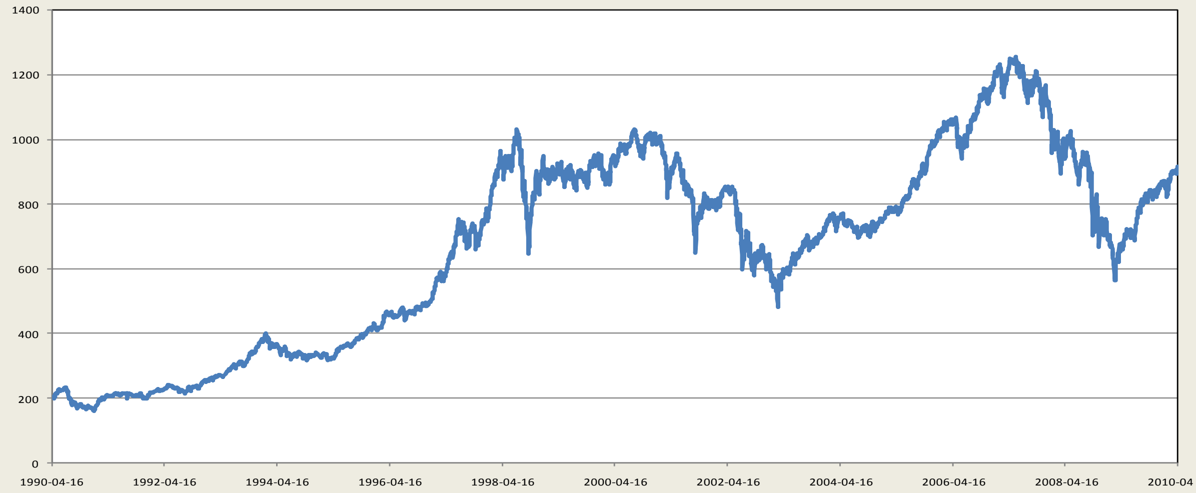
Intercept:	☒ 0,0622	Serial correlation:	☒ 0,0000
Trend:	☑ 0,0380	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9985		

Index: S&P 500

Name:	S&P 500	From:	1990-04-16
Initial price:	345	Observations:	5220
Final price:	1192	B&H:	6,12% / yr

Intercept:	☒ 0,0874	Serial correlation:	☒ 0,0000
Trend:	☒ 0,1435	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9987		

Index: Switzerland



Name:	Swiss Market Index	From:	1990-04-16
Initial price:	205	Observations:	5220
Final price:	906	B&H:	7,38% / yr
Intercept:	☒ 0,1878	Serial correlation:	☒ 0,0000
Trend:	☒ 0,1381	Heteroskedasticity:	☒ 0,0000
Unit root:	0,9989		

Appendix B

		1 vs 20				1 vs 50				1 vs 100				1 vs 150				1 vs 200				2 vs 50			
		None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
COMMODITIES	Copper	4,69	0,25	9,53	10,65	10,22	5,35	11,41	9,89	11,44	7,88	12,2	7,31	7,42	-0,13	8,43	2,77	6,07	7,91	7,2	6,6	10,78	1,25	9,66	7,7
	Nickel	13,37	10,89	12,33	11,77	13,53	13,32	12,56	14,01	12,93	-2,04	12,93	5,89	14,02	11,2	13,14	15,06	11,58	10,94	10,48	7,05	11,67	2,16	14,95	11,91
	Oil	-6,86	-8,91	-2,94	-0,84	2,19	3,73	4,89	9,23	2,48	-0,63	5,76	-8,63	-3,68	1,57	5,13	2,52	0,27	18,7	4,61	-9,28	5,65	7,61	5,73	4,92
	Zing	-2,31	-3,25	3,48	9,64	6,15	-1,34	6,12	8,16	5,48	8,19	1,87	5,03	7,53	-2,5	7,88	10,2	7,55	-3,22	8,27	8,2	1,91	3,03	4,72	6,28
ETF	Emerging	7,4	-13,2	17,13	17,71	16,63	1,91	9,08	-3,09	4,09	-18,3	16,77	14,1	-0,5	10,62	2,11	1,58	8,78	4,47	12,51	-6,84	-3,27	2,41	3,42	10,53
	Europe 350	7	-21,2	-8,38	-5,7	-5,53	-3,71	0,45	0,09	-6,31	-3,94	-2,78	-1,79	-2,42	-3,42	2,65	-1,23	4,23	-7,6	7,12	7,86	-7,23	-11,4	-5,25	-0,06
	Germany	-5,57	4,57	5,23	6,01	5,66	1,36	7,49	2,87	0,63	-0,58	6,79	3,37	4,12	-10,4	6,63	6,03	-0,2	-14	5,23	4,75	7,32	9,79	8,06	5,67
	Japan	-1,6	4,11	6,29	1,27	-6,99	-17,8	-5,05	-3,42	-12,1	-14,7	-6,86	-0,68	-2,42	0,97	-3,08	1,53	-5,88	0,85	-3,09	-3,2	-2,62	6,64	-2,61	-1,02
	Latin 40	1,16	13,37	5,88	1,53	5,84	-26,6	18,59	20,48	15,92	-17,1	19,97	22,62	18,27	26	15,15	-19,9	24,31	1,26	24,68	23,38	18,12	2,71	15,79	19,91
	Russell 3000	-11,8	14,16	28,1	-15,5	-30	-3,78	-6,85	-6	-14,4	-1,22	-17,5	-10,8	-21,2	-9,76	-8,9	-11,6	-13	11,15	-9,64	-14,2	-12,6	-38,2	-7,6	-7,09
	SP500	-3,75	-2,94	-4,41	-1,27	-1,57	8,09	3,92	-0,99	7,72	3,97	8,95	-4,88	-5,75	0,19	-0,39	3,76	2,63	4,5	5,86	3,03	-2,3	-11,3	0,52	-9,11
	SP500 Short	52,66	-56,6	-40,4	70,23	-42,5	-27,7	-19,5	-33,2	-34,6	-29,2	-84,5	58,69	21,63	55,76	40,96	33,87	21,5	67,29	36,05	46,85	-37,9	0	-26,3	-51,7
	Switzerland	-5,54	5,86	-26,5	-5,76	0	-7,57	-1,65	32,16	-0,09	-5,39	13,5	-9,09	1,56	-4,19	32,18	-10,5	1,01	-10,2	-6,73	-3,6	14	2,66	2,69	-1,23
INDEX FUNDS	Emerging	11,5	-5,01	9,31	8,33	9,54	-1,54	8,65	7,29	9,08	-4,58	7,8	2,54	7,7	-4,22	6,45	5,89	5,1	2,19	4,3	4,47	9,1	7,65	8,8	5,95
	Europe 350	4,95	-13,6	5,21	0,52	-8,68	9,25	3,45	5,59	9,07	0,82	7,3	8,41	8,79	0,98	9,43	10,47	8,19	4,57	9,46	9,01	3,21	1,71	3,57	6,77
	Germany	-1,02	14,84	-12,7	0,34	0,2	-4,68	1,06	29,12	2,36	-0,35	4,85	2,67	2,2	0,16	1,86	1,98	3,22	-0,27	4,15	5,3	0,77	-0,03	-1,84	-2,89
	Japan	-1,29	1,92	-5,25	-9,11	1,36	7,91	-1,92	-10,2	1,04	-0,07	0,95	-2,78	0,65	-6,05	0,71	0,76	-3,36	-2,76	-3,19	11,51	-0,77	-2,08	-1,64	-2,6
	Latin 40	16,48	15,93	14,94	2,05	17,18	11,56	16,88	15,84	17,74	6,97	18,05	15,33	17,54	11,34	16,67	12,26	17,3	-9,87	16,5	14,17	18,9	15,77	17,18	17,93
	Russell 3000	-12,1	-3,46	-0,72	3,73	7,54	13,19	6,06	0,13	2,56	-4,38	3,29	-0,34	1,91	-3,27	5,79	4,84	5,92	1,18	7,16	4,27	-0,14	-8,9	-0,93	-8,91
	SP500	-3,84	-1,68	-3,66	-11	-0,84	1,2	3,12	-2,86	-8,52	-3,95	-3,95	-14,7	-3,4	2,47	2,77	5,33	4,79	-3,98	7,39	4,18	-2,27	-1,88	-1,17	-0,55
	Switzerland	6,97	-5,83	3,37	4,43	7,24	-0,2	5,79	6,07	8,82	7,15	8,36	8,87	10,39	-7,5	11,48	10,07	9,04	7,69	9,92	8,4	6,73	8,32	5,31	2,58
	Av. Return	3,36	-2,37	0,76	4,71	0,34	-0,86	4,03	4,82	1,68	-3,40	1,61	4,82	4,02	3,33	8,43	4,08	5,67	4,32	7,54	6,28	1,86	-0,10	2,53	0,72

	2 100				2 200				5 50				5 150				5 200			
	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Copper	12,22	2,65	12,48	7,26	7,01	6,05	5,99	5,69	8,86	-5,33	9,91	11,3	9,02	7,66	8,24	8,27	7,19	0	4,8	4,76
Nickel	12,7	7,02	13,67	9,48	12,02	-8,41	10,73	10,83	13,88	-5,74	15,65	16,57	13,35	0,61	14,15	12,21	9,77	-8,05	10,82	13,02
Oil	5,29	-6,88	7,46	5,08	1,15	-5,82	3,16	6,49	4,43	3,02	2,84	-10	2,28	-3,51	-0,53	3,88	1,36	-5,63	1,24	4,29
Zing	4,13	-6,45	3,43	8,84	7,55	-0,72	7,12	7,42	4,63	-1,79	5,52	5,75	8,45	-9,79	8,76	7,26	8,2	8,94	8,43	8,62
Emerging	12,77	-30,4	16,2	17,05	10,57	-2,75	2,25	6,02	5,58	-20,4	1,3	2,29	10,24	-13	13,82	10,07	1,39	0	5,14	1,03
Europe 350	-4,4	-9,62	-2,53	-2,89	6,57	17,52	7,32	6,04	-2,73	-11,6	-1,23	-0,06	4,35	0	5,29	4,06	7,35	0	9,21	7,23
Germany	4,56	-0,53	7,77	5,61	1,57	4,8	4,46	4,65	6,54	8,05	5,07	5,64	4,8	0,79	4,6	4,37	4,74	-5,91	5,68	3,63
Japan	-5,08	0,74	-8,82	-9,76	-2,29	0,24	-4,03	-6,79	-3,16	9,31	-0,97	-0,69	0,72	5,4	-1,36	0,25	-5,96	0	-1,51	-8,8
Latin 40	14,28	9,05	18,69	21,9	22,6	0,47	26,37	4,26	17,52	-16,5	20,96	10,71	15,37	11,18	20,24	24,59	24,59	-12,8	25,87	28,2
Russell 3000	-14,6	3,12	-11,3	-7,15	-8,94	0	-8,68	-8,4	-6,07	0	-8,82	-10,2	-8,21	0	-12,9	-18,6	-10,9	0	-10,3	-6,89
SP500	10,23	5,62	-10,3	-4,17	6,41	8,29	5,32	3,34	2,48	0	3,06	-6	3,16	0	5,06	2,3	4,56	3,9	3,1	6,04
SP500 Short	-58,2	17,54	-50,4	-32,7	34,15	-45,4	44,8	37,22	-31,4	0	-34,2	-39,3	30,43	0	21,8	66,03	27,69	0	40,7	57,83
Switzerland	14,67	6	-8,66	-6,8	-12,4	-0,55	-6,13	-1,32	-2,14	-0,69	1,18	1,11	12,78	-3,05	-15,3	-2,18	-4,73	1,69	-4,86	1,12
Emerging	8,24	0,96	7,5	7,29	4,85	-15,9	4,09	1,08	8,58	6,15	7,17	6,41	7,02	0	6,47	5,84	4,44	0	4,18	3,03
Europe 350	8,14	0,41	7,2	8,54	8,75	0,34	9,81	9,08	3,28	0	4,51	6,79	9,78	0	10,42	10,26	9,04	0	9,55	9,31
Germany	3,45	-0,87	4,64	2,74	5,27	11,06	4,07	5,22	-2,59	-4,35	-3,49	-26,8	0,61	0	2,59	2,57	-0,14	-14,6	-0,06	-0,99
Japan	0,33	-2,75	0,3	-0,6	-1,53	-2,78	-3,93	-3,72	-1,17	3,95	-1,95	-4,29	1,17	0	1,13	0,93	-3,36	0	-4,41	-2,36
Latin 40	16,32	8,63	18,2	17,97	16,48	3,96	16,3	17,33	16,89	11,85	16,9	17,6	16,78	4,5	17,59	14,11	15,24	2,19	15,11	16,78
Russell 3000	-3,34	1,93	2,14	2,82	6,9	-9,12	6,77	5,36	-0,66	0,77	1,46	1,2	5,88	0	5,36	4,48	5,96	0	6,1	7,4
SP500	-9,43	-6,07	-5,08	0,01	6,61	-3,8	6,59	4,51	15,1	0	-6,2	7,5	6,06	0	5,82	1,81	5,83	0	5,08	6,92
Switzerland	7,96	6,77	6,45	7,98	9,91	-5,88	9,51	9,3	2,55	-7,38	2,46	4,42	10,79	0	10,26	10	9,2	-3,04	9,12	8,81
Average Return (%)	1,92	0,33	1,38	2,79	6,82	-2,30	7,23	5,89	2,88	-1,46	1,96	0,00	7,85	0,04	6,26	8,22	5,78	-1,59	6,81	8,05

Appendix C

		1 vs 20				1 vs 50				1 vs 100				1 vs 150				1 vs 200				2 vs 50			
		None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
COMMODITIES	Copper	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Nickel	0	0	0	0	0	0	0	0	0	0,696	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Oil	0	0	0	0,912	0	0	0	0	0	0	0	0,984	0	0	0	0	0	0	0	0,978	0	0	0	0
	Zinc	0,008	0,05	0	0	0	0	0	0	0	0	0	0	0	0,014	0	0	0	0,066	0	0	0	0	0	0
ETF	Emerging	0	0	0	0	0	0	0	0,958	0	0	0	0	0	0	0	0	0	0	0	0,972	0	0	0	0
	Europe 350	0	0	0	1	0	0	0	0	0	0	0	0,892	0	0	0	0,684	0	0	0	0	0	0	0	0,02
	Germany	0,014	0	0	0	0	0	0	0	0	0,014	0	0	0	0,014	0	0	0,014	0,014	0	0	0	0	0	0
	Japan	0	0	0	0	0	0	0	0,933	0	0	0	0,193	0	0	0	0	0	0	0	0,953	0	0	0	0,053
	Latin 40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,967	0	0	0	0	0	0	0	0
	Russell 3000	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0,006	1
	SP500	0	0	0	0,994	0	0	0	0,988	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
	SP500 Short	0	0,009	1	0	0,007	0,004	0,933	1	0,004	0,004	1	0	0	0	0	0	0	0	0	0	0,1	0,004	1	1
	Switzerland	0	0	0	0,996	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0,978	0	0	0	0,264
INDEX FUNDS	Emerging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Europe 350	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Germany	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	Japan	0	0	0,996	1	0	0	0,279	1	0	0	0	1	0	0,012	0	0	0	0	0,849	0	0	0	0,945	1
	Latin 40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,119	0	0	0	0	0	0
	Russell 3000	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
	SP50	0	0	0,213	1	0	0	0	1	0	0	0,278	1	0	0	0	0	0	0	0	0	0	0	0,043	1
	Switzerland	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Insignificant	0	0	3	7	0	0	2	7	0	1	2	9	0	0	0	4	0	2	1	5	1	0	2	9

	2 vs 100				2 vs 200				5 vs 50				5 vs 150				5 vs 200			
	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Copper	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nickel	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	0
Oil	0	0	0	0	0	0	0	0	0	0	0	0,992	0	0	0	0	0	0	0	0
Zinc	0	0,212	0	0	0	0	0	0	0	0,16	0	0	0	0,99	0	0	0	0	0	0
Emerging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Europe 350	0	0	0	0,996	0	0	0	0	0	0	0	0,006	0	0	0	0	0	0	0	0
Germany	0	0,014	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,014	0	0
Japan	0	0	0	0,936	0	0	0	0,889	0	0	0	0,001	0	0	0	0	0	0	0	0,635
Latin 40	0	0	0	0	0	0	0	0,001	0	0	0	0	0	0	0	0	0	0	0	0
Russell 3000	0	0	0,12	1	0	0	0,027	1	0	0	0,888	1	0	0	0,979	1	0	0	0,947	1
SP500	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
SP500 Short	0,358	0	1	1	0	0,635	0	0	0,877	0,004	1	1	0	0,004	0	0	0	0,004	0	0
Switzerland	0	0	0	0,996	0	0	0	0,404	0	0	0	0	0	0	0	0,239	0	0	0	0
Emerging	0	0	0	0	0	0,114	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Europe 350	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Germany	0	0	0	0	0	0	0	0	0	0	0,051	1	0	0	0	0	0	0	0	0,904
Japan	0	0	0	1	0	0,001	1	1	0	0	1	1	0	0	0	0	0,603	0	1	1
Latin 40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Russell 3000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SP50	0,001	0	0,814	0,005	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Switzerland	0	0	0	0	0	0	0	0	0	4,8	0	0	0	0	0	0	0	0	0	0
Insignificant	1	1	3	7	0	3	1	4	1	3	5	6	0	1	1	2	1	1	2	4

Appendix D

	1 20				1 50				1 100				1 150				1 200				2 50			
	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Copper	-3,54	-7,98	1,30	2,42	1,99	-2,88	3,18	1,66	3,21	-0,35	3,97	-0,92	-0,81	-8,36	0,20	-5,46	-2,16	-0,32	-1,03	-1,63	2,55	-6,98	1,43	-0,53
Nickel	3,14	0,66	2,10	1,54	3,30	3,09	2,33	3,78	2,70	-12,27	2,70	-4,34	3,79	0,97	2,91	4,83	1,35	0,71	0,25	-3,18	1,44	-8,07	4,72	1,68
Oil	-14,51	-16,56	-10,59	-8,49	-5,46	-3,92	-2,76	1,58	-5,17	-8,28	-1,89	-16,28	-11,33	-6,08	-2,52	-5,13	-7,38	11,05	-3,04	-16,93	-2,00	-0,04	-1,92	-2,73
Zinc	-7,62	-8,56	-1,83	4,33	0,84	-6,65	0,81	2,85	0,17	2,88	-3,44	-0,28	2,22	-7,81	2,57	4,89	2,24	-8,53	2,96	2,89	-3,40	-2,28	-0,59	0,97
Emerging	-12,74	-33,34	-3,01	-2,43	-3,51	-18,23	-11,06	-23,23	-16,05	-38,44	-3,37	-6,04	-20,64	-9,52	-18,03	-18,56	-11,36	-15,67	-7,63	-26,98	-23,41	-17,73	-16,72	-9,61
Europe 350	6,84	-21,36	-8,54	-5,86	-5,69	-3,87	0,29	-0,07	-6,47	-4,10	-2,94	-1,95	-2,58	-3,58	2,49	-1,39	4,07	-7,76	6,96	7,70	-7,39	-11,56	-5,41	-0,22
Germany	-8,98	1,16	1,82	2,60	2,25	-2,05	4,08	-0,54	-2,78	-3,99	3,38	-0,04	0,71	-13,81	3,22	2,62	-3,61	-17,41	1,82	1,34	3,91	6,38	4,65	2,26
Japan	0,85	6,56	8,74	3,72	-4,54	-15,35	-2,60	-0,97	-9,65	-12,25	-4,41	1,77	0,03	3,42	-0,63	3,98	-3,43	3,30	-0,64	-0,75	-0,17	9,09	-0,16	1,43
Latin 40	-20,86	-8,65	-16,14	-20,49	-16,18	-48,62	-3,43	-1,54	-6,10	-39,12	-2,05	0,60	-3,75	3,98	-6,87	-41,92	2,29	-20,76	2,66	1,36	-3,90	-19,31	-6,23	-2,11
Russell 3000	-11,18	14,78	28,72	-14,88	-29,38	-3,16	-6,23	-5,38	-13,78	-0,60	-16,88	-10,18	-20,58	-9,14	-8,28	-10,98	-12,38	11,77	-9,02	-13,58	-11,98	-37,58	-6,98	-6,47
SP500	-9,46	-8,65	-10,12	-6,98	-7,28	2,38	-1,79	-6,70	2,01	-1,74	3,24	-10,59	-11,46	-5,52	-6,10	-1,95	-3,08	-1,21	0,15	-2,68	-8,01	-17,01	-5,19	-14,82
SP500 Short	61,19	-48,07	-31,87	78,76	-33,97	-19,17	-10,97	-24,67	-26,07	-20,67	-75,97	67,22	30,16	64,29	49,49	42,40	30,03	75,82	44,58	55,38	-29,37	8,53	-17,77	-43,17
Switzerland	-9,82	1,58	-30,78	-10,04	-4,28	-11,85	-5,93	27,88	-4,37	-9,67	9,22	-13,37	-2,72	-8,47	27,90	-14,78	-3,27	-14,48	-11,01	-7,88	9,72	-1,62	-1,59	-5,51
Emerging	7,67	-8,84	5,48	4,50	5,71	-5,37	4,82	3,46	5,25	-8,41	3,97	-1,29	3,87	-8,05	2,62	2,06	1,27	-1,64	0,47	0,64	5,27	3,82	4,97	2,12
Europe 350	-0,44	-18,99	-0,18	-4,87	-14,07	3,86	-1,94	0,20	3,68	-4,57	1,91	3,02	3,40	-4,41	4,04	5,08	2,80	-0,82	4,07	3,62	-2,18	-3,68	-1,82	1,38
Germany	-0,54	15,32	-12,22	0,82	0,68	-4,20	1,54	29,60	2,84	0,13	5,33	3,15	2,68	0,64	2,34	2,46	3,70	0,21	4,63	5,78	1,25	0,45	-1,36	-2,41
Japan	1,89	5,10	-2,07	-5,93	4,54	11,09	1,26	-7,02	4,22	3,11	4,13	0,40	3,83	-2,87	3,89	3,94	-0,18	0,42	-0,01	14,69	2,41	1,10	1,54	0,58
Latin 40	0,05	-0,50	-1,49	-14,38	0,75	-4,87	0,45	-0,59	1,31	-9,46	1,62	-1,10	1,11	-5,09	0,24	-4,17	0,87	-26,30	0,07	-2,26	2,47	-0,66	0,75	1,50
Russell 3000	-18,55	-9,91	-7,17	-2,72	1,09	6,74	-0,39	-6,32	-3,89	-10,83	-3,16	-6,79	-4,54	-9,72	-0,66	-1,61	-0,53	-5,27	0,71	-2,18	-6,59	-15,35	-7,38	-15,36
SP500	-9,96	-7,80	-9,78	-17,12	-6,96	-4,92	-3,00	-8,98	-14,64	-10,07	-10,07	-20,82	-9,52	-3,65	-3,35	-0,79	-1,33	-10,10	1,27	-1,94	-8,39	-8,00	-7,29	-6,67
Switzerland	-0,41	-13,21	-4,01	-2,95	-0,14	-7,58	-1,59	-1,31	1,44	-0,23	0,98	1,49	3,01	-14,88	4,10	2,69	1,66	0,31	2,54	1,02	-0,65	0,94	-2,07	-4,80

	2 100				2 200				5 50				5 150				5 200			
	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both	None	Band	Lag	Both
Copper	12,22	2,65	12,48	7,26	7,01	6,05	5,99	5,69	8,86	-5,33	9,91	11,3	9,02	7,66	8,24	8,27	7,19	0	4,8	4,76
Nickel	12,7	7,02	13,67	9,48	12,02	-8,41	10,73	10,83	13,88	-5,74	15,65	16,57	13,35	0,61	14,15	12,21	9,77	-8,05	10,82	13,02
Oil	5,29	-6,88	7,46	5,08	1,15	-5,82	3,16	6,49	4,43	3,02	2,84	-10	2,28	-3,51	-0,53	3,88	1,36	-5,63	1,24	4,29
Zink	4,13	-6,45	3,43	8,84	7,55	-0,72	7,12	7,42	4,63	-1,79	5,52	5,75	8,45	-9,79	8,76	7,26	8,2	8,94	8,43	8,62
Emerging	12,77	-30,4	16,2	17,05	10,57	-2,75	2,25	6,02	5,58	-20,4	1,3	2,29	10,24	-13	13,82	10,07	1,39	0	5,14	1,03
Europe 350	-4,4	-9,62	-2,53	-2,89	6,57	17,52	7,32	6,04	-2,73	-11,6	-1,23	-0,06	4,35	0	5,29	4,06	7,35	0	9,21	7,23
Germany	4,56	-0,53	7,77	5,61	1,57	4,8	4,46	4,65	6,54	8,05	5,07	5,64	4,8	0,79	4,6	4,37	4,74	-5,91	5,68	3,63
Japan	-5,08	0,74	-8,82	-9,76	-2,29	0,24	-4,03	-6,79	-3,16	9,31	-0,97	-0,69	0,72	5,4	-1,36	0,25	-5,96	0	-1,51	-8,8
Latin 40	14,28	9,05	18,69	21,9	22,6	0,47	26,37	4,26	17,52	-16,5	20,96	10,71	15,37	11,18	20,24	24,59	24,59	-12,8	25,87	28,2
Russell 3000	-14,6	3,12	-11,3	-7,15	-8,94	0	-8,68	-8,4	-6,07	0	-8,82	-10,2	-8,21	0	-12,9	-18,6	-10,9	0	-10,3	-6,89
SP500	10,23	5,62	-10,3	-4,17	6,41	8,29	5,32	3,34	2,48	0	3,06	-6	3,16	0	5,06	2,3	4,56	3,9	3,1	6,04
SP500 Short	-58,2	17,54	-50,4	-32,7	34,15	-45,4	44,8	37,22	-31,4	0	-34,2	-39,3	30,43	0	21,8	66,03	27,69	0	40,7	57,83
Switzerland	14,67	6	-8,66	-6,8	-12,4	-0,55	-6,13	-1,32	-2,14	-0,69	1,18	1,11	12,78	-3,05	-15,3	-2,18	-4,73	1,69	-4,86	1,12
Emerging	8,24	0,96	7,5	7,29	4,85	-15,9	4,09	1,08	8,58	6,15	7,17	6,41	7,02	0	6,47	5,84	4,44	0	4,18	3,03
Europe 350	8,14	0,41	7,2	8,54	8,75	0,34	9,81	9,08	3,28	0	4,51	6,79	9,78	0	10,42	10,26	9,04	0	9,55	9,31
Germany	3,45	-0,87	4,64	2,74	5,27	11,06	4,07	5,22	-2,59	-4,35	-3,49	-26,8	0,61	0	2,59	2,57	-0,14	-14,6	-0,06	-0,99
Japan	0,33	-2,75	0,3	-0,6	-1,53	-2,78	-3,93	-3,72	-1,17	3,95	-1,95	-4,29	1,17	0	1,13	0,93	-3,36	0	-4,41	-2,36
Latin 40	16,32	8,63	18,2	17,97	16,48	3,96	16,3	17,33	16,89	11,85	16,9	17,6	16,78	4,5	17,59	14,11	15,24	2,19	15,11	16,78
Russell 3000	-3,34	1,93	2,14	2,82	6,9	-9,12	6,77	5,36	-0,66	0,77	1,46	1,2	5,88	0	5,36	4,48	5,96	0	6,1	7,4
SP500	-9,43	-6,07	-5,08	0,01	6,61	-3,8	6,59	4,51	15,1	0	-6,2	7,5	6,06	0	5,82	1,81	5,83	0	5,08	6,92
Switzerland	7,96	6,77	6,45	7,98	9,91	-5,88	9,51	9,3	2,55	-7,38	2,46	4,42	10,79	0	10,26	10	9,2	-3,04	9,12	8,81
Av. Return	1,92	0,33	1,38	2,79	6,82	-2,3	7,23	5,89	2,88	-1,46	1,96	0	7,85	0,04	6,26	8,22	5,78	-1,59	6,81	8,05