An Empirical Analysis of the Profitability of Technical Analysis Across Global Markets

The Case of Equities, Commodities and Foreign Exchange Rates

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ABSTRACT

Four technical indicators are tested on 14 return-series, covering the years 2000 – 2016 and representing 3 different asset types: equity, commodity and currency, with a further division of equity into developed and developing markets. The indicators assessed are Moving Averages with fixed and variable holding periods, MACD, and RSI. The purpose is to determine if there are any differences in the effectiveness of technical trading between the markets. Furthermore, the technical indicators tested, are evaluated for their predictive power using the t-test, and profitability, taking adequate market conditions into account. A further purpose of the study is to observe if markets are, in line with previous research, becoming more efficient with time, especially taking the introduction of ETFs into account. The study finds that all technical indicators perform poorly in terms of profitability and predictive power. The market type that shows most profitability is developing equity markets, although the results are not conclusive. This result supports the notion that markets are becoming increasingly efficient and gives merit to the efficient market hypothesis.

Keywords: Technical Analysis, Efficient Market Hypothesis, Random Walk, Moving Average, RSI, MACD, Equity Market, Commodity Market, Foreign Exchange Market

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Terminology

B&H – Buy and Hold

BB – Bollinger Bands

BLL – Bootstrap methodology named after the creators Brock, Lakonishok and LeBaron.

EMA – Exponential Moving Average

EMH – Efficient Market Hypothesis

ETF – Exchange Traded Fund

FMA – Fixed length Moving Average

MA – Moving Average

MACD – Moving Average Convergence Divergence

Oversold/Overbought – An oversold (bought) asset is considered to be a short-term under/overvalued asset. Used in reference to oscillators.

RC – Reality Check, a data snooping robustness test.

RSI – Relative Strength Indicator

RW – Random Walk

SMA – Simple Moving Average

SPA - Superior Predictive Ability, a data snooping robustness test.

TA – Technical Analysis

Trader/Investors – Are used interchangeably in this study. Often "investor" is used to refer to someone who invests in the long-term and "trader" to someone who does short-term trades[1].

TRB – Trading Range Breakout

VMA – Variable length Moving Avera

[1] To put things into perspective, according to Swiss law, you are a trader if 1. You spend lots of time trading, preferably, you don't have a regular full-time job; 2. You have established a regular and continuous pattern of making lots of trades; 3. Your goal is to profit from short-term market swings rather than from long-term gains or dividend income.

1. Introduction

Technical analysis (TA) is the study of historical price and volume data, in order to unveil patterns, trends, reversals or any other clues as to forecasting future asset price movements. The purpose is to time market positions using predefined technical trading strategies and thereby outperform a passive strategy. Although the usefulness of TA has been, and still is, widely contested by many financial economists, several professional traders rely on computer-based technical trading systems and many more amateur traders[2] apply fairly simple technical rules to determine when to buy or sell. A large survey conducted in 2010, found that technical analysis is widely applied by hedge fund managers around the world (Menkhoff, 2010).

Together with fundamental analysis, which aims to determine the intrinsic (or fundamental) value of an asset based on financial indicators, supply and demand data or economic news, TA makes up the foundation of most asset trading (Karevold and Dahl, 2014). Whereas fundamental analysis usually is applied to find the long-term value of an asset, TA is more commonly used to predict short-term movements in the markets. Although both strategies could be used for all investment horizons, this pattern is somewhat reflected in the empirical application of the two approaches. Neely (1997) concludes that technical trading rules are predominantly used for just short time horizons, defining "short" as less than a week. The two disciplines stand in contrast to one another, as technical trading contradicts much of modern portfolio theory[3]. For example, technical analysis aims to create excess returns without taking on a greater risk. This would indicate a "free lunch", something that should be impossible in an efficient market. A third school, the efficient market hypothesis, claims that both strategies are inefficient and cannot predict future price movements.

Malkiel (1999) states that he is biased against technical traders, in his book *A Random Walk Down Wall Street.* He says it might seem unfair of the academic world to pick on technical trader as they are such easy target, but that the goal, to save people's money, justifies the attitude. Following Fama's (1970) formulation of the efficient market hypothesis, and Fama's answer to the consequent critique (1991, 1998), the prevailing view among financial

[2] By "amateur traders", we mean traders not professionally employed to trade.
[3] Mean-variance analysis.

economists is that markets are efficient, considering transaction costs and allowing for some behavioral biases on a micro-level. Much empirical evidence support this notion too, and many studies that find technical rules to outperform a market benchmark are criticized for cherry picking results and over regressing trading strategies to find significant results.

In an interview with Xetra.com (2015), professional trader and technical analysist advisor Dan Gramza, gave his view on the matter. Gramza's view is that many traders find technical analysis very important and that it is an efficient tool to summarize human behavior. Whereas fundamental analysis looks at the numbers and make a prediction, TA looks at the market's reaction to the numbers and what important information it can unveil. This makes the scope more holistic, as more than one dimension of information is considered. Gramza claims that TA is not affected by high frequency trading, as the algorithms are created by humans, and therefore still gives information on human behavior. He does, however, add one reservation: a trader needs to ask the right questions about what a technical action signal means. This indicates that there is a large degree of subjectivisms to the field, and that, apart from applying the models, practical experience might be critical to succeed in TA strategies.

The two prior paragraphs illustrate the division between much of the academic community and the technical traders. This study is aimed at concisely and methodically untangle the rift and contribute to the already well-researched field of market efficiency and technical trading. More specifically, the study sets out to test the effectiveness of common and simple technical trading strategies on three different types of asset classes to observe difference of effectiveness given the asset type. The markets tested are equity markets, foreign exchange markets and commodity markets. Equity markets are further divided into developed and less developed markets. The study applies relevant benchmarks to assess the profitability and the simple t-test to assess the predictive power of the strategies.

When testing the effectiveness of technical trading strategies, there are a few things to consider: 1. Are the strategies predictive of the future price movements, or are the correlations just by chance? 2. Are the strategies profitable given adequate assumptions about market conditions, including transaction costs (courtage and spreads) and adjusting for non-synchronous trading? 3. Are the returns abnormal or expected given the risk involved? 4. Are the strategies consistently outperforming the benchmark? [4]

More than just testing the trading strategies, as several studies have done before, this study seeks to compare the market conditions on the three named markets, and through the empirical analysis draw conclusions about if certain markets are more suited for the application of technical trading, if any at all.

The main findings of the study suggest poor predictive power and profitability for all technical indicators tested. Developing equity markets show the highest returns in relation to benchmark, and commodities and developed equity the lowest returns. Although foreign exchange markets show some more promise, in the context of profitably applying TA, than commodities and developed equity, the results hold up poorly to robustness tests.

The thesis has the following layout: Chapter 2 covers some important aspects of technical analysis and its origins. This if followed by a discussion about the efficient market hypothesis and an introduction to behavioral finance. The chapter then introduces the three market types assessed in this study, followed by a technical introduction to selected technical indicators. Chapter 3 covers previous literature on the topic and chapter 4 argues for the data selection and introduces relevant methods to investigate the research question. In chapter 5, the empirical findings of the study are presented, together with an analysis of relevant results. Finally, in chapter 6, the thesis is summarized and my personal opinions and conclusions about the results are presented.

2. Foundations of Technical Analysis

This chapter introduces the reader to the theoretical foundations of TA, and briefly describes its origins and how it is applied today. Furthermore, the concept of efficient markets is introduced and the three investigated asset markets are assessed given their theoretical foundation.

[4] This could be due to survivorship bias, which will be more thoroughly explained in section 2.3.3.

2.1 Theoretical Foundations of Technical Analysis

All technical analysis is based on three principles and the most fundamental assumption is that historical market data discounts everything. In historical data, prices, volumes and transactions are included. The second principle is that asset prices display regularities which contain information about the future price movement, that is: asset prices move in trends. This is sometimes compared to Newton's law of motion, analogously stating that a trend will remain in uniform motion in a straight line unless an external force is applied upon it. The third principle is that the regularities are repeating and long-lasting enough to be recognized and traded upon. Furthermore, the effect of the regularities need to be big enough to facilitate transaction costs. Given the first principle, technical analysis implicitly says that fundamental analysis lack predictive power (fundamental analysis, similarly, says that technical analysis lack predictive power) (Neely, 1997).

TA has been put to extensive academic scrutiny and critique regarding TA and its principles has broadly been brought forth, not least by Eugene Fama, the man who coined the efficient market hypothesis. Not only do the principles contradict the EMH, but they also put the mean-variance framework into question: if TA can generate risk adjusted profits above a reasonable benchmark, why is the profit opportunities arbitraged away? Menkhoff and Taylor (2007) state that given TA's assumptions "all relevant information should already be embodied in asset prices, making it impossible to earn excess returns on forecasts based on historical price movements, once suitable risk-adjustment is made." Or reversely, if a trend is underway, should not the trend become a self-fulfilling price movement, feeding itself with new buy-signals? There are several potential answers to these questions, including elements of how risky TA is and how technical indicators are interpreted. Although the most convincing explanation comes from the simple realization that technical trading seldom is applied without any consideration to fundamentals, which creates an element of uncertainty. In other words, testing TA without any consideration to fundamental analysis might be a misrepresentation of how TA is applied, and lack proper connection to the application of the field. Although the principles above clearly state that fundamental analysis is without merit, few of the technical practitioners would deny that fundamentals are a part of the equation.

Furthermore, there is a staggering amount of technical trading strategies when you consider different specifications of strategies as well as combinations of individual trading rules and many of them can give diametrically opposite indications of future market movements. This highlights the fact that TA not is a uniform field. Whereas fundamental analysis has a clearer causal relationship, for example, a rising interest will attract more capital and raise the exchange rate, TA is to a large extent subjective.

It is not uncommon to find up to 70 technical indicators on an investment website, and each indicator can be specified in hundreds of plausible ways, changing data points included (period), weights or data frequency, to name a few. One way to divide TA into subcategories, labels these kinds of quantifiable indicators mechanical rules, in contrast to charting, where lines and geometrical figures are drawn upon a price chart to accentuate trends, resistances and supports. Candlestick patterns also belong to the latter category. Charting is also routinely used to refer to the entire field of technical analysis. Charting as described here however, is rarely tested in academic literature as it is inherently subjective and not easy (or even possible) to quantify. Lo et al. (2000), however, mathematically defines five geometrical patterns, and identify their occurrence using a Gaussian Kernel smoothing regression on the original data, to sort out noise in the data. Another exception is candlestick patterns, which are relatively easy to quantify and have received large academic attention. This study will only concern mechanical indicators.

2.2 History of Technical Analysis

The roots of TA can be traced back to Japanese rice traders in the 1600s (where candlestick price analysis of future rice prices was developed) and the Dutch markets in the 1700s. The modern use of TA, however, can be accredited to Charles Dow[5], who between 1900 and 1902 wrote 255 editorials in the Wall Street Journal. In his Dow theory, Dow stated that there are three “movements” or “swings” in the market, what modern economist would refer to as cycles. Furthermore, the market has three trends; number one, an accumulation phase when insiders buy a stock but the trades are small in relation to the total equity so the price is hardly affected; number two, an absorption phase, when the public realizes the value of a share and

[5] Dow was one of three founders of Dow Jones and Company, which today still publishes the Dow Jones indexes.

the price increase is rapid; and number three, a distribution phase, when well informed investors begin to distribute (sell) their shares in the stock (Achelis, 2001). Dow also popularized the notion that trends are confirmed by volumes and that a trend is still ongoing until proof of the opposite can be obtained. Many of these characteristics are still used in technical trading today.

Another notable contributor to the field of TA is Ralph Nelson Elliot, who published his theories about market behavior in his 1938 book "The Wave Principle". He suggested that the market unfolds in specific patterns, or waves, which repeat themselves over time. Elliot believed that these waves were caused by crowd psychology (the tendency to mimic the behavior of those around you) and that optimism and pessimism move in natural cycles, which is reflected in price movements. According to the wave principle, market prices follow impulsive and corrective waves. Every cycle (which can occur with many different intervals) is made up of 5 waves, with number 1,3 and 5 following the market trend (impulse waves), and 2 and 4 correct (correction waves) the optimism in wave 1 and 3 (given a bull market). Each of these waves is then divided into smaller fractions, the impulse waves into another 5 waves, following the same pattern, and the correction waves into 3 waves, following the same pattern, but stopping at wave three. Elliot later concluded that this wave principle follows the Fibonacci sequence[6], which would give some further support to the explanation of why the waves would repeat in the given patterns.

Concerning historical prices, technical traders seek to find patterns that repeat themselves due to psychological factors. From this assertion sprung the field of behavioral economics, which later, in combination with advancements in the field of cognitive psychology, led to behavioral finance as presented by Tversky and Kahneman (1979). In their ground-breaking paper, they introduced behavioral biases in relation to financial decisions such as reference dependence, loss aversion and non-linear probability weighting, lending some theoretical

[6] Named after the mathematician Leonardo of Pisa, known as Fibonacci. It is a number sequence starting at 1, where every number is added to the last one to create the next (1,1,2,3,5,8,13…). Iterating this process and the ratio of a number divided by the previous number in the sequence approaches approximately 1,618 (or 0,618 if you do it the other way around). This number is known as the golden ratio, and is commonly observed to be naturally occurring in nature. As the ratio is a natural phenomenon, some investors believe it can predict human nature, and will therefore be reflected in stock pricing psychology.

support for the technical approach to trading. Behavioral biases will be more thoroughly covered in the section 2.4 Behavioral Finance.

2.3 The Efficient Market Hypothesis

Although the term efficient market hypothesis (EMH) was first coined by Eugene Fama (1965) the basic concepts of the EMH were put forward by Jules Regnault as early as 1863, when he suggested that stock market prices followed a random walk (RW). Regnault also developed statistical models for the French stock market, making him one of the pioneers in this endeavor. Regnault's work was later confirmed by Louis Bachelier, as he found that French government bonds followed a RW in 1900 (Jovanovic and Le Gall, 2001).

The EMH states that asset prices fully reflect all available information and that any new information will be reflected instantaneously in the price. EMH, in all its forms, implicitly says that all future price movements are entirely based on information not contained in historical data, and that there are no arbitrage opportunities in the market. This also implicitly means that the market follows a RW, hence the connection to Regnault's work[7]. When Eugene Fama formally presented the EMH in the survey article "Efficient Capital Markets" in 1970, the idea of the efficient market was already spread through the academic community. In fact, Fama first used the term "efficient markets" in a paper 1965, stating that efficient markets were characterized by an unbiased and instantaneous incorporation of information. The notion that capital markets are efficient and that agents are rational, has been, and still is, the ruling academic theory of markets. The rationale for the EMH is that intense competition among investors will force information to be correctly priced into an asset. It is important to emphasize that all investors do not need to be rational for the EMH to be fulfilled, as long as the average reaction is rational, the pricing will be correct. This assumption is also used for investor's expectations: on average, the expectations comply with expected utility theory.

2.3.1. Three Forms of EMH

The EMH comes in three forms: the weak form, the semi-strong form, and the strong form. The three forms differ in how "all available information" should be interpreted. The weak form states that all market information, i.e. historical data, is discounted in asset prices. Therefore,

[7] EMH is at times referred to as the random walk theory.

no abnormal excess, i.e. risk-adjusted, returns can be earned in the long run. And as soon as new market information arises, it is quickly spread and discounted for in asset prices. Since news with new information are per definition unknown, the future price movements are to be considered random. Under this assumption, TA is useless, but fundamental analysis might still work, as investors applying this technique still can gain an edge over uninformed investors. It should be noted that the no arbitrage assumption made takes transaction costs into account. If, for example, an arbitrage opportunity is too costly to execute, the market is still to be considered efficient. There is strong evidence for markets being weak-form efficient (Clarke et al, 2001).

Semi-strong efficiency goes further in that it defines all available information to include all public information. This means that not only is TA useless, but also fundamental analysis. Empirical evidence for the semi-strong hypothesis is also strong (Clarke et al, 2001). The strong form efficiency also adds private information to all available information: all information is priced in to an asset. This implies that it is impossible for an insider to use insider information to make a profit. The strong form of efficiency does not have strong support from empirical evidence however.

2.3.2 Critique of the EMH

Critics of the EMH object that if markets are in fact semi-strong efficient, how come there are so many employed with investing other people's money? Should they not be driven out of market if they cannot add value? Proponents of the EMH argue that even though fund managers on average do not outperform a passively managed fund, their existence is justified by their ability to create value for customers through diversification, and assigning appropriate risk-reward profiles to portfolios. Furthermore, acquiring all available information and interpreting it is very costly in terms of money and time, a specialization could therefore be explained by the same mechanism that explain why we have experts in meteorology or car repairs. Fund managers are also able to reduce transaction costs by trading larger volumes than a sole investor as well as helping clients plan their taxes and allocate funds to low tax environments. In fact, proponents say, the experts are necessary to uphold the efficiency of the market and make sure that assets remain at their intrinsic value. Only a small proportion of the investors are required to be rational and invest rationally to make sure the market remains efficient (Clarke et al, 2001).

Other criticism involve proof of over- and underreaction and slow information adaptation in asset markets (Jegadeesh and Titman, 1993) (Hirshleifer et al. 2007), and observing differences in how value and growth stocks are priced. DeBondt and Thaler (1985, 1987) find that contrarian strategies are significantly effective on a long-term investment horizon, indicating there is a momentum effect in the markets. Studies comparing developed markets to developing markets often find that less developed capital markets are less efficient, which would indicate that markets are becoming more efficient with time (Risso, 2009). Hsu et al. (2010) find that the introduction of exchange traded funds (ETFs) significantly increases efficiency of markets in Asia, and that in effect decreases the profitability of TA strategies. The notion that markets are getting more efficient is also widely supported by TA studies, as profitability is found to be consistently declining with more sophisticated investment vehicles and information technology. However, there is some support that profitability is not declining if implementing intra-day data as opposed to inter-day data (Schulmeister, 2009). Another puzzle for the EMH is the prevalence of calendar effects, such as the weekend effect, the January effect and the turn-of-the month effect.

2.3.3 Survivorship Bias

How does the EMH then explain the examples of investors who have managed to continuously beat the market over extended periods of time? This factor is accounted for through the concept of survivorship bias[8]. The concept is straight forward: portfolio theory states that actively managed portfolio will beat the passive portfolios exactly 50% of the time (Clarke at al, 2011). Consequently, if 10.000 portfolio managers invest randomly in year one, 50% will beat the market. The second year 50% of those 50% will beat the market. Now 25% of the portfolio manager have beaten the market two years in a row. Continuing with this line of reasoning, 10 years from now $0{,}5^{10} \approx 0{,}001$, or 10 managers have beaten the market

[8] A classic example of literal survivorship bias involved RAF airplanes during the WWII. It was noted that airplanes that survived their missions into enemy territory all had received damage to the same areas. The command ordered to relocate armor to those areas of the airplanes, as the trade-off between weight and armor did not allow for more protection. This, however, had no effect on the rate of damaged airplanes returning from missions. The problem was that they had only looked at the surviving airplanes, those who made it back. If they would have seen the airplanes not returning to base, they would have noted that they were hit in places which made the air plane go down, and that it was in fact these areas that needed the armor the most.

consistently for 10 years, just by chance. In fact, the probability that at least one investor beats the market in the example above, is above 99.99%. This example shows how some investors can beat the market purely by chance.

2.3.4 The EMH and Exchange Traded Funds

Financial innovation makes markets more efficient and the introduction of exchange traded funds (ETFs) does not seem to be an exception. Several studies have found evidence for TA profitability (Park and Irwin, 2007)[9], although the effects tend to be diminishing in more recent time series, at least when looking at daily data. Hsu et al. (2010) explicitly look at this relation in 16 Asian equity markets and find that all significance of the results disappeared after ETF introductions. The first ETF[10] was launched in 1993, following a few failed attempts in the prior years. Due to the popularity of the ETF, and a growing awareness of the advantages of passive investing, many more soon followed. The growth has been steady: there were 100 ETFs in 2002 and 1000 in 2009. The projected growth per year for the coming five years was 15-30 %, in 2014 (Forstenhausler et al, 2014) although mutual funds still outnumber ETFs by far. ETFs can be viewed as a democratization of markets, making it possible for small capital investors to go into futures markets and trade on a vast variety of assets without having to buy large contracts or know that much about the mechanics of the market itself.

2.4 Behavioral Finance

Behavioral finance describes how individual investors act irrationally and create market anomalies. The field combines behavioral and cognitive psychology with economics and finance (behavioral finance is a subfield to behavioral economics). The irrational behaviors have many times been proven in isolated studies, and could explain why technical trading strategies could be consistently viable and profitable. Whereas the EMH states that actors are on average rational, behavioral finance introduces biases (tendencies to base decisions on feelings or unfounded beliefs), heuristics (problem solving approaches) and myopia (short-sightedness). Amos Tversky and Daniel Kahneman are considered the creators of the field of behavioral finance, as they introduced the concepts of heuristics, subsequent biases, and prospect theory in their 1974 and 1979 papers. One year later in 1980, working together with

[9] Although still disputed by a fraction of researchers (Clarke et al. 2001).
[10] It had the S&P500 as underlying index and is still today one of the most traded ETFs.

Richard Thaler, the concepts of mental accounting and the endowment effect were introduced. In 1998, Fama stated that anomalies could be observed in the market, but that they were short lived, and in the long-term, markets are efficient. However, some effects that are attributed to behavioral finance, have been observed to appear regularly. To these anomalies, we can count the January effect: the stock market has historically rendered significantly higher returns in January than other months. The turn-of-the-month effect: the observation that stocks on average increase more in value during the last and first trading days of the months, and the weekend effect: the observation that Fridays have remarkably higher returns than other days of the week, especially Mondays. Through awareness of the presence of irrational behavior, investors can learn how to avoid making behavioral mistakes, and possibly benefit from it.

2.5 Characteristics of the Markets

In accordance with the EMH, all traded markets can be expected to follow a RW. What sets the markets apart is instead how they are traded, who trades in them, if there is a drift and primarily, what fundamentals are driving price movements (fundamentals can still drive prices, although no excess profits can be made from applying a fundamental strategy). These differences can be of importance in explaining differences in results of asset classes. Based on which asset type an investor is trading, fundamental analysis can differ in its nature. Silber (1994) finds that technical trading rules are useful in markets where non-maximizing participants, i.e. governments are active. This lends support to technical analysis being profitable in foreign exchange markets and for short term interest rates, but not for equity or commodities where direct government interventions are rare.

Menkhoff and Taylor (2007), surveying and analyzing a large share of the literature on TA on foreign exchange markets, identify four distinct arguments for why technical trading could work: The market is not fully rational; Influence of official interventions can be exploited; TA is an efficient form for processing information; and TA may provide information about non-fundamental influences. The authors deem the fourth and last argument the most satisfying, indicating that TA is an instrument to extract additional information about an asset.

2.5.1 The Case for Equity Markets

Most of the empirical literature covering the topic of TA concerns equity markets. Hence this study will use the equity market as a sort of benchmark when describing other asset markets, pointing out the differences between the market types and how that might affect technical trading in them.

Formally, a stock's price is a function of all future expected dividends, discounted to today's price. The expectations of the future dividends are derived using fundamental analysis and projecting future operating income and cash flows. Popular metrics for determining equities value include price-to-book, price over earnings (P/E), debt-to-equity and free cash flow. Apart from looking at the financial statements and balance sheets of a firm, firm-specific news are important, possibly affecting future revenues. On a macroeconomic level, political and economic factors can affect the pricing of future dividends and general risk appetite. Even though a shock is short-lived this can have a large effect on short-term pricing as more closely upcoming dividends have a larger weight in the pricing due to the discounting factor.

Although the equity markets are dominated by mutual funds and major shareholders (Business Insider, 2016) (in terms of value), it is a relatively easily accessible market for non-professional investors. This is reflected in the fact that almost 50% of American households (retail investors) own equity and virtually everyone who saves for their retirement in the Western world are invested in equity (ICI, 2016). In less financially developed countries, the share of retail investors is lower[11], making them potentially more efficient as a larger share of smart money is prevalent. However, the EMH states that only a small fraction of investors must be smart for a market to be efficient, so absolute number might very well be as important a factor, at least in the long run. In less developed markets, regulations might lead to less transparency, and combined with a larger share of foreign investors, with arguably less knowledge about idiosyncratic factors, this can make them harder to assess and more prone to accommodate TA.

The main purpose for investing in equity is to make a profit. With an average annual return, including dividends, from the Dow Jones 30 index of almost 10%, this has historically been a

[11] In India, only 1,8% (18 million out of 1 billion inhabitants) were invested in equity as of 2011 (Business Today, 2011)

very profitable investment. The main driver of equity prices should accordingly be directly connected to profits. The justification for such high profits is, according to traditional portfolio theory, the risk the investors take on by investing in equity, although the equity premium puzzle still puts this explanation into question. Technical trading is highly prevalent in equity markets, with a majority of market analysts including technical aspects in their analyses.

2.5.2 The Case for Foreign Exchange Markets

While fundamentals, such as relative prices and relative monetary velocity, have been proven to predict long-term exchange rate movements (Taylor and Taylor, 2004), short-term (in this case: less than twelve months) movements have yet to be explained by a fundamental model. Generally, we would expect the interest rate parity to hold, and therefore exchange rates would be determined by interest rates, inflation and perceived risks, given free capital movements. This also encompasses expectations about inflation and future monetary policy.

The interest rate parity states that:

$$\mathbf{r_t^{\alpha} = i_t^{\alpha} + \Delta X_t - i_t^{\beta}} \tag{1}$$

Where r_t^{α} is the return from investing in currency α, buying it with currency β, i_t^{α} is the interest rate in currency α, i_t^{β} is the interest rate in currency β and ΔX_t the change in exchange rate. The expected return on this investment would be zero, if it was not for the foreign exchange rate risk involved (note that the risk premium can be negative). Nevertheless, deducting the risk premium from the return, there should be no gains from investing in a currency, so that the following equation holds true:

$$E[r_t^{\alpha}] - RP_t = 0 \tag{2}$$

Where $E[r_t^{\alpha}]$ is the expected return from investing in α and RP_t is the risk premium. Note that this study assumes that all trades are done through derivatives or other investment vehicles. Hence, only the exchange rate is observed when calculating profits, not interest rate differences. This ensures that all price series are approached in the same fashion, and accurately depicts technical trading, as it does not take fundamentals into account (Neely, 1997).

There are some important differences between equity markets and foreign exchange (FX) markets. Firstly, the turn-over in the global FX market is several times higher than the combined turn-over of the world's largest stock exchanges. Secondly, FX market operators are almost entirely professionals. Thirdly, the share of short-term interdealer trading is higher than in equity markets, and fourthly, there is less consensus of what a fair price is in the FX market (Menkhoff and Taylor, 2007). Furthermore, in contrast to the equity market, where 20 % of fund managers are found to prefer TA to fundamental analysis in the short run, in the FX market, most investors use TA as their primary tool for short term trading (Taylor and Allen, 1992), indicating that technical trading rules are more profitable in FX markets.

Further, Menkhoff and Taylor (2007) put forward six stylized facts about the usage of TA on the FX markets, based on six previous studies: 1. Almost all foreign exchange professionals use technical analysis as a tool in decision making at least to some degree. 2. Most foreign exchange professionals use some combination of technical analysis and fundamental analysis. 3. The relative weight given to technical analysis as opposed to fundamental analysis rises as the trading or forecast horizon declines. 4. The consideration of transaction costs and interest rate costs actually faced by professionals do not necessarily eliminate the profitability of technical currency analysis. 5. Technical analysis tends to be more profitable with volatile currencies. 6. The performance of technical trading rules are highly unstable over time.

The first three facts indicate a widespread usage by all FX traders over shorter time periods. Facts 4 and 5 indicate profitability given the assumptions made by technical analysts. Finally, fact 6 affirms the EMH's idea that no trading strategy can be profitable over time periods that are long enough. These facts share similarities with what is observed in the equity market, as will be seen in the literature review.

Whereas equity generally is an investment, currency is a necessity for international companies who need to pay foreign suppliers. It is also common that firms hedge against currency price fluctuations using derivatives. Apart from the interest rate parity, if international deals are settled in a specific currency, this will increase the demand for that currency. Also, certain currencies are seen as safe havens in times of uncertainty, most notably the Swiss franc and the US dollar. Obviously, there is a lot to discuss concerning the supply side of currency, but that is beyond the scope of this study. Given the complexity of determining the intrinsic value of a currency pair, it could be assumed that it is harder to accurately assess than for equity. This would indicate that technical trading is more efficient in the foreign exchange markets.

2.5.3 The Case for Commodity Markets

In commodity markets, similarly to FX markets, the intrinsic value is theoretically harder to determine than for equity, since it is almost entirely based on expectations of future supply and demand[12]. The difference of the two can be observed in change in inventories. Another important factor is the cost of production, as certain price levels can make production lines unprofitable and force producers to reduce output (assuming decreasing marginal returns) to break even, and thereby adjusting the supply to the sinking demand.

Commodities are often denominated in US dollars, which make their prices sensitive to changes in the US dollar index, and some commodities are more sensitive than others. This relationship is inverse, as a stronger dollar would mean more expensive commodities. As opposed to in the equity and currency markets, all commodities are not uniform. Maybe the most straight forward example of this is the price difference between the American WTI (Western Texas Intermediate) crude oil and the North European Brent crude oil. WTI oil is sweeter than Brent, meaning that it is thinner, or lighter, and is generally traded at a 1-2 dollars discount to Brent (Levy-Mayer, 2013).

Commodities are primarily traded with derivatives to hedge future price risks. Many of contracts for difference (CFD – a general expression encompassing derivatives where a future cashflow based on a price is made) are never exercised and/or settled in cash without any delivery of the good (Pindyck, 2001). Although many of the contracts never result in any commodity changing hands, the presence of transportation costs and storage costs (generally referred to as cost of carry together with forgone interest) of a physical good somewhat sets the market apart from the two previously mentioned. Depending on the commodity, apart from the spot market, there is a separate market for storage. The storage is not necessarily owned by the same investor as the commodity, and so a fee is taken for the storage. That fee

[12] A flagrant example of a commodity where this is not true is diamonds. The company de Beers has historically owned 85% of all diamond production and held the distributors to anti-dumping rules, effectively controlling the supply and keeping prices high in relation to the abundance of accessible diamonds in the earth's soil. This monopoly is deemed one of the most successful in history and one of the most successful marketing campaigns as well. Who has not heard their slogan "A diamond is forever" (Business Insider, 2011).

is based on supply and demand, and consequently a commodity that needs storage, such as oil, can rapidly fall in value if oil storages begin to fill up.

Another aspect of the commodity market is a built-in sluggishness of supply. Demand for a commodity can increase rapidly, but the production rate takes longer to adjust. This can lead to big prices swings, and commodities do generally have high volatility. Inventories work as a cushion for these shifts in demand, as producers can sell out inventory in times of high demand, and build up inventories in times of low demand.

Gold, and to some extent other precious metals, are percieved as safe havens in uncertain times, as their value is perceived to be more robust than that of fiat currencies (which are guaranteed by a central bank that could default) and equity (which is a share of a company that can default). Owning a physical piece of gold, which does not spoil with time nor takes a lot of space to store, is deemed safe. These features have made some analysts call gold the hardest thing to accurately price, as so many factors go into its pricing, and many of them are purely based on investors' sentiments.

2.6 An Overview of Technical Indicators

"It is difficult to make predictions, especially about the future" – Yogi Berra

This section introduces the strategies assessed in this study. Every strategy is first presented in an intuitive and simple way, to be followed by a technical explanation if deemed necessary. Previous studies have tested up to 40.000 trading strategies (Hsu and Kuan, 2005), both simple and complex. For the scope of this thesis, only a handful of the most common strategies have been selected. Although the selection is made ad hoc, all selected strategies are; firstly, solely based on price data, and secondly, simple enough for an amateur investor to fully understand. All strategies are also commonly presented as analysis tools on brokers' websites, indicating a demand for them from the public. All technical indicators are presented as explained in Achelis (2001).

There are a few ways to divide technical investment strategies into subgroups. In this study, two subgroups are formed: leading and lagging indicators. Leading indicators aim to sense a price movement before it happens, whereas a lagging indicator reacts to a change in price movement or a break through.

Traders have their own preferences among these indicators, and some are considered to work well for certain assets or even specific stocks. Moreover, some work better in bull, trading (side-ways) or bear markets and there is always a trade-off between sensitivity and accuracy, depending on how the intervals are specified and what rules are set for triggering a buy or sell-signal. As this study uses daily data, all specifications assume daily data. However, the strategies could just as well be applied to weekly, monthly or intra-day data.

2.6.1 Leading Indicators

The two leading indicators used are relative strength index and stochastic. Both are so called oscillators, because they oscillate between values of 0 and 100 depending on whether the asset is to be considered overbought or oversold. Generally, leading indicators generate more signals than lagging indicators and can potentially generate higher profits as an earlier signal enables the investor to time the market more perfectly. Leading signals are considered to work best when combined with the trend of the market, that is to say, buy-signals are more accurate in a bull market and sell-signals more accurate in a bear market. This is because the oscillators are meant to identify reversals in the market, and in an up market, they might signal a reversal (sell) when the price is following its upward trend. In a trading market, however, leading indicators are considered to work well for both signals. The combination of generating more signals and earlier signals, make leading indicator strategies more volatile than lagging strategies.

2.6.1.1 Relative Strength Index

Relative strength index (RSI) is used to determine if an asset is oversold/overbought. The value of the oscillator oscillates between 0 and 100, a higher number indicating a strong up trend. If the asset price increases (decreases), so does the RSI and if the indicator goes above (below) a certain threshold value, usually set at 70 (30), this is a sign that the asset is oversold (overbought). The usual lookback period is 14 days. The RSI is a contrarian strategy, as a high value indicates a rapid increase in price for an asset. Given this nature of the indicator, it is recommended to control for the underlying cause of sudden price movements, such as quarterly reports and macroeconomic news.

The RSI is defined as:

$$RSI_{t,p} = 100 - \frac{100}{1 + RS_{t,p}} \quad (3)$$

$$RS_{t,p} = \frac{U_{t,p}}{| D_{t,p} |} \quad (4)$$

Where *t* is today's date, *p* the period use for the indicator, *RS* is relative strength, *U* is the average values of all the positive returns in the period and *D* the absolute average value of all the negative returns in the period.

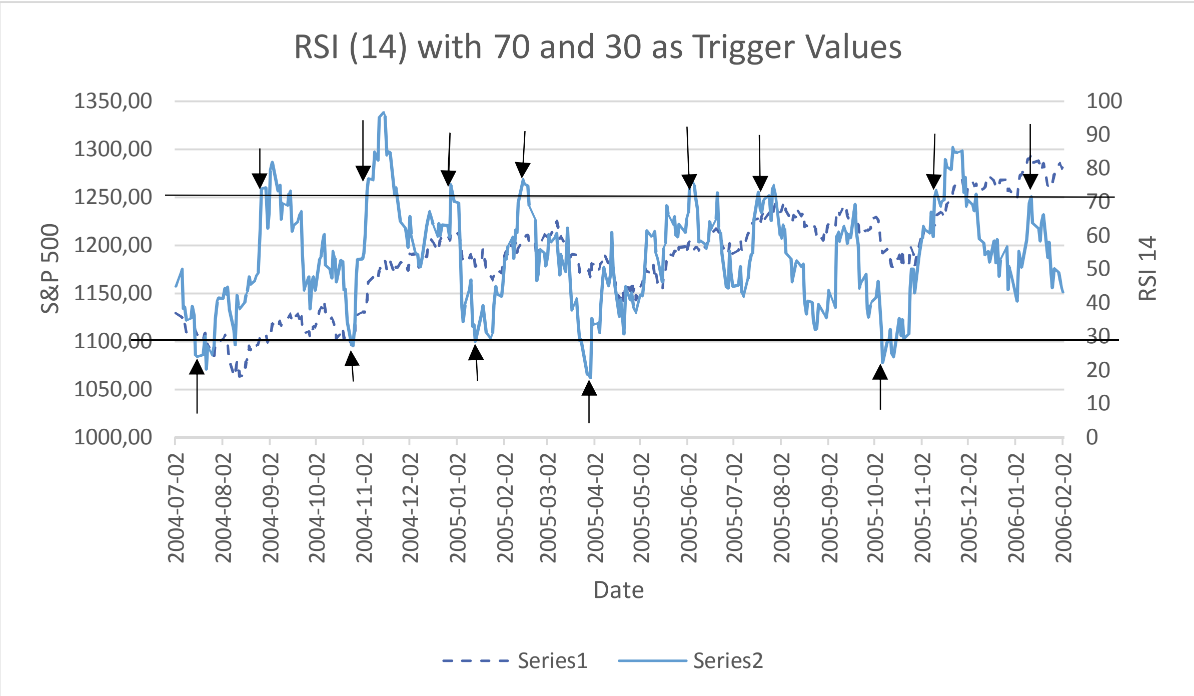


Figure 1. When the RSI index crosses the predefined values, a buy (sell) signal is generated, as indicated by the arrows. Series 1 is the price of S&P 500 and Series 2 the RSI (14) for the price series.

2.6.1.2 Stochastic

Stochastic is, just as the RSI, used to determine if an asset is oversold/overbought and oscillates between 0 and 100. For stochastic two values are calculated: a period value (%D) and a signal value (%K). When the signal value crosses the period value, and the values are in the outer regions of the range, this is taken as a sign of a reversal in the market. The border lines for what constitutes oversold/undersold are, again subjective. But below 20 and above 80 seems to be standard for buy and sell-signals. The period value is usually a 3-day SMA (Simple Moving Average) of the signal value, but can be changed depending on what sensitivity an investor requires. An alternation of standard stochastic is Stochastic with trend. That is, the oscillator moves more heavily down in an up-trend and less in a down-trend. The trend is defined by an SMA or an EMA (Exponential Moving Average), whatever has the best fit to historical data. It is common to combine stochastic, as well as RSI, with trading ranges (Achelis, 2001).

The components of the stochastic oscillator are defined as:

$$\%K(N) = \frac{C_t - L_{t-n}}{H_{t-n} - L_{t-n}} * 100 \quad (5)$$

$$\%D(n) = SMA_3(\%K(n)) \quad (6)$$

Where C_t is the closing price of today, L_{t-n} the lowest price in an *n* day interval, H_{t-n} the highest price in the interval and $SMA_3(\%K(n))$ a three-day SMA of $\%K(n)$.

2.6.2 Lagging Indicators

Lagging indicators can also be referred to as trend following indicators and react to an already observed reversal in the market. The trader enters a position given a signal, and can remain there until an opposing signal is generated. This can be very profitable as it can, in the right market, involve very few trades. In contrast to leading indicators, lagging indicators are not considered to work well in trading markets, where no clear trend is to be observed. Another drawback is the late reaction of lagging indicators (depending on the specification of the intervals of course), possibly triggering a signal after most of the price movements have already occurred.

2.6.2.1 Trading Range Breakout

The trading range breakout (TRB) strategy is based on the idea that price data moves within psychological boundaries. TRB is also referred to as filter rules in some literature, although the term TRB appears to be a bit wider. The geometrical figure created between the lines consists of an upper support, and a lower resistance. These supports/resistances can either be a psychologically important barrier (as exemplified by the recent DJIA brake through 20.000, which is, of course, nothing but an arbitrary number) or a trendline, with a fixed slope, which the asset price has followed over a certain number of periods. The most common form is a simple, fixed value for a resistance or support, the lines then create a channel. Other common shapes based on non-fixed values include different versions of a triangle and a flag.

A breakout is said to occur when an asset price definitively breaks through one of these boundaries, indicating a new trend direction. In this case, "definitively" is often defined as an increase in trade volume, as well as moving well above the boundary. Although the concept of "trader's remorse" is common, where traders start to question the validity of the new price level and prices go back to the previous trendline. Breakouts are also seen as a foreteller of increased volatility (Achelis, 2001).

TRB is associated with a plentitude of technical patterns, including head-and-shoulders, broadening tops and double tops. These techniques for analyzing if a price will break through a trading range also come in reversed form, to analyze both resistance and support lines. TRB is hard to model, especially using daily data. In this study a lagging maximum and minimum value is calculated. If the closing price of a day is higher (lower) than a previous maximum (minimum) within the lagging period, it is identified as a break out and an appropriate sell/buy-signal is generated.

2.6.2.3 Moving Averages

Simple Moving Average

Simple moving average (SMA) displays the average value based on a set interval. Every data point included is given the same weight to the moving average. This is used to smoothen data, and to detect if the current price movements are deviating from the average drift. Although the interpretation of an SMA still can be argued to be subjective, it is generally believed that if an asset price crosses its SMA, this could be a sign of a continued trend in that direction.

$$SMA = \frac{1}{n}\sum_{t=1}^{n} P_t^C \tag{7}$$

Where n is the number of periods used and P_t^C the closing price of day t.

Exponential Moving Average

Exponential moving average (EMA) displays a weighted average value where more weight is given to more recent observations. This means that an EMA moves faster than a SMA and will therefore give more buy/sell-signals than an SMA.

The EMA for a series may be calculated recursively:

$$EMA_t(n) = \alpha * P_t^C + (1 - \alpha) * EMA_{t-1} \tag{8}$$

Where usually is set to $\alpha = \frac{2}{1+n}$, but can be any number between 0 and 1.

n is the number of periods included, P_t the closing price at day t, and EMA_{t-1} the previous periods EMA. The first EMA in a series is set to be equal to the first closing price, that is:

$$EMA_{First} = P_{First}^C \tag{9}$$

Dual Moving Averages

As the name implies, it is simply the usage of two moving averages at once. This changes the interpretation slightly: instead of looking for a moving average to cross the price, a faster (with shorter interval) moving average should cross the slower, indicating the prevalence of a trend.

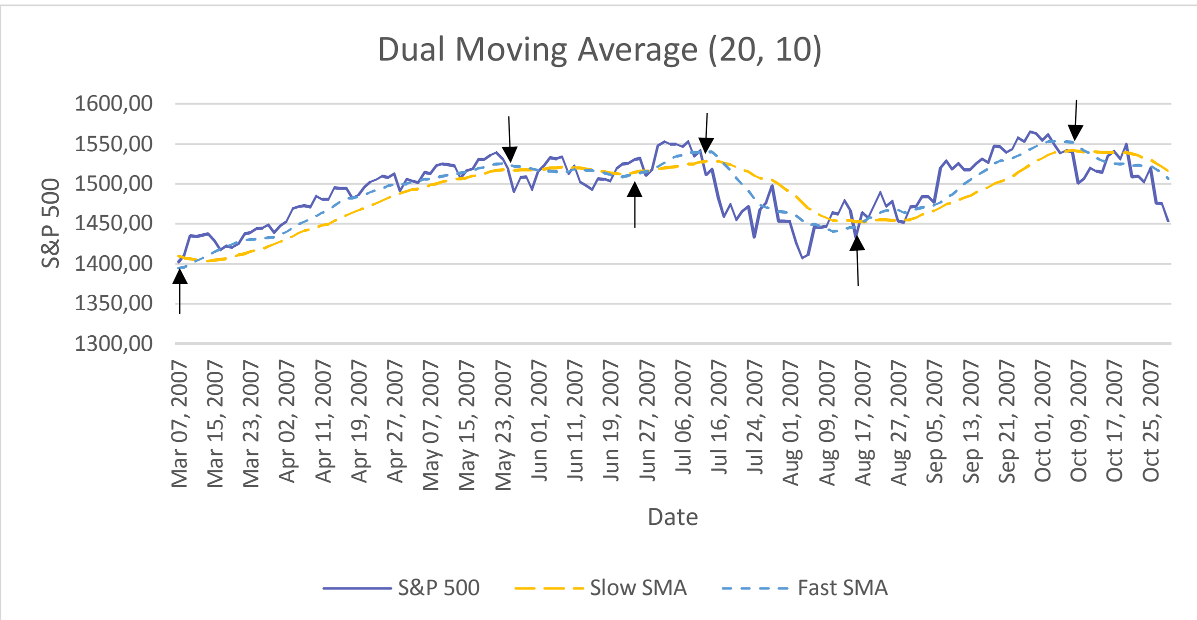


Figure 2. Dual moving average of S&P 500 with arrows indicating buy and sell-signals.

2.6.2.4 Bollinger Bands

Bollinger bands (BB) are used for both detecting when an asset is oversold/overbought and for predicting volatility. The indicator measures the standard deviation, usually set to two deviations from the mean (±2σ), based on an SMA, usually set to include 20 historical data points. This produces two "bands" that follow the price: one band two standard deviations below the price, and one band two standard deviations above the price. If the price is moving closer to the upper (lower) band, or even breaking through, the asset is considered to be overbought (oversold). Moreover, if the bands are closing in on each other (the standard deviation decreases) this can be seen as an indication that a break up or down is about to occur. However, a position should not be entered until the volatility increases again, as volatility clustering is common in financial data.

2.6.2.5 Moving Average Convergence Divergence

Moving Average Convergence Divergence (MACD) is the use of two EMAs of a time series simultaneously, where one has a shorter interval and one a longer, commonly called fast and slow because of how they differ in sensibility to price changes. By subtracting the long EMA from the short EMA, the shorter trend in relation to the longer trend can be observed, also known as the MACD. A signal line, which is an SMA of the MACD with a length usually shorter than the fast EMA, is calculated. The signal line is then subtracted from the MACD to create a number that oscillates above and below zero based on the trend of the price. If MACD breaks through, or goes above (below) the zero-line, this generates an indication of a future incline (decline) in an asset prices. This relation is usually visualized by bars beneath the graph, indicating the direction and strength of a trend.

$$MACD = (EMA(slow) - EMA(fast)) \tag{10}$$

$$MACD(signal) = SMA(EMA(slow) - EMA(fast)) \tag{11}$$

$$HISTOGRAM = MACD - MACD(signal)) \tag{12}$$

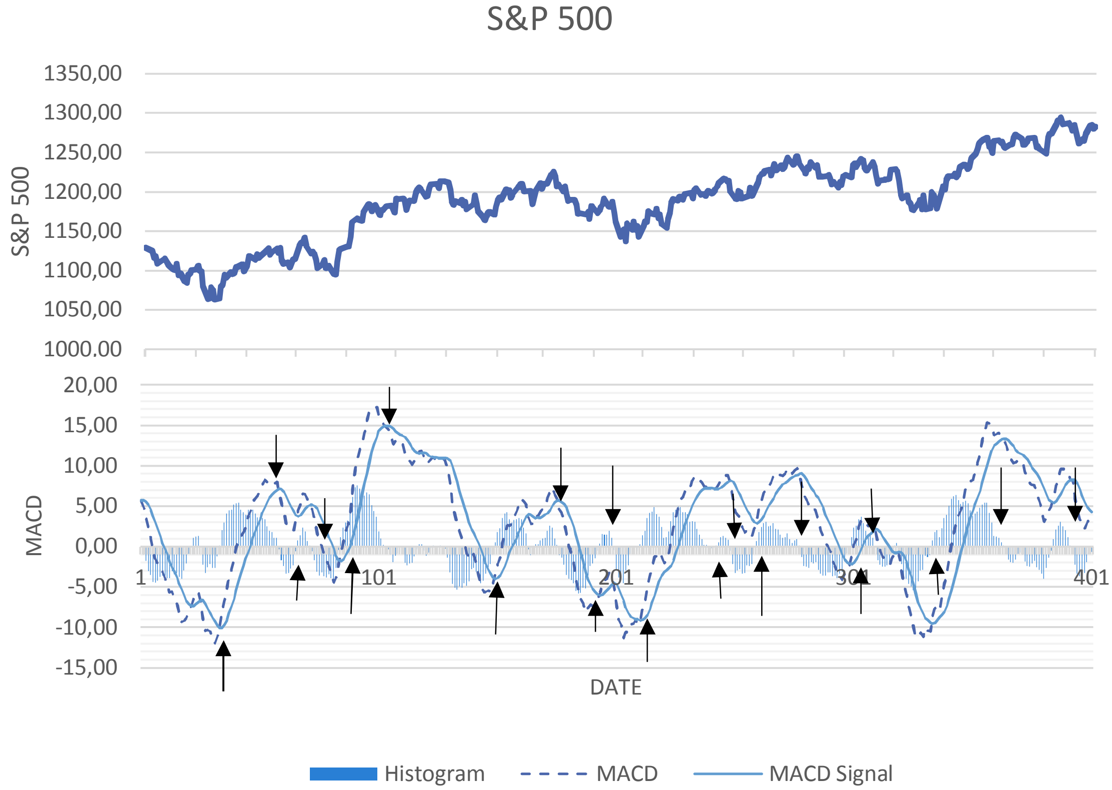


Figure 3. The S&P 500 and its MACD. The histogram (staples) oscillates around 0. The black arrows indicate buy and sell-signals.

2.7 The prevalence of Technical Analysis

In an international survey conducted in 2010, 692 fund managers in five countries were asked to evaluate how much emphasis they put on fundamental analysis in relation to technical analysis and other methods, in investing the fund's money. Although fundamental analysis was the most popular technique by far, almost all the respondents used TA to some degree and over 50% responded that TA corresponded to over 20% of their total analysis. For investment horizons up to a couple of weeks, TA was the most important method for analyzing asset prices (Menkhoff, 2010). This definition of short-term is somewhat different from the "less than a week" that Neely (1997) argues for concerning usefulness of TA on foreign exchange markets, indicating that there might be a discrepancy in the application depending on what type of asset is traded. Taylor and Allen (1992) do not specify what a short time horizon is, but further supports this notion, as well as the wide usage of technical indicators.

3. Literature Review

As new methods are developed and new standards are put in place, old empirical findings can swiftly become obsolete. This is particularly true in the field of TA, as many studies show diminishing, if not eliminated, profitability of technical trading strategies as markets develop. Consequently, this section will mostly concern recent studies, to capture the current state of the usefulness of technical trading.

3.1 Methodological Advances

Brock, Lakonishok and LeBaron (1992) test 26 technical indicators on daily data from Dow Jones Industrial index 30 from 1897-1986. They use, what later has become standard in the literature, a framework for testing for significance with a t-test and for presenting the results. Furthermore, a parametric bootstrap methodology, hereafter referred to as the BLL bootstrap, is introduced to further test for significance given the suboptimal characteristics of financial data. The method involves estimating a "null model" that best fits the data, and then drawing the residuals with replacement to create new price series with the same statistical characteristics as the original data. This process is repeated 500 times to ensure accurate results. The technical indicators are then tested on the 500 series to see if they can outperform the benchmark more than 95% of the time. Significant positive results are found for moving averages (MA) and trading range breakout (TRB), and the bootstrapped results are similar to those of the t-test. Non-overlapping sub-periods are used to control for data-snooping bias.

Seven years later, Sullivan Timmerman and White (1999) revisits the dataset used by Brock, Lakonishok and LeBaron (BLL), adding 10 years for out-of-sample analysis (1897-1986+1987-1996) and a data snooping test called Reality Check (RC) to the study. The RC utilizes a parametric bootstrap to assess if the best strategy's return is by chance or due to predictive power. This is achieved through measuring how large a fraction of the best performing strategy's return from the simulated series exceeds that of the original series. The RC finds no data snooping bias for BLL's results, which further ensures their robustness. Both buy-and-hold (B&H) and the risk-free rate are used as benchmarks, and the excess returns are adjusted for risk using a Sharpe ratio.

3.2 Empirical Results for Equity

The clear majority of studies concerning the effectiveness of TA involves equity time series. As such, this will be the baseline for the other two asset classes as the variety of methods, technical indicators and data samples have the biggest scope. Some results from the equity markets might be assumed to be similar in the currency and commodity markets.

Kwon and Kish (2002) examine 24 simple trading rules on daily data from the New York Stock Exchange (NYSE) value-weighted index between 1962 and 1996. The study accounts for data snooping by testing several moving averages and use B&H as a benchmark. Both a simple t-test and the BLL bootstrap are used to test for significance of excess returns. The study indicates excess returns for the techniques applied, especially when moving averages are combined with volume data, and prices change indicators are accounted for. The volatility is found to be greater in sell periods.

Hsu and Kuan (2005) test 40.000 technical trading strategies on daily data from 4 indices between 1989 and 2002. The trading rules consist of circa 18.000 simple rules, circa 18.000 contrarian strategies, and circa 4000 complex strategies, including learning strategies and vote strategies. The indices are divided into two subgroups: mature and new markets. The mature indices are DJIA and S&P 500, and the new indices are NASDAQ and Russell 500. The authors apply the RC and Superior Predictive Ability (SPA – an alternative method to RC) (Hansen, 2005) bootstrap methodologies to control for data snooping. Hsu and Kuan (2005) find that TA works on the newer markets, but not on the mature markets and that more complex trading strategies are more successful in general, although simple moving average (SMA) is the most profitable rule. However, no strategy can consistently beat B&H. The RC and SPA indicates that there is no data snooping bias.

Marshall and Cahan (2005) test 12 moving averages and trading range breakout strategies on daily data from the New Zealand stock exchange (NZSE) between 1970 and 2002. They divide the sample into three, non-overlapping 11-year subperiods. They apply a fixed holding period of 10 days for all indicators and perform a t-test as well as a BLL bootstrap to check for significance. For the bootstrap AR, GARCH-M and E-GARCH are applied as null models respectively. The authors do not check for data snooping bias as the dataset is unlikely to have been used for developing the tested trading strategies. To adjust for non-synchronous trading, a stock is bought/sold at the closing price the day following the signal. The results show significant positive returns for the first sub-period, in the third period all significance is lost. Weighted moving average (WMA) and TRB outperform simple moving average (SMA) and exponential moving average (EMA). The BLL bootstrap indicates the strategies have predictive power in the first period, but none in the last.

Chong and Ng (2008) test MACD and RSI on daily data from the London FT30 index between 1935 and 1994 with a fixed holding period of 10 days. The sample is divided into subperiods to control for snooping bias and significance is tested by using a t-test. The authors do not address non-synchronous trading or any transaction costs and find that all strategies are consistently significant and profitable.

Marshall, Cahan and Cahan (2008) test 8.000 rules on 5-minute intraday data on an ETF tracking S&P 500 between the years of 2002 and 2003, where 2002 is considered a bear market and 2003 a bull market. The BLL bootstrap with GARCH-M as a null model is applied to control for significance and RC to control for data snooping. No strategy is consistently beating the benchmark and the RC indicates there is a data snooping bias.

Metghalchi, Chang and Marcucci (2008) test MA strategies on daily data from the OMXS30 index between 1986 and 2004. A t-test is applied to test for significance and RC to control for snooping bias. Only strategies using more than one moving average at a time shows significance. Several strategies prove both significant and profitable results, given a 0,5 % transaction fee.

Schulmeister (2009) tests MA and RSI strategies on intra- and inter-daily data from the S&P 500 spot and futures market between 1960 and 2007. The study looks at both the whole sample period and divide it into subperiods to account for possible snooping bias. A t-test is used to test for significance. The daily data shows declining significance and returns with time, the intra-daily data of 30-min intervals, however, shows no declining returns.

Marshall, Qian and Young (2009) test MA and RSI strategies on daily data on stocks listed NASDAQ and NYSE between 1990 and 2004. The sample is chosen to fit into different subgroups based on size, liquidity and industry. The study applies a BLL bootstrap and adjusts for non-synchronous trading by entering positions the day after a signal. The results indicate weak support for the technical strategies and find no effect for industry. Small and illiquid stocks show more support for profitability, as does indicators for longer term patterns.

Hsu, Hsu and Kuan (2010) test 16500 MA and filter strategies on growth and developing markets between 1988 and 1999 and ETFs tracking the indices between 1996 and 2005. The sample is divided into pre- and post ETF subperiods. SPA is applied to control for snooping bias. The SPA indicates that the strategies are predictive before the introduction of ETFs, but after ETFs are introduced, no significance is found in either of the datasets.

Wong, Manzur and Chew (2003) test MA and RSI strategies on the Singapore stock exchange (SES) between 1974 and 1994. The sample is divided into three subperiods and significance is tested for using a t-test. SMA strategies prove to have the highest profitability, and the strategies generate substantial returns for all periods.

Metghalchi, Marcucci and Chang (2012) test SMA on data from 16 European markets between 1990 and 2006. A t-test is applied to control for significance, and RC to control for data snooping. The strategies are found to do well in all markets, where the best rule has predictive power in 13 out of 16 markets. In general, the strategies work better on small and midcap markets.

3.3 Empirical Results for Foreign Exchange and Commodities

Qi and Wu (2006) test 2.127 strategies on daily data on seven exchange rates against the dollar between 1973 and 1998. The strategies are different calibrations of filter rules, MA and TRB (resistance/support and channel), and the sample is divided into two sub-periods. Using a t-test, significant profitability is found using MA and channel break out on all seven exchanges. RC is applied to control for data snooping, making this the first study on TA in FX markets applying the methodology, but no data snooping is detected at a 1% significance level. However, the second period suffers more from snooping bias than the first, and profitability decreases as well. After transaction costs are considered, the strategies still show significant profitability, and more volatile exchange rates are found to be more profitable. This is in line with what Park and Irwin (2005) found a year before looking at Euro and Yen exchange ratios.

Charlebois and Sapp (2007) test MA strategies on daily data on the Dollar-Deutsche Mark exchange rate between 1988 and 1998. The study applies a t-test to test for significance and finds significant excess returns, which increase when data of the open interest differentials on options (difference in value of outstanding sell and call options) is considered. The authors interpret the open interest data's contribution as additional fundamental data that is reflected in the option market, where more informed investors might trade because of the leverage provided.

3.4 Main Conclusions

To sum up the literature review, here are the key results and findings:

Firstly, in the last three decades, methodological advances in accounting for problems with significance and checking for data snooping bias were made. These methods are consistently found in the literature since their conception, although not applied by all studies.

Secondly, the scope of technical indicators tested is extensive although the focus lies on moving averages, filter rules and relative strength index. More complex strategies have been tested including learning strategies and vote strategies, proving to be generally more than simple rules, however, moving averages seem to be the consistently best strategy.

Thirdly, there is evidence to support a declining profitability of TA starting in the mid 90's, some studies linking it to the advent on ETFs. This is in general accredited to financial innovation and thus increasingly effective markets. One study finds that the decline in profits might not hold true for intra-day data, which can more realistically reflect a real-world scenario.

Fourthly, several studies find that less developed financial markets are more profitable than mature markets. But profits are decreasing in developing markets too, as they become more refined.

Fifthly, the lion's share of the literature concerns equity markets, with some degree of evidence from foreign exchange to complement it. Commodity markets, however, do not get much attention in modern TA literature.

To conclude, Park and Irwin (2007) find that out of 95 modern studies reviewed, 56 show evidence for significant profitability of TA, 20 studies show no evidence, and 19 show mixed evidence. However, not all studies account for data snooping bias or transaction costs properly.

4. Method and Data

This chapter encompasses a more detailed description of the trading strategies being applied in the study, description of data and selection motivation, as well as a description of how sell and buy-signals are generated. Furthermore, the statistical techniques used are presented together with considerations for making the trading strategies as realistic as possible. If the reader is not familiar with the terminology connected to technical trading, a brief list of terminology and abbreviation is supplied in the preface.

4.1 Technical Strategies

Of the indicators presented in Section 2.5, all are simulated in Excel and tested on external price data (Which means data not used in the study, in this case data from the OMXS30 index for the years 2001-2016. This is done to avoid any risk of data snooping bias). The indicators are assessed based on how accurately they can be represented to mimic real life sell and buy actions. Bollinger bands and trading range breakout are concluded to be relatively subjective. Furthermore, the results from relative strength index and stochastic are similar, and RSI is preferred as it only applies closing price data, reducing the input data needed. Consequently, three indicators are chosen for the analysis: moving average, MACD (which is a dual EMA combined with a SMA) and RSI. Moving averages have been extensively analyzed before, and often found to be among the most profitable technical strategies. A variable and fixed length holding period is applied as it has in previous studies (Brock et al., 1992) to capture different investor behaviors. RSI complements the MA by representing leading indicators, having a contrarian approach to trading rather than trend following.

For MA, different lengths of SMAs, EMAs and dual SMAs are analyzed, with the EMA and SMA lengths being 5,10, 20 and 50 days. For the dual SMA two period lengths are combined: 5 and 10, 10 and 20, 20 and 50, and 50 and 200. The specifications of the lengths are chosen to capture the short-term and long-term trends in the market. The variable length moving average (VMA) holds a position until the signal is reversed whereas a fixed length moving average (FMA) holds a position for a predefined amount of days. The holding periods included are: 1, 3, 5, 10 and 20 days. This span of fixed length holding periods follows previous studies (Brock et al, 1992) but adds but adds additional holding periods in the shorter part of the spectrum, to more accurately distinguish differences of short holding periods. The fixed holding period set for 20 should capture the real-world application of TA found by Menkhoff (2010), where the respondents said they apply technical strategies for time horizons up to a couple of weeks.

The SMAs, EMAs and dual SMAs each generate a three indicator buy and sell-signal series: one for buy only, one for sell only, and one for buy and sell combined. This gives us the opportunity to see the results of the individual directions in the market. Given the specifications mentioned above, this gives 180 different FMA buy/sell-signal series and 36 for VMA. As no filters are applied, a buy or sell-signal is generated as soon as the closing price of a day results in a shift of the indicator.

For MACD, the standard setting of 26, 12 and 9 (Achelis, 2001) (where 26 is the slow EMA, 12 the fast EMA and 9 the SMA of the difference of the two, that is the signal line) is tested together with a slower moving MACD of 50, 20 and 18. Only a variable holding period is applied and buy, sell and buy/sell series are created separately, rendering in 6 series.

For RSI, only the commonly practiced 14-day interval is used. However, three threshold combinations are tested: 70/30, 60/40 and 50/50, following the findings of Wong et al. (2003). Furthermore, both a value above/below trigger and a crossover trigger is used to generate buy and sell-signals (for example, the first one sending a buy-signal as soon as the RSI goes below 30 and the latter first when the RSI crosses 30 from below). This accounts to 18 RSI series. In total that means 240 unique indicators.

4.2 Data Selection

To observe if different asset types are differently receptive to technical analysis, three asset class price series are considered: equity, currency and commodity. Equity is further divided into new and old markets, to see if there is any difference in the effectiveness of the markets. A correlation matrix and more descriptive statistics can be found in the appendix. The data is downloaded as prices series and are gathered from Investing.com (commodities and currencies) and Yahoo Finance (equities, adjusted for dividends). The selection of time series included is done based on availability and trading volumes, where higher volumes is preferred,

Table 1. Descriptive Statistics for Return Series, 2000-2016

Variable	**Count**	**Mean (Daily)**	**Mean (Annual, %)**	**Standard Deviation**	**Standard Error of Mean**
COPPER	2576	*0.006%*	1.58%	0.01823	0.000359
GOLD	4330	*0.040%*	10.45%	0.011509	0.000175
SILVER	2761	*0.031%*	8.01%	0.020767	0.000395
WTI_OIL	4328	*0.044%*	11.31%	0.02428	0.000369
Average Commodities	**13995 (total)**	*0.030%*	7.84%	**0.0187**	**0.000325**
EUR_GBP	4458	*0.009%*	2.26%	0.0053	7.93E-05
EUR_USD	4488	*0.003%*	0.82%	0.0064	9.53E-05
USD_JPY	4459	*0.004%*	0.99%	0.0066	9.82E-05
USD_CHF	4459	*-0.008%*	-2.02%	0.0073	0.00011
Average Currencies	**17864 (total)**	*0.002%*	0.51%	**0.0064**	**9.55E-05**
NIKKEI	4186	*0.009%*	2.46%	0.014	0.00022
DAX	4331	*0.022%*	5.64%	0.015	0.00023
S_P	4276	*0.020%*	5.20%	0.012	0.00019
Average Developed	**12793 (total)**	*0.013%*	3.46%	**0.014**	**0.00021**
INDIA	4208	*0.052%*	13.42%	0.016736	0.000258
IDX	4123	*0.063%*	16.28%	0.014246	0.000222
SAO_PAOLO	4227	*0.048%*	12.38%	0.018071	0.000278
Average Developing	**12558 (total)**	*0.054%*	14.02%	**0.0164**	**0.000253**
All	**57210 (total)**	*0.024%*	6.34%	**0.0143**	**5.99E-05**
LIBOR	4487	*0.005%*	1.28 %	5.65E-05	8.43E-07

especially for markets with a high degree of speculative trading. For equity, a geographical spread is desired, to make the results more general and to minimize the effects of local disturbances. In all other regards, the data selection, as the initial technical indicator selection, is made ad hoc, based on the author’s perception of interesting markets.

Following the results of Metghalchi, Marcucci and Chang (2012), that smaller and less traded markets (less liquid) show higher significance for technical analysis, developing, or new markets are added to see if this result can be replicated for less developed financial markets. Developing markets will be referred to as new markets, while developed markets will be referred to as old markets, this to easier tell them apart and simplify tables. Although the financial markets are arguably less developed, the added indices are not illiquid. Illiquid assets generally have a much higher bid-ask spread, making it costly to enter and exit the market.

The data stretches from the beginning of 2000 until the end of 2016, except for copper and silver, for which the price data begins in 2007. For the remaining time series, the period of 2000 until 2016 will be applied, for copper and silver, 2007 until 2017. The data frequency is daily, and include circa 4300 observations per asset (circa 2600 for Copper and Silver).

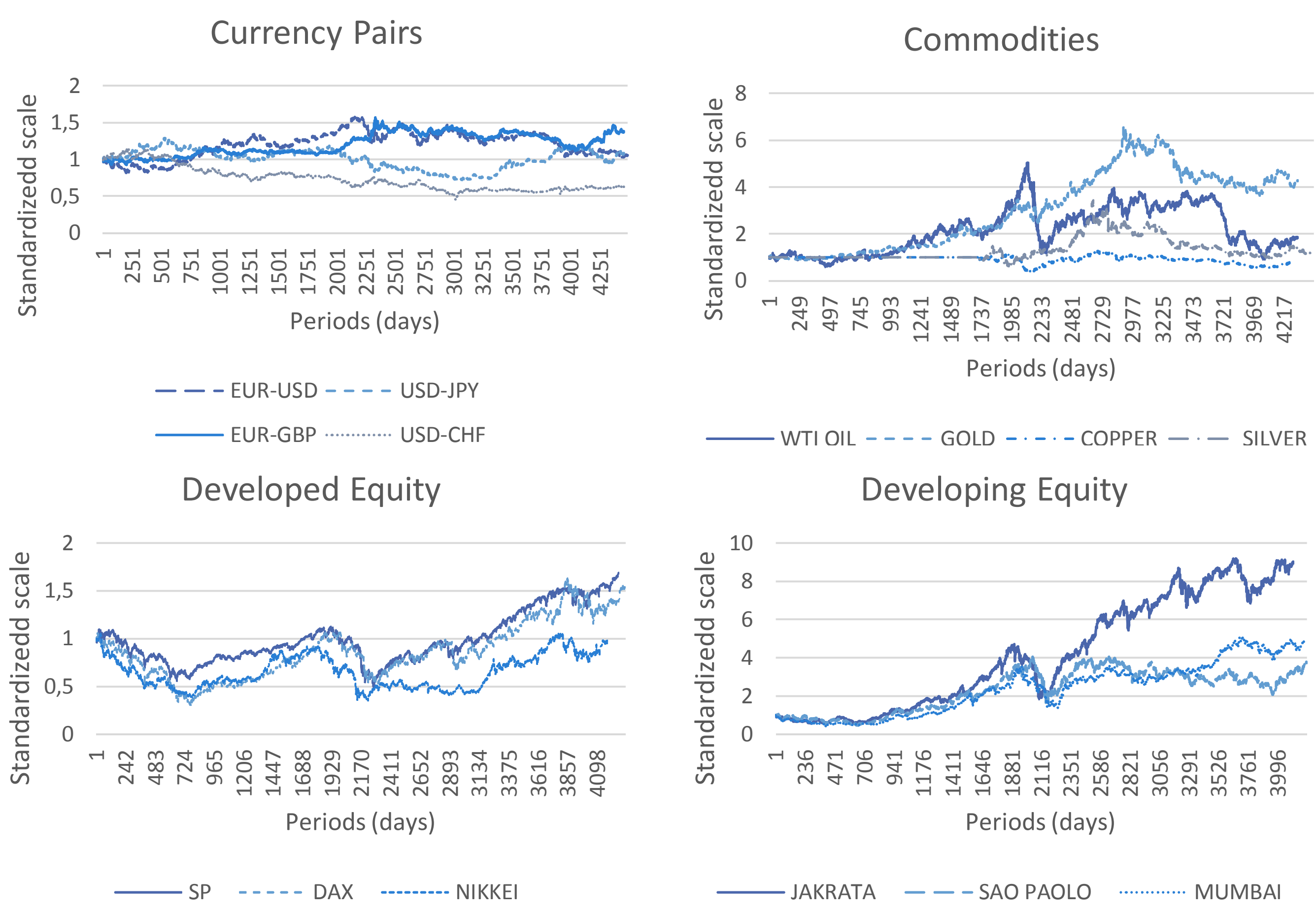
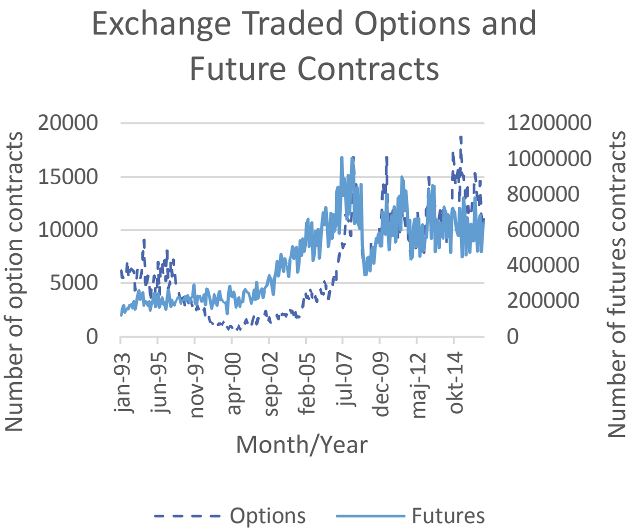


Figure 4. The time series visualized grouped by asset type.

Descriptive statistics can be viewed in Table 1, including the LIBOR rate, the price series are visualized in Figure 4, and a correlation matrix is supplied in the appendix. The data leading up to the start of the study will be used to generate indicators that requite a long price interval.

The reason for beginning the study in 2000 is based on the assumption that markets get more efficient with time and with technological and financial innovations. Considering Hsu et al. (2010), the advent of ETFs had a significant effect on the efficiency of Asian stock markets. It has both become cheaper and easier to invest in a large array of assets, including, but not limited to, all the assets included in this study. Starting off in the EMH, a market only requires a small number of informed investors for markets to become efficient. Nevertheless, easier access, and consequently a larger investor base, will improve efficiency as long as a few of the new investors are considered informed. Hence, many of the studies which find significant technical trading strategies might not have done so using newer data sets.



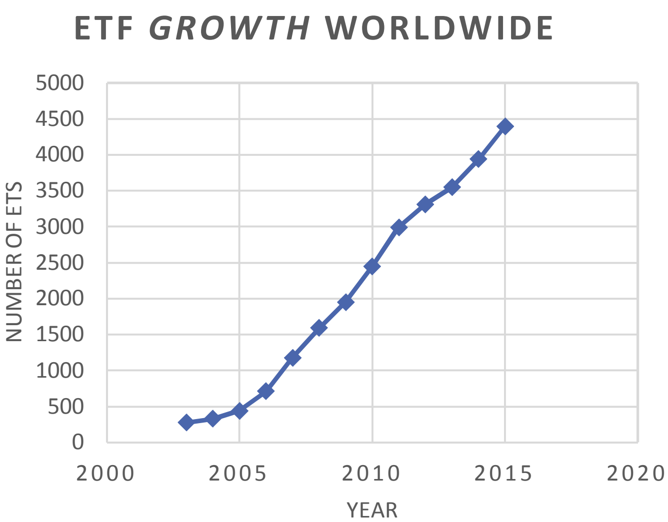


Figure 5 (to the left) and Figure 6 (to the right). The growth in ETFs and derivatives should make markets more efficient and possibly decrease the effectiveness of technical trading

Moreover, derivatives markets have also seen significant growth, not only at the same pace as the ETFs. Options are commonly used to trade all asset types, whereas futures are more applicable on commodities and currencies, as firms commonly use them to hedge price risks. Both these factors, along with the introduction of online trading platforms and economic information, has made investing and trading vastly more accessible, although still with a relatively high knowledge threshold and with a significant advantage in terms of time and infrastructure for professional traders.

4.3 Market Efficiency and Technical Indicator Performance

In this section, the method for measuring the performance is presented and argued for. An initial test of the data is done to implicitly predict if any of the strategies will be successful based on the assumptions of the EMH.

4.3.1 Testing for Random Walk

For the price series, in line with the EMH, a random walk process should be observed, no excess return should be earned applying technical strategies. The first step is accordingly to test the price data for a RW process.

Two types of RW are considered: a RW without drift:

$$y_t = y_{t-1} + \varepsilon_t \tag{13}$$

And a RW with drift:

$$y_t = \mu + y_{t-1} + \varepsilon_t \tag{14}$$

where y_t is the price at time t, μ the drift constant, y_{t-1} previous day's price and ε_t a random disturbance term with $\varepsilon_t \sim iid(0, \sigma^2)$.

For both models the expected value and variance given the starting value is:

$$E[X_t \mid X_0] = X_0 + \mu t \tag{15}$$

$$Var[X_t \mid X_0] = \sigma^2 t \tag{16}$$

Where μ is equal to 0 for a RW without a drift.

The random walk hypothesis is tested using a Variance-Ratio Test, following Lo and MacKinley (1988). The test is applied using the relaxed assumptions where the disturbance term can follow a conditional heteroscedastic form. The original prices series are used for the test.

The Variance-Ratio Test makes use of the property of variance in (13) and tests if variance is constant over time. The test compares the cumulative variances added up one by one to the variance of the whole period. Given a RW, the variance given q-periods should be equal to q times the variance of one-period. More formally, the ratio of the two should be 1:

$$VR_q = \frac{\sigma_q^2}{q\sigma_1^2} \tag{17}$$

With other estimates for the test being:

$$\hat{\mu} = \frac{1}{nq}(X_{nq} - X_0) \tag{18}$$

$$q\sigma_1^2 = \frac{1}{nq-1}\sum_{k=1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2 \tag{19}$$

$$\sigma_q^2 = \frac{1}{m}\sum_{k=q}^{nq}(X_k - X_{k-q} - \widehat{q\mu})^2 \tag{20}$$

$$m = q(nq - q + 1)(1 - {}^{q}/_{nq}) \tag{21}$$

Instead of assuming the drift properties of the time series, both models will be tested. However, in the case of equity, a drift model seems most appropriate, and in the case of currencies, a no drift model should be more applicable. In the case of commodity, prices can be expected to keep up with inflation, making a drift model more appropriate.

The Variance Ratio is tested using null hypothesis of a RW by calculating the z-statistic for the probability of a RW as follows:

$$z(q) = (VR(q) - 1 * [s^2(q)]^{-1/2} \tag{22}$$

Where q is the interval tested, is the $z(q)$ is the test statistic, $VR(q)$ the variance ratio, and

$$s^2(q) = \frac{2(2q-1)(q-1)}{3qT} \tag{23}$$

Where T is the length of the sample tested.

4.3.2 Generating Buy and Sell-signals

Using the price series, return series are calculated using a geometrical method as follows

$$r_t = \ln(P_t/P_{t-1}) \tag{24}$$

Where r_t is the return of day t, P_t the closing price of day t and P_{t-1} the closing price of day t-1. Compared to arithmetic returns ($r_t = (P_t - P_{t-1})/P_{t-1}$), the geometrical method is advantageous in terms of a more intuitive reversions, and additive properties. Although the geometrical method is an approximation, it is a very exact one for small changes.

The return series are tested for stationarity using an augmented Dickey-Fuller test for unit root, a Jarque-Bera test for normality to visualize the distribution and a Ljung-box Q-statistic is used to check for auto correlation.

The return series are then used to create technical indicator series in Excel, given the indicators mathematical definitions, described in Section 2.6. The technical indicator series are in turn interpreted by a buy and a sell column respectively, to result in a one for buy (sell) and a zero for doing nothing or exiting the market. Doing nothing is the same as staying out of the market and earning risk-free interest. The monthly LIBOR rate, represented as daily rates, is used as the risk-free out-of-market rate for all assets. This feature, however, is only used for comparing returns, it is not a feature of the statistical models. The buy and sell-signals can now either be used on their own, observing the effect an isolated direction in the market has, or combined to test the indicator for both directions in the market.

The generation of buy and sell columns differ depending on the technical indicator and the chosen interpretation of the indicators, but all apply an if-function, rendering a 1 if true and a 0 if false. In combination with the if-function, the and- and or-functions are commonly applied. To make the Excel spreadsheets dynamic, the offset-function is used, referring to a cell (or cells) specifying the length of the look-back period and, when applicable, how long the fixed holding period should be, as specified in Section 4.1. This feature facilitates the option to test a large set of indicators on several time-series using only Excel.

The method of applying filters to the indicators is considered, but rejected for two reasons: 1. It will add an arbitrary element to the application of the indicators, as filters are not commonly specified in the context of technical analysis 2. It will increase the number of unique applied indicators by at least doubling them (adding one filter). A large number of specifications is a path to false positives, in a similar fashion as data mining, using more variables than observations, is. Keeping the number of unique indicators low also decreases the risk of accidental data snooping, when the data snooping bias is a result of chance rather than from actually looking at the data first.

Using the sell and buy series, new return series are calculated. For each technical indicator and specification, one buy returns series, one sell return series, and one buy-and-sell return series is calculated. The mean and variance of buy (sell) return series is calculated as:

$$\bar{r}_{b(s)} = \frac{\sum_{t=1}^{N} r_t * I_{t-1}^{b(s)}}{N_{b(s)}} \tag{25}$$

$$\hat{\sigma}_{b(s)}^2 = \frac{\sum_{t=1}^{N} (r_t - \bar{r}_{b(s)})^2 * I_{t-1}^{b(s)}}{N_{b(s)}} \tag{26}$$

Where $\bar{r}_{b(s)}$ is the mean return of the buy (sell) signals, $I_{t-1}^{b(s)}$ is an indication value (1 for market action), and $N_{b(s)}$ is the number of days (as daily data is applied) a signal is in the market. The reason why $I_{t-1}^{b(s)}$ is lagged one period will be explained in Section 4.3.3.

4.3.3 Testing for Profitability

The indicator values of the buy and sell series, $I_{t-1}^{b(s)}$, are lagged one period to account for non-synchronous trading. Applying no filter, a position is taken at the closing price of the day the signal is observed. This is the most straight forward application of the trading strategies, but assumes that it is possible to observe a signal and enter a position on the same day. Many previous studies account for non-synchronous trading by entering positions either at the opening price of the day following the observation or at the closing price of the following day. However, given the findings of Schulmeister (2009) concerning disappearing profits using inter-daily data in later samples, and assuming that intra-day data is indeed easily available to everyone with a computer and an internet connection, this approach appears most realistic as to represent how trading is performed.

The excess returns from the buy and sell-signals are measured as:

$$r_t^{b(s)e} = r_t^{b(s)} - E[r_t^{b(s)}] \tag{27}$$

$$E\left[r_t^{b(s)}\right] = \frac{1}{N}\sum_{t=1}^{N} r_t \tag{28}$$

Where $r_t^{b(s)e}$ is the excess return for a buy (sell) signal, $r_t^{b(s)}$ is the return of a buy (sell) signal, and r_t the return of the benchmark series used.

As benchmarks, to measure the relative performance of the technical indicators, buy and hold is used. For the currency pairs, as the long-run expected return is 0, the LIBOR rate is used as a benchmark as well. Commodities are not necessarily increasing in value in the long-run either, and hence, both LIBOR and buy and hold are used. Initially the daily returns of the strategies are compared to the benchmarks, only the results that generate a positive excess return is considered for a test of significance. The significance test is presented under a separate header. Furthermore, for the significant results, if any, a Sharpe ratio[13] will be calculated to account for risk premia associated with taking higher risks. The Sharpe ratio for a technical indicator *i* is then:

$$SR_i = \frac{r_t^{b(s)e}}{\sqrt{\hat{\sigma}_{b(s)}^2}} \tag{29}$$

The Sharpe ratio for an indicator is then compared to that of the benchmark. The abnormal return (risk-adjusted) for a technical indicator is then calculated as:

$$r_A = SR_i - SR_B \tag{30}$$

[13] Other risk adjusting measurements such as Jensen's alpha and Treynor index are considered, but rejected as both apply β as the risk measurement. β is notoriously hard to determine as the market portfolio is impossible to observe and furthermore, when looking at such broad equity indexes as the S&P 500, it will be biased towards a lower risk for these indeed risky investments.

Where $\bar{r}_A$ is the abnormal return, SR_i the Sharpe ratio for the indicator *i*, and SR_B the Sharpe ratio of the benchmark. This comparison has, however, not taken transaction costs into account yet, which is further discussed in Section 4.3.4.

4.3.4 Testing for Predictive Power

To test if the excess returns are significant, and not by chance, a t-test[14] is applied. At first glance, using a t-test in inappropriate, as financial data seldom follow a normal distribution but exhibit leptokurtosis (or fat tails), is auto correlated, contain conditional heteroscedasticity and changing conditional means. This was in fact the exact reasons why Brock et al (1992) created the BLL bootstrap methodology, to circumvent the problems of non-normal data. This is done by generating simulated p-values based on a technical indicator's ability to consistently beat the benchmark in 500 bootstrapped data series with the same statistical properties as the original series. However, the bootstrap methodology comes with its own set of problems.

Most prominently, the data must be fitted to a "null model". Several null models are generally tested to see which model fits the original data best. To conclude which model's parameters fit the data best, t-tests are used, which bring us back to the original problem. Secondly, relating back to the interview with Gramza in the introduction, the idea of technical trading is based on the human factor affecting price movements. With 500 bootstrapped series, it is impossible to know if those effects are preserved, even if we assume that the t-test is correct in specifying the null model.

Furthermore, although the notion that the t-test is biased if the data does not meet certain requirements[15] is correct, the t-test has been proven to be highly efficient when the sample size of the two variables compared are equal, regardless of distribution (Markowski and Markowski, 1990). The t-test is also generally robust to smaller deviations from the assumptions, especially for large samples.

[14] Commonly referred to as the "student's t-test" as its creator, William Sealy Gosset, used student as his pseudonym, being forbidden to publish his findings by his employer, the Guinness Brewery in Dublin.
[15] Generally, the data should be normally distributed, have equal variances and be independently sampled.

There are generally two approaches when evaluating the significance of a trading strategy using the t-test; either the mean return can be tested to see if it is significantly different from zero, or the excess return (using a benchmark) can be tested to see if it is significantly different from zero. Following Brock et al (1990), the latter is applied in this study, accompanied with a test of the buy-sell spread, which tests if the buy and sell-signals are jointly different from 0, having the same result as the first approach.

Accordingly, the first null hypothesis is that the trading strategy return is not different from that of the benchmark:

$$H_0: \bar{r}_{b(s)} - \bar{r} = 0 \qquad H_A: \bar{r}_{b(s)} - \bar{r} \neq 0 \tag{31}$$

The second null hypothesis is that the buy-sell spread is zero:

$$H_0: \bar{r}_b + \bar{r}_s = 0 \qquad H_A: \bar{r}_b + \bar{r}_s \neq 0 \tag{32}$$

Where $\bar{r}_{b(s)}$ is the average return of a technical indicator and $\bar{r}$ is the average return of the asset. Normally the null hypothesis is that $\bar{r}_b - \bar{r}_s = 0$. In this study, however, the sell-signals generate positive returns as the sign is converted when generating the trading strategy return series. This notation renders the term “spread” a bit confusing, but as it in fact is the spread between going long during sell and buy-signals respectively, this terminology will be consistently used. Personally, I believe this way of presenting the data is more intuitive and consistent, as a short position would be taken to generate a positive return, and not a long position to generate a negative return.

The test statistic for excess return is:

$$t = \frac{\bar{r}_{b(s)} - \bar{r}}{\sqrt{\frac{\sigma^2_{b(s)}}{N_{b(s)}} + \frac{\sigma^2}{N}}} \tag{33}$$

And the test statistic for the buy-sell spread is:

$$t = \frac{\bar{r}_b + \bar{r}_s}{\sqrt{\frac{\sigma_b^2}{N_b} + \frac{\sigma_s^2}{N_s}}} \tag{34}$$

The t statistic is compared to a critical, but arbitrarily chosen, t-value, usually set at ca (-)1,97 for a two-tailed test. This corresponds to a 95% confidence interval, depending on the number of observations (and in extension on the degrees of freedom).

4.3.5 Accounting for Transaction Costs

Instead of assuming a transaction fee for every change in position, the break-even cost is calculated and it is defined as

$$break\ even = \frac{(\bar{r}_{b(s)} - \bar{r}) * N}{NC_{b(s)}} \tag{35}$$

for only long and short positions separately in the market, and

$$break\ even = \frac{((\bar{r}_b + \bar{r}_s) - \bar{r}) * N}{NC_b + NC_s} \tag{36}$$

for combined long and short positions, where $NC_{b(s)}$, NC_b and NC_s are the number of entries into the market and N the number of days in the sample. An entry into the market also implies exciting the market, as all indicators start out of the market and are assumed to exit the market at the end of the period included. The break-even is simply the percentage cost per trade that a strategy can support before all the profits are consumed by the fees.

When considering transaction costs, many studies focus only on the courtage, the fee a broker charges for executing a trade. However, there are internet brokers who charge as little as 0,025% per trade, up to certain limits[16]. Previous studies which consider transaction costs assume courtage of 0,05-0,15% (Karevold and Dahl, 2014), at least twice that amount, up to six times higher. The price series used in this study is not available at these prices however, since they are either equity portfolios or not applicable for this price range.

[16] See https://www.degiro.se/priser/

If individual stocks were the subject, a courtage of 0,025% would be applicable. A more realistic way of taking directional positions in the assets used in this study, is to buy ETFs or using derivatives. However, these securities come with different costs, as there usually is either a management fee or a time value connected to the security. For ETFs, there are internet brokers who offer free courtage, but the selection is limited[17]. The median annual fee for ETFs on Avanza.se is 0,4% [18]. For simplicity and generalization of the study, as it spans several national and international markets, a fixed courtage of 0,05% is assumed.

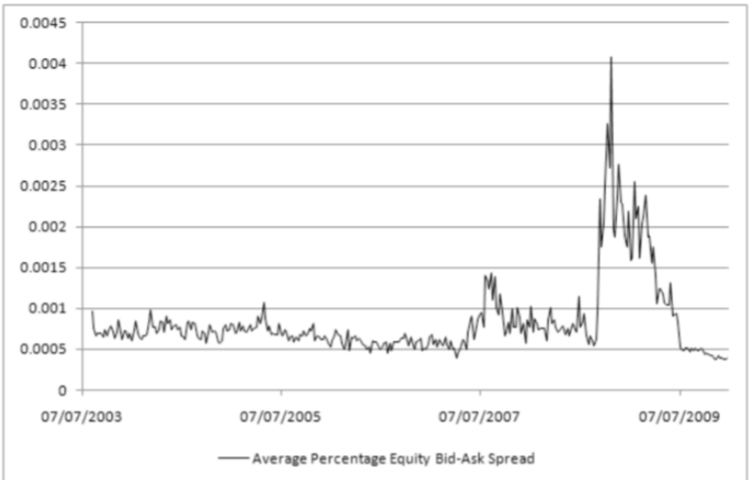


Figure 7. Average Bid-Ask spread on American Equity (Damodaran, 2014)

Another important transaction cost to consider is the bid-ask spread. All assets included in this study are to be considered liquid, which indicates that the spread should be relatively small. However, relatively small can still add up over numerous transactions. For ETFs, several major issuers offer funds with bid-ask spreads as low as 0,01%, but with an average of 0,04%. As a comparison, the average bid-ask spread for 51 large American companies is presented in figure 7, showing an average value of under 0,1%. As a middle road, a 0,05% spread is assumed, making the total transaction cost for one trade 0,15%, as a round trip in an asset incurs the cost of the spread plus two fees for courtage.

Regarding taxes, the framework can differ a lot from country to country and even vary within them. For example, the annual ISK (Investment Savings Account) rate in Sweden 2017 is 0,375%, whereas the capital gains tax is 30%. In Switzerland, there is no capital gains tax (for non-professionals). Although the tax would influence the results given that a trader would have to pay a percentage of realized profits on an annual basis, the tax factor can be ignored if we instead assume that both the technical strategies and the benchmarks are invested in

[17] See https://www.degiro.se/priser/etf
[18] See https://www.avanza.se/borshandlade-produkter/etf-torg/lista.html

the framework of an ISK with a fixed fee or do not incur taxes. This also makes the results of the study more general.

Another common robustness check is to divide the sample into three non-overlapping subperiods. Since this study concerns more than a few time series however, the same effect is achieved through the inclusion of several price series, testing the indicators on many sets of data. Furthermore, the main focus of this study is not to test if the indicators are efficient per say, but rather if they are equally efficient across different asset types.

Concerning data-snooping, neither Reality Check nor Superior Predictive Ability is applied. The technical indicators tested are widely known and used before the start of the sample. Furthermore, this study is more concerned with detecting differences between the asset classes than testing individual specifications of technical trading strategies. As such, average success rates of the indicators are of interest and data snooping bias in the best model would not affect the results noticeably.

5 Empirical Results and Analysis

This chapter starts out describing the data characteristics, the average results, and highlighting differences between the time series and the technical indicators. Differences between sell and buy-signals are presented and lastly transaction costs are accounted for.

5.1 Data Characteristics

The Variance Ratio tests for RW in Table 2 show ambiguous results. For most of the series, the null hypothesis of a random walk (or formally a Martingale process) cannot be rejected for the joint test. Only the results given allowance of a drift are included, as the test results were similar and the inclusion of drift are considered to be more realistic for the data and period. The time series that do reject a RW, are spread out between the asset classes and no conclusion regarding difference in efficiency between asset classes can confidently be made. Gold and Silver, having a high price correlation, show the strongest rejections, which indicates that TA will have lower profitability when applied to these assets. Commodities are the only asset class that show no rejection of a RW. For currencies, USD-JPY and USD-CHF are significant at a 10% level, and are both close to the 5% cutoff. More specifically, the assets for which a RW is rejected at a 5% level are S&P, SENSEX, and USD-JPY.

Following the initial test for a RW, the data is used to calculate return series and standard statistical tests are used to assess the series. The Augmented Dickey-Fuller test rejects the null of a unit root for all return series. In other words, all series are stationary. The Jarque-Bera statistics strongly rejects normality for all series. The Ljung-Box Q-statistics show no significant autocorrelation for Gold, Silver, Dax, BOVESPA, USD-CHF and EUR-USD. For the other assets, however, small but significant autocorrelation is observed, especially in the first lag.

Table 2. Variance ratio test	*Value max /Z/*	*degrees of Freedom*	*Probability*
Equity - Old			
S&P	3.065	4276	0.009
DAGS	1.18	4331	0.661
NIKKEI	1.85	4186	0.235
Equity - New			
IDX	2.42	4123	0.061
SENSEX	3.42	4208	0.003
BOVESPA	1.8	4227	0.235
Commodities			
Gold	0.58	4330	0.963
WTI Oil	1.55	4328	0.402
Copper	2.14	2576	0.124
Silver	0.41	2761	0.989
Currencies			
EUR-USD	0.98	4488	0.792
USD-JPY	2.54	4459	0.043
EUR-GBP	1.25	4458	0.614
USD-CHF	2.48	4459	0.052

5.2 Average Results

Taking a holistic view at the results of the technical strategies, a comparison can be made between the assets, and asset classes, averaging the results of all indicators for all return series. Note that results are only shown for one of the specifications of the MACD, as the results of the two are similar.

5.2.1 Market Performance

Table 3. Average per Asset	*> 0*	*Mean Return*	*> LIBOR*	*> B&H*	*Sig. > B&H 10%*	*Sig. > B&H 5%*	*Sharpe> B&H*
Equity - Old	**0.404**	**-0.0058%**	**0.340**	**0.310**	**0.015**	**0.008**	**0.321**
S&P	0.342	-0.0112%	0.275	0.208	0.000	0.000	0.225
DAX	0.479	0.0023%	0.413	0.317	0.021	0.008	0.333
NIKKEI	0.392	-0.0087%	0.333	0.404	0.025	0.017	0.404
Equity - New	**0.685**	**0.0351%**	**0.654**	**0.461**	**0.124**	**0.086**	**0.468**
IDX	0.758	0.0520%	0.733	0.492	0.175	0.117	0.500
SENSEX	0.717	0.0450%	0.683	0.554	0.188	0.138	0.554
BOVESPA	0.579	0.0082%	0.546	0.338	0.008	0.004	0.350
Commodities	**0.410**	**-0.0161%**	**0.349**	**0.307**	**0.008**	**0.003**	**0.314**
Gold	0.496	-0.0034%	0.417	0.154	0.000	0.000	0.188
WTI Oil	0.371	-0.0088%	0.329	0.283	0.017	0.008	0.271
Copper	0.379	-0.0222%	0.308	0.463	0.013	0.000	0.458
Silver	0.396	-0.0299%	0.342	0.329	0.004	0.004	0.338
Currency	**0.428**	**-0.0023%**	**0.305**	**0.409**	**0.028**	**0.014**	**0.401**
EUR-USD	0.458	-0.0049%	0.313	0.421	0.000	0.000	0.421
USD-JPY	0.483	0.0016%	0.329	0.442	0.017	0.008	0.442
EUR-GBP	0.463	0.0009%	0.338	0.275	0.038	0.017	0.279
USD-CHF	0.308	-0.0066%	0.242	0.500	0.058	0.029	0.463

The first data column shows the share of indicators which render positive results, the second the mean return, the third and fourth column the share that outperforms passive strategies in LIBOR and buy and hold. The fifth and sixth show the share of indicators that are positive and significantly different from the mean of buy and hold. The last column show the share of indicators that outperform buy and hold taking risk exposure into account. The headlines for each asset class is followed by the averages of the averages, which are bolded for clarity.

In Table 3 the average results can be viewed. Most notably, three assets show no positively significant results for the indicators. These are S&P, Gold and EUR-USD, all very commonly traded assets. A higher mean return is observed for the new markets compared to the other assets, and the effect is preserved when looking at the share that exceeds B&H and share of significant results. Commodities and old equity shows the least profitability, with only 30% of the indicators outperforming B&H. The significance is also very low: only 0,3% of the indicators pass the t-test for a significance level of 5%.

The indicators are performing best on new equity, and the observation is robust to both the B/H benchmarks and to the Sharpe ratios. The SENSEX stock exchange is the relatively most profitable market, which together with USD-CHF is the only market where the indicators outperform B&H more than 50% of the time. Commodities are the markets where the indicators perform the worst, with not a single positive mean return and an average of just over 30% outperformance of B&H.

5.2.2 Indicator Performance

Looking at the performance of the groups of technical indicators in Table 4, none outperform B&H more than 50% of the time and MACD is the only indicator group which manages to outperform LIBOR more than 50% of the time. However, 0 of the MACDs are found to be positive and significantly different from B&H. The RSI shows especially poor results for mean returns, although the share that is positive is larger than for all other groups but MACD. This indicates a high volatility in results for MACD.

Table 4. All Series	*FMA 5,10*	*FMA 10,20*	*FMA 20,50*	*FMA 50,200*	*VMA*	*MACD*	*RSI*
> 0	0.454	0.446	0.471	0.486	0.478	0.619	0.500
Mean Return %	*-0.0016%*	*-0.0011%*	*-0.0039%*	*0.0072%*	*0.0056%*	*0.0124%*	*-0.0028%*
> LIBOR	0.373	0.387	0.408	0.451	0.373	0.548	0.357
> B&H	0.352	0.346	0.389	0.417	0.343	0.452	0.333
Sig. > B&H 10%	0.048	0.043	0.030	0.051	0.034	0.024	0.032
Sig. > B&H 5%	0.030	0.033	0.017	0.032	0.020	0.000	0.012
Sharpe>B&H	0.349	0.356	0.386	0.425	0.359	0.452	0.317

The numbers following FMA indicates the intervals used when acquiring the results. The table displays the average results for all return series.

The mean returns are positive for FMA 50/200, VMA and MACD, all other strategies are rendering negative average returns. VMA, however, does not do particularly well when considering the benchmarks. The B&H shares and Sharpe ratio shares are similar for all assets, and there is no clear pattern. This indicates that the trading strategy returns have similar volatility to that of B&H. Regarding positive and significant results, the FMAs outperform the other groups, although the share of significant indicators is still very low, with FMA 50/200 just over 5% significant results at a 10% level and FMA 10/20 with 3,3% significant results at a 5% level.

Going further into detail of the trading strategies, and the differences between buy and sell-signals, Table 5 reveals that buy-signals generate higher returns than sell-signals. As 13 out of 14 of the return series have a positive mean over the period included. This indicates that going with the market trend is advisable. It also reaffirms that MACD is the most profitable of the indicators, and SMA the second most profitable indicator. The most unprofitable indicators, in turn, are RSI touch followed by DMA. However, no strategy is profitable when taking both sell and buy-signals into account. SMA outperforms both DMA and EMA, indicating that a simpler strategy may be preferred.

Looking at the grand total of the FMA strategies, a trend with decreasing unprofitability for longer holding periods can be observed, with longer holding periods being less unprofitable. The VMA performs similarly to the longer holding period FMAs and the VMA buy-signals are positive for all indicators. The RSI shows negative results except for 50, 50 cross. None of the indicators show positive average profitability for both buy and sell-signals. The most profitable signal is the MACD buy, but the buy+sell-signal is still negative.

5.2.3 Indicator Performance per Asset Class

To be able to investigate the differences between the efficiency of the asset classes, Table 6-9 display the results for the indicator groups per asset class. These tables complement Table 3 and show in greater detail how the indicators perform on the different market types. Results for the individual assets can be found in the appendix.

Old equity shows the highest returns for FMA 20, 50 and 50, 200. Although the mean returns for these indicators are positive, none has a share greater than B&H above 50%. They are also

Table 5. All series	Indicator	SMA	DMA	EMA	RSI Cross	RSI Touch	MACD	Grand Total
FMA (1)	Sell	-0.006%	-0.022%	-0.022%				-0.016%
	Buy	0.011%	-0.077%	0.005%				-0.020%
	Buy+Sell	0.002%	-0.048%	-0.008%				-0.018%
FMA (3)	Sell	-0.015%	-0.026%	-0.021%				-0.021%
	Buy	0.010%	-0.015%	0.010%				0.002%
	Buy+Sell	0.002%	-0.020%	-0.002%				-0.007%
FMA (5)	Sell	-0.024%	-0.023%	-0.023%				-0.023%
	Buy	0.001%	-0.011%	-0.003%				-0.004%
	Buy+Sell	-0.011%	-0.017%	-0.014%				-0.014%
FMA (10)	Sell	-0.025%	-0.015%	-0.026%				-0.022%
	Buy	-0.008%	0.001%	-0.010%				-0.006%
	Buy+Sell	-0.024%	-0.006%	-0.030%				-0.020%
FMA (20)	Sell	-0.024%	-0.022%	-0.021%				-0.022%
	Buy	0.002%	-0.001%	-0.004%				-0.001%
	Buy+Sell	-0.006%	-0.010%	-0.011%				-0.009%
VMA	Sell	-0.020%	-0.023%	-0.021%				-0.021%
	Buy	0.005%	0.004%	0.002%				0.004%
	Buy+Sell	-0.006%	-0.007%	-0.008%				-0.007%
RSI (70, 30)	Sell				-0.026%	-0.032%		-0.029%
	Buy				0.000%	-0.006%		-0.003%
	Buy+Sell				-0.015%	-0.022%		-0.018%
RSI (60, 40)	Sell				-0.038%	-0.031%		-0.035%
	Buy				-0.018%	-0.002%		-0.010%
	Buy+Sell				-0.031%	-0.018%		-0.025%
RSI (50, 50)	Sell				-0.013%	-0.032%		-0.022%
	Buy				0.015%	-0.008%		0.004%
	Buy+Sell				0.005%	-0.023%		-0.009%
MACD	Sell						-0.014%	-0.014%
	Buy						0.012%	0.012%
	Buy+Sell						-0.001%	-0.001%
Tot. Avg. Sell		-0.019%	-0.022%	-0.022%	-0.026%	-0.031%	-0.014%	-0.021%
Tot. Avg. Buy		0.003%	-0.017%	0.000%	-0.001%	-0.005%	0.012%	-0.004%
Tot. Avg. Buy+Sell		-0.007%	-0.018%	-0.012%	-0.014%	-0.021%	-0.001%	-0.012%

Table 5 displays the average returns for buy-signals, sell-signals and buy and sell-signals combined. The data is sorted by indicator on the vertical axis and by specification type on the horizontal axis. FMA shows holding periods in parenthesis.

the indicators with the highest share of significant results. MACD shows the worst results, and can be concluded to be inefficient when applied to the three equity series.

Table 6. Equity old	*FMA 5,10*	*FMA 10,20*	*FMA 20,50*	*FMA 50,200*	*VMA*	*MACD*	*RSI*
> 0	0.34	0.30	0.50	0.53	0.34	0.22	0.44
Mean Return %	*-0.0150%*	*-0.0180%*	*0.0020%*	*0.0077%*	*-0.0086%*	*-0.0110%*	*0.0004%*
> LIBOR	0.25	0.24	0.42	0.50	0.29	0.22	0.33
***>** B&H*	0.24	0.25	0.40	0.48	0.19	0.11	0.28
Sig. > B&H (10%)	0.00	0.01	0.03	0.04	0.00	0.00	0.00
Sig. > B&H (5%)	0.00	0.01	0.01	0.02	0.00	0.00	0.00
Sharpe>B&H	0.24	0.26	0.41	0.49	0.24	0.11	0.24

The vertical axis is the same as the horizontal axis in Table 3. The horizontal axis shows the indicator and the specifications of intervals included for the FMA indicators.

New equity show the best results of the asset classes, with three indicators outperforming B&H more than 50% of the time. The highest mean return is generated by FMA 10,20, both FMA 20, 50 and FMA 50, 200 show high returns as well. The only indicator that shows negative return is the RSI, which together with MACD, is the only indicator that show no return that is positive and significantly different from B&H.

Table 7. Equity New	*FMA 5,10*	*FMA 10,20*	*FMA 20,50*	*FMA 50,200*	*VMA*	*MACD*	*RSI*
> 0	0.64	0.73	0.77	0.61	0.81	0.78	0.41
Mean Return %	*0.036%*	*0.049%*	*0.047%*	*0.017%*	*0.047%*	*0.043%*	*-0.012%*
> LIBOR	0.61	0.70	0.73	0.59	0.76	0.78	0.33
> B&H	0.41	0.50	0.56	0.42	0.55	0.44	0.19
Sig. > B&H (10%)	0.16	0.17	0.10	0.08	0.16	0.11	0.02
Sig. > B&H (5%)	0.12	0.15	0.05	0.07	0.09	0.00	0.00
Sharpe>B&H	0.42	0.51	0.55	0.46	0.54	0.44	0.17

For commodities, VMA, MACD and RSI show no significant results at a 10% level, although MACD shows the highest mean return of the indicators. All other indicators but FMA 50, 200 show negative returns. FMA 50, 200 is also the indicator that has the highest significance for commodities, although less than 40% of the returns are greater than the B&H benchmark.

Table 8. Commodities	*FMA 5,10*	*FMA 10,20*	*FMA 20,50*	*FMA 50,200*	*VMA*	*MACD*	*RSI*
> 0	0.37	0.38	0.36	0.45	0.43	0.75	0.46
Mean Return %	*-0.021%*	*-0.022%*	*-0.043%*	*0.004%*	*-0.005%*	*0.018%*	*-0.005%*
> LIBOR	0.30	0.34	0.32	0.41	0.33	0.67	0.33
> B&H	0.28	0.26	0.29	0.38	0.29	0.50	0.29
Sig. > B&H (10%)	0.01	0.01	0.01	0.03	0.00	0.00	0.00
Sig. > B&H (5%)	0.00	0.00	0.01	0.01	0.00	0.00	0.00
Sharpe>B&H	0.28	0.28	0.29	0.39	0.32	0.50	0.28

For currencies, the RSI is the best performing indicator, with the highest mean it outperforms B&H over 50% of the time. It does not, however, outperform the LIBOR return more than circa 42% of the time. MACD has the highest share of results that outperform LIBOR and B&H, but only shows half the mean return of RSI and no significant results. Among the MAs, FMA 50, 200 is the only indicator with a positive mean return but the share of outperformance of B&H is only at 40%. Currencies is the only asset class where LIBOR outperforms B&H.

Table 9. Currencies	*FMA 5,10*	*FMA 10,20*	*FMA 20,50*	*FMA 50,200*	*VMA*	*MACD*	*RSI*
> 0	0.48	0.42	0.33	0.39	0.38	0.67	0.65
Mean Return %	*-0.001%*	*-0.005%*	*-0.008%*	*0.003%*	*-0.004%*	*0.002%*	*0.004%*
> LIBOR	0.36	0.30	0.24	0.34	0.19	0.50	0.42
> B&H	0.47	0.38	0.35	0.40	0.35	0.67	0.53
Sig. > B&H (10%)	0.04	0.01	0.01	0.06	0.00	0.00	0.10
Sig. > B&H (5%)	0.02	0.00	0.01	0.03	0.00	0.00	0.04
Sharpe>B&H	0.44	0.39	0.33	0.39	0.35	0.67	0.53

5.2.4 Volatility and Entries into the Market

The Volatility (table found in appendix) for the sell-signals is greater for all indicators but for RSI, where the opposite is observed. The effect is especially emphasized in the VMA volatility, where the difference is the greatest. This is consistent with what has been found in previous studies, and as the RSI is a contrarian strategy, we also expect the buy-signals to have a higher volatility for this indicator. Sell-signals for VMA, RSI 70, 30 and 60, 40, and MACD, show the highest volatility. Over the whole sample, volatility does not differ that much.

Table 7. number of signals	*Average of N(Sell)*	*Average of N(Buy)*
FMA (1)	236.0	236.2
FMA (3)	204.4	205.5
FMA (5)	181.8	182.4
FMA (10)	142.0	142.0
FMA (20)	99.1	99.9
VMA	238.1	238.2
RSI (70, 30)	61.5	61.4
RSI (60, 40)	102.8	135.3
RSI (50, 50)	120.5	153.5
MACD	86.7	86.7
Grand Total	**174.5**	**176.6**

In Table 7, the average number of entries into the market can be viewed. Since the buy and sell-signals are the exact opposite of one another, the number of changes in position should be the same for the two. Slight differences are observed as the last exit out of the market is not counted, but implicit when the sample ends. Naturally, the shorter fixed length holding periods render more entries into the market (note that every entry also implies an exit). RSI (70, 30) show the least amount of changes in direction in the market, which is beneficial when taking market conditions into account. VMA and FMA (1) have the most changes in direction, which increases the effect of the transaction costs.

5.2.5 Break-Even

In Table 8, the average break-even transaction costs for all return series larger than their respective B&H benchmark, and the share of indicators that passes the transaction cost bar is shown. In addition, the share larger than the B&H benchmark from Table 3 is added for easier comparison. Consistent with previous results, new equity show the best results in terms of how large share of indicators are profitable in relation to the B&H benchmark. Moreover, the results for new equity are fairly robust to transaction costs, with SENSEX holding up the best, and showing more than half of the results larger than B&H after taking feasible transaction costs into account.

Table 8. Break-even costs	*Avg. be > 0*	*share > 0.001*	*share > B&H*		*Avg. BE > 0*	*share > 0.001*	*share > B&H*
Equity - Old	**0.02**	**0.22**	**0.31**	**EQUITY - NEW**	**0.01**	**0.40**	**0.46**
S&P	0.03	0.15	0.21	IDX	0.01	0.42	0.49
DAX	0.01	0.24	0.32	SENSEX	0.01	0.51	0.55
NIKKEI	0.02	0.28	0.40	BOVESPA	0.01	0.26	0.34
Commodities	**0.03**	**0.18**	**0.31**	**CURRENCIES**	**0.01**	**0.23**	**0.41**
Gold	0.03	0.08	0.15	EUR-USD	0.01	0.23	0.42
WTI Oil	0.07	0.25	0.28	USD-JPY	0.01	0.22	0.44
Copper	0.01	0.36	0.46	EUR-GBP	0.00	0.13	0.28
Silver	0.03	0.02	0.33	USD-CHF	0.01	0.33	0.50

Currencies are the most vulnerable to transaction costs, and almost half of the indicators that outperformed B&H without transaction costs are now outperformed by the benchmark. As currencies perform worse against LIBOR, this implicitly means an even lower share using the risk-free rate as benchmark. Old equity, commodities and currencies show similar shares of indicators that pass as profitable, just over 20%, whereas new equity almost reaches 40%. The asset that performs the worst, in regards of profitability, is gold.

Looking at the average breakeven transaction cost for all indicators outperforming B&H, currencies show a much smaller value than old equity, and foremost commodities. The low value for new equity can be explained by the inclusion of more indicators, as a larger share are found to be profitable. For the individual assets, WTI oil show the largest breakeven cost, at 6,6%, due to some outliers.

5.3 Analysis

The results do not allow for any clear-cut conclusions, nor a clear-cut analysis. Overall, there is no support for efficiency of TA. However, differences observed between individual assets and market types, which are big enough, can be considered to carry information. 240 unique specifications, of which most are FMAs, are tested on each return series, and all VMA indicator groups include 36 indicators, RSI 18 indicators and MACD 6.

The results suggest that commodity and exchange market trading, using the tested technical indicators, is not only unprofitable because of no predictive power and transaction costs, but also because the signals consistently underperform the market. The results for equities are more ambiguous, but still not conclusive. MAs have continuously been proven successful in previous literature, in the sense that it has been found to be profitable and carry predictive power. No such signs are observed in this study, and support to critique regarding cherry-picked results because of an unwillingness to publish negative results is somewhat strengthened, at least for studies strictly using the same techniques and type of data.

The results of the Variance Ratio Test suggest that at least 10 out of the 14 price-series follow a RW. This does not, however, seem to be a good predictor of which assets are more susceptible to profitable technical trading. Although a RW would make TA inefficient, the absence of a RW does not mean that TA will be efficient. TA should be driven by the human factor, the behavioral biases and heuristics. Assuming that fundamental analysis is an effective way to predict future price movements, a price-series could be non-random, but still show no signs of behavioral patterns.

The possible explanatory reasons for opportunities of earning abnormal returns in certain markets presented in Section 2.5 are mute in light of the results. It is, however, still possible that that both excess and abnormal returns can be earned using TA, given a more sophisticated approach, which can be expected from a professional trader.

The robustness checks, apart from testing the indicators on 14 time-series, show that the results would have been robust if higher shares of significance were observed. For most assets, both the inclusion of the Sharpe ratio and of plausible transaction costs were absorbed in an expected manner. The exception being currencies, which seem to be the least robust assets type of the three.

6 Conclusion

In this study, four simple technical trading rules are tested on 14 time-series. The time-series represent 3 different asset types: equity, commodity and currency, with a further division of equity into developed and developing markets, and stretch from 2000 to 2016. The purpose of the study is to determine if there are any differences of the successfulness of technical trading given the assets traded. Furthermore, the technical strategies tested (moving averages, moving average convergence divergence (MACD) and relative strength index) are evaluated for their predictive power using the t-test and profitability, taking adequate market conditions into account. A third cause is to observe if markets are, in line with previous research, becoming more efficient with time. Especially with the introduction of ETFs in mind.

6.1 Summary of Results

Considering the averages of the results, developing markets show the most promise for technical trading overall. The reasons for this are ambiguous, but the three market types included in the study all exhibit very high returns for buy-and-hold. Furthermore, based on the analysis of the developing equity markets, possible explanations include less liquidity, less transparency and higher transaction costs. As developed markets do not show the same relative returns, generic explanations regarding equity do not apply.

Commodities show the worst overall performance for technical trading relative to a buy-and-hold benchmark, although developed equity markets are almost at par. Currency markets show a middle ground considering the buy-and-hold benchmark, but looking at the risk-free interest rate benchmark, the technical strategies perform worst on currencies.

For all markets and asset classes, results significantly larger than that of the buy-and-hold benchmark are rare. Developing markets show the highest average of significance at a 5% critical level of just above 8,5%, and the best performing individual market being SENSEX with 13,75% significant results. The market where technical trading performs the worst is gold, followed by S&% 500.

Testing for a random walk on individual markets, there are two markets that strongly rejects a random walk: S&P 500 and SENSEX. Surprisingly, the connection between a random walk and profitability is very much vague. Although SENSEX does show potential for successful technical trading, S&P 500 allows for 0 significant technical indicators and show very low profitability.

Regarding the technical indicators tested in the study, the MACD performs the least bad over all assets in terms of profitability, although it lacks in significance. A fixed-length moving average using 20 and 50 day periods show the worst profitability, and the RSI the worst performance in relation to the benchmarks. Along with the MACD, a variable length moving average and a fixed length with long lookback periods show positive mean returns, all other render negative returns. No indicator group manages to outperform buy-and-hold more than 50% of the time.

At a market type level, long moving averages perform best on developed equity markets, and the MACD worst. For developing markets, the MACD and moving averages in general show the best results, and three out of seven indicator groups outperform buy-and-hold 50% of the time. The RSI performs the worst. For commodity markets, the MACD performs the best, but shows no significant results. Short period moving averages perform the worst. For foreign exchange markets, the mean results are lower than for all other asset types. Here, the RSI performs the best in terms of mean return and significance, but MACD has a higher share of returns outperforming the buy-and-hold benchmark.

In line with previous research, sell return series have a higher volatility than buy return series for all indicators but for RSI. This is consistent with what is expected, as RSI is a contrarian strategy as opposed to moving averages. Moreover, accounting for realistic transaction costs reduces the share of return series that beat the buy-and-hold benchmark across the board. The effect it greater for foreign exchange markets, where profitable series are almost cut in half.

Overall, the results show that the technical trading strategies are inefficient and unprofitable. In fact, trading on the opposite of the buy and sell-signals would be more profitable. Although all markets are not equally unprofitable, there is not a single market where technical analysis can convincingly or consistently show effectiveness. These results give support to the efficient market hypothesis in relation to pure technical trading, but says nothing about the effectiveness of fundamental analysis or a more complex combination of fundamental analysis and technical analysis.

6.2 Concluding Remarks

While this study strictly tests the profitability and efficiency of technical trading strategies, in line with previous research, it does not give an accurate picture of how technical analysis is applied in a real-world setting. While technical analysis is prevalent in most markets, it is highly rare for traders to solely rely on technical indicators or gut feeling. An analysis of a market includes fundamental factors and conducting a study given the principles set out in Section 2.1 totally disregards this.

Moreover, as technical indicators might perform differently given different markets (bull, bear or trading), a more realistic approach would try to identify what market trend is currently underway. Another factor to consider could be volatility clustering, as contrarian strategies should be more profitable with more volatile prices. Including short-term optimization could be another improvement, allowing for indicator specifications to change given simulated returns for a prespecified moving window period.

The common wisdom, that technical analysis is useful for shorter time periods, is contradictive to this study's results. Although few statistical certainties are proven, slower moving averages and longer holding periods appear to be more profitable than faster moving averages and shorter holding periods. Optimizations of the indicators (which clearly causes data snooping) for the time series used in this study, all point to longer lookback periods being more profitable. For all results, trend following indicators appear to be the more efficient than contrarian ones, although no conclusions can be made.

It seems plausible, that studies conducted on data following 2000 and using daily data, are doomed to fail in proving usefulness of technical analysis. In this study's literature review, no study specifically looking at this kind of data is represented. Schulmeister (2009) find declining profitability for daily data stretching over the 2000's however, but not for 30-minute interval data. Using more precise data could prove to enhance the results for short term trading performance.

Finally, the indicators as applied in this study are, as emphasized before, not necessarily representative of how they are applied in real life. The limitations of this study are primarily in its ability to mimic the actions of a full-time trader with a universe of technical indicators at disposal and taking the current news flow into account. It is quite possible that it is practically impossible to achieve a realistic simulation of that process, and that, consequently, the debate of the usefulness of technical trading will continue for many years still.

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7.2 List of Figures

Figure 1: Own calculation using data from figure 4

Figure 2: Own calculation using data from figure 4

Figure 3: Own calculation using data from figure 4

Figure 4: Equity market data: Yahoo [http://finance.yahoo.com/world-indices] [2017-01-28]

Currency and commodity data: investing.com

[https://www.investing.com/commodities/] [2017-01-28]

[https://www.investing.com/currencies/] [2017-01-28]

Figure 5: Data from Bank of International Settlements

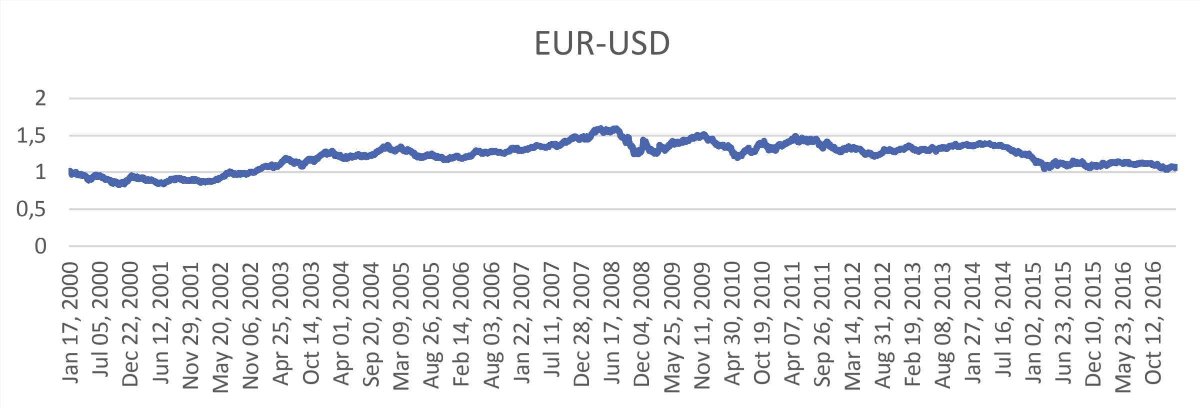
Figure 6: Data from Bank of International Settlements

Figure 7: Screenshot from: Damodaran, A. Trading costs and taxes, [http://people.stern.nyu.edu/adamodar/pdfiles/invphiloh/tradingcosts.pdf] [2017-03-14]

8 Appendix

8.1 Price Series Presentations and Graphs

Equity - Old	
S&P	*an index of 500 stocks seen as a leading indicator of U.S. equities and a reflection of the performance of the large cap universe*
DAX	*An index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange*
NIKKEI	*is a stock market index of 225 companies listed on the Tokyo Stock Exchange*
Equity - New	
IDX	*an index of all 532 stocks listed on the Indonesia Stock Exchange*
SENSEX	*an index of 30 well-established and financially sound companies listed on Bombay Stock Exchange*
BOVESPA	*an index of about 50 stocks that are traded on the Sao Paolo Stock Exchange*
Commodities	
Gold	*Spot price of CFDs for gold*
WTI Oil	*Spot price of CFDs for WTI Crude oil*
Copper	*Spot price of CFDs for copper*
Silver	*Spot price of CFDs for silver*
Currency	
EUR-USD	*Spot price of CFDs for EUR-USD*
USD-JPY	*Spot price of CFDs for USD-JPY*
EUR-GBP	*Spot price of CFDs for EUR-GBP*
USD-CHF	*Spot price of CFDs for USD-CHF*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1
0,5
0
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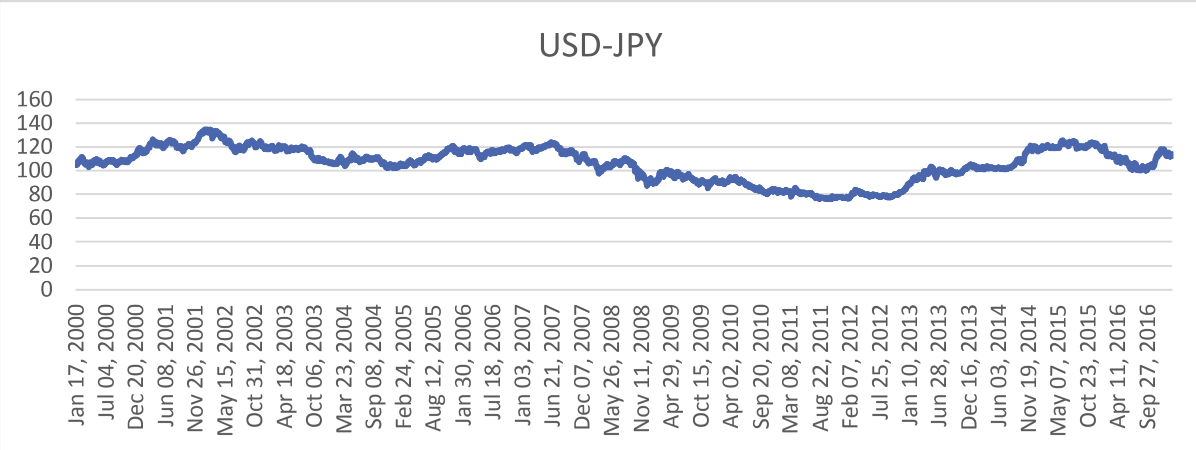
USD-JPY
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140
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100
80
60
40
20
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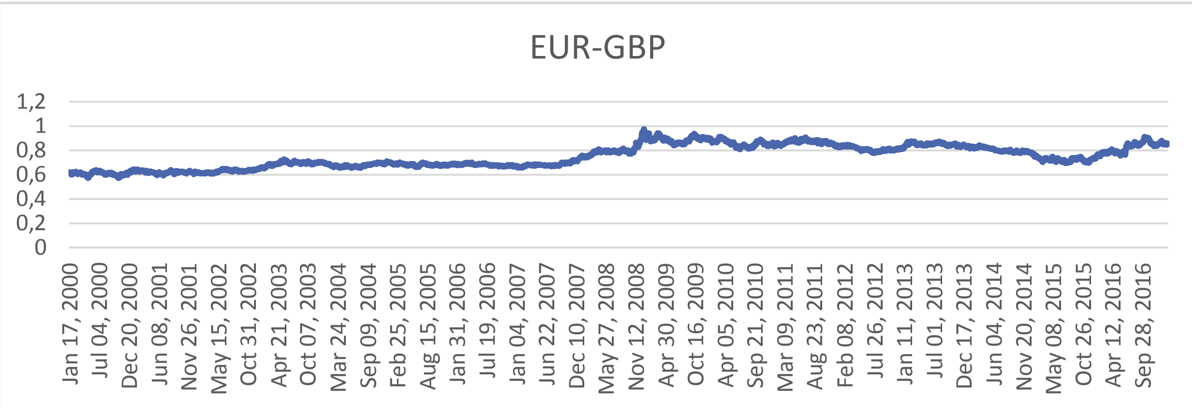
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1
0,8
0,6
0,4
0,2
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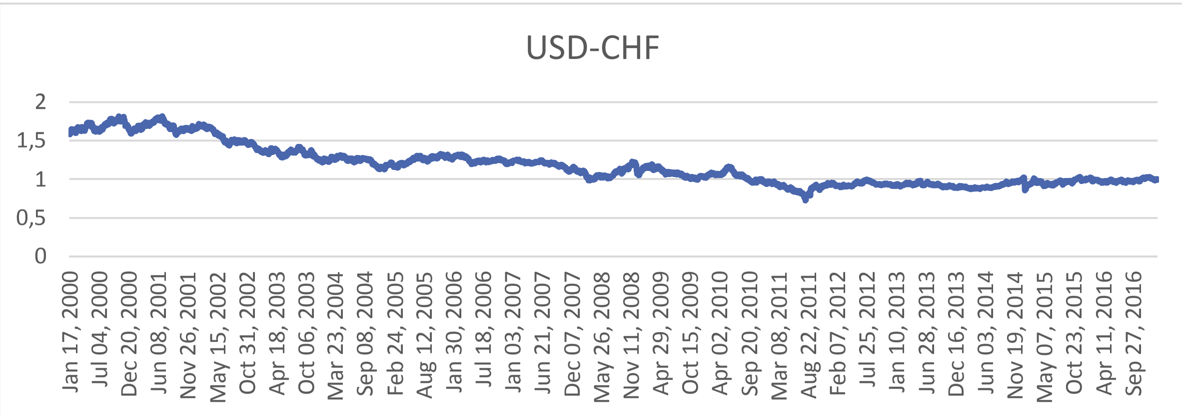
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0,5
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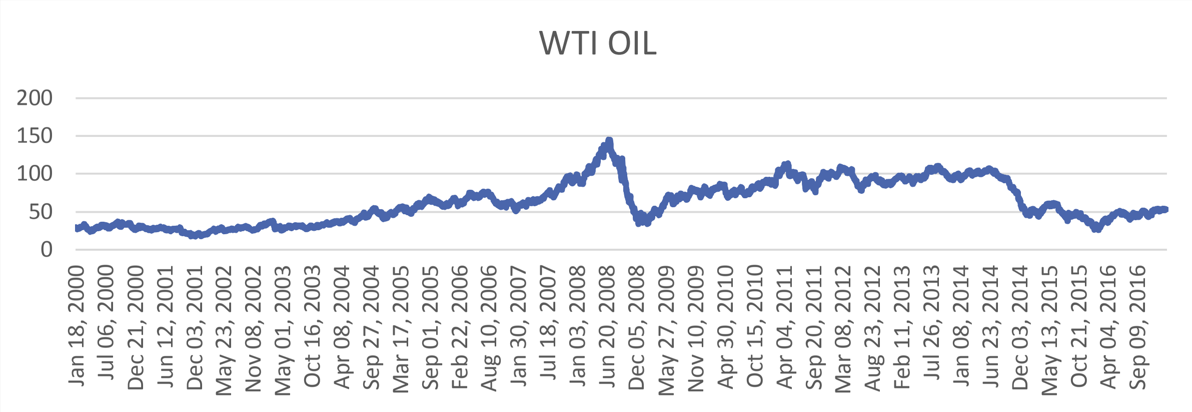
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100
50
0
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Jul 06, 2000
Dec 21, 2000
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Dec 03, 2001
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May 01, 2003
Oct 16, 2003
Apr 08, 2004
Sep 27, 2004
Mar 17, 2005
Sep 01, 2005
Feb 22, 2006
Aug 10, 2006
Jan 30, 2007
Jul 18, 2007
Jan 03, 2008
Jun 20, 2008
Dec 05, 2008
May 27, 2009
Nov 10, 2009
Apr 30, 2010
Oct 15, 2010
Apr 04, 2011
Sep 20, 2011
Mar 08, 2012
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Jul 26, 2013
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May 13, 2015
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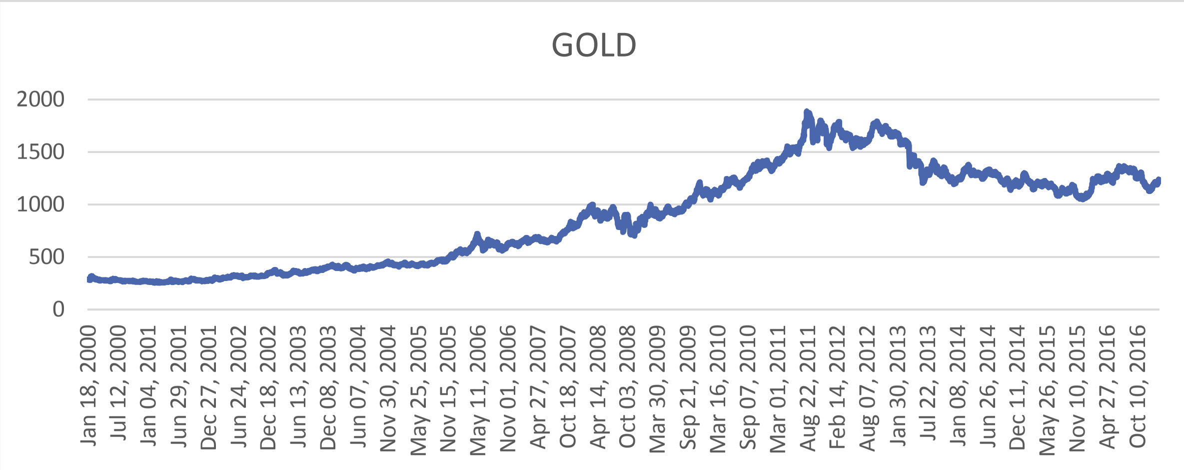
Apr 04, 2016
Sep 09, 2016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1000
500
0
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Jun 29, 2001
Dec 27, 2001
Jun 24, 2002
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Jun 13, 2003
Dec 08, 2003
Jun 07, 2004
Nov 30, 2004
May 25, 2005
Nov 15, 2005
May 11, 2006
Nov 01, 2006
Apr 27, 2007
Oct 18, 2007
Apr 14, 2008
Oct 03, 2008
Mar 30, 2009
Sep 21, 2009
Mar 16, 2010
Sep 07, 2010
Mar 01, 2011
Aug 22, 2011
Feb 14, 2012
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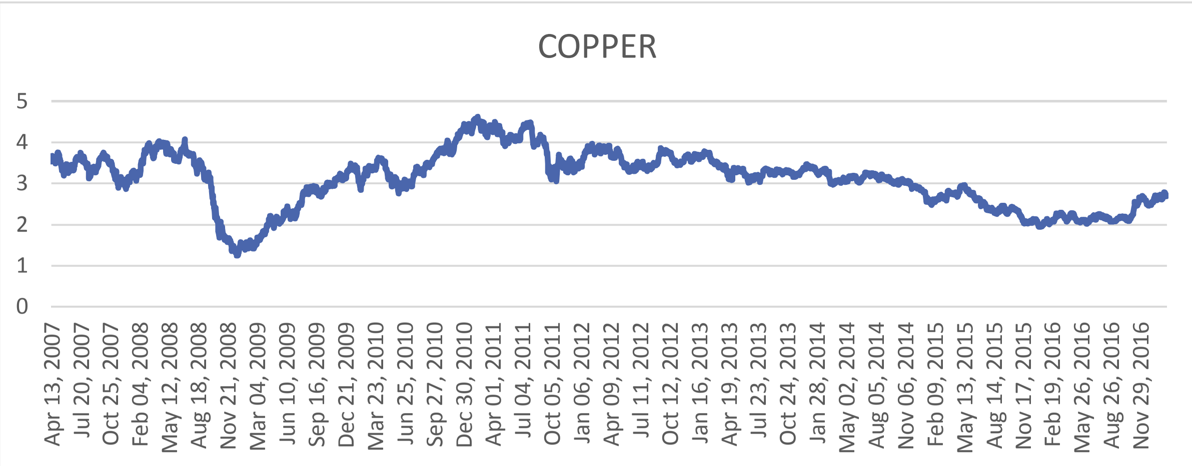
Apr 27, 2016
Oct 10, 2016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Jul 11, 2012
Oct 12, 2012
Jan 16, 2013
Apr 19, 2013
Jul 23, 2013
Oct 24, 2013
Jan 28, 2014
May 02, 2014
Aug 05, 2014
Nov 06, 2014
Feb 09, 2015
May 13, 2015
Aug 14, 2015
Nov 17, 2015
Feb 19, 2016
May 26, 2016
Aug 26, 2016
Nov 29, 2016


SILVER
60
50
40
30
20
10
0
Apr 13, 2007
Oct 04, 2007
Apr 04, 2008
Sep 02, 2008
Jan 02, 2009
May 06, 2009
Sep 04, 2009
Dec 10, 2009
Mar 08, 2010
Jun 07, 2010
Sep 02, 2010
Nov 29, 2010
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Apr 25, 2013
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Oct 17, 2013
Jan 14, 2014
Apr 11, 2014
Jul 09, 2014
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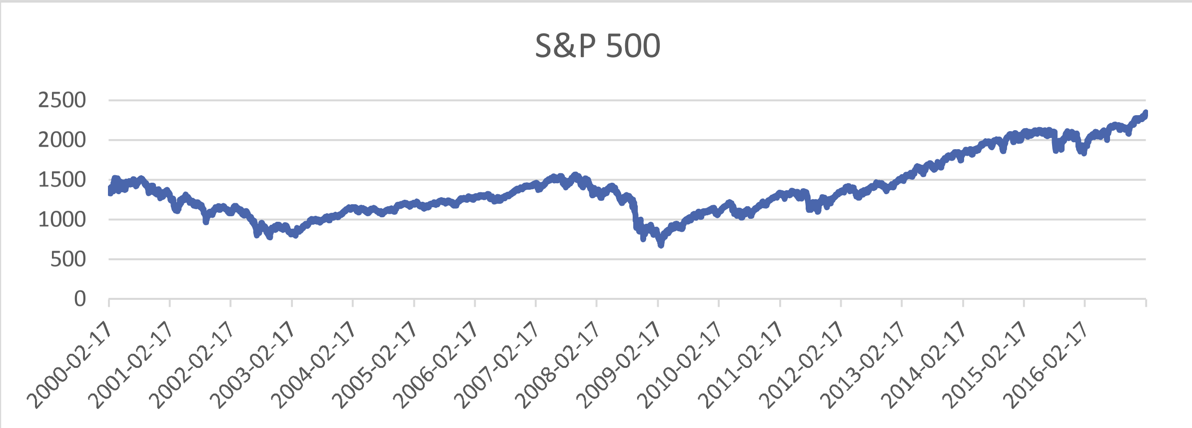
Sep 21, 2015
Dec 17, 2015
Mar 16, 2016
Jun 13, 2016
Sep 08, 2016
Dec 06, 2016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2000
1500
1000
500
0
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2003-02-17
2004-02-17
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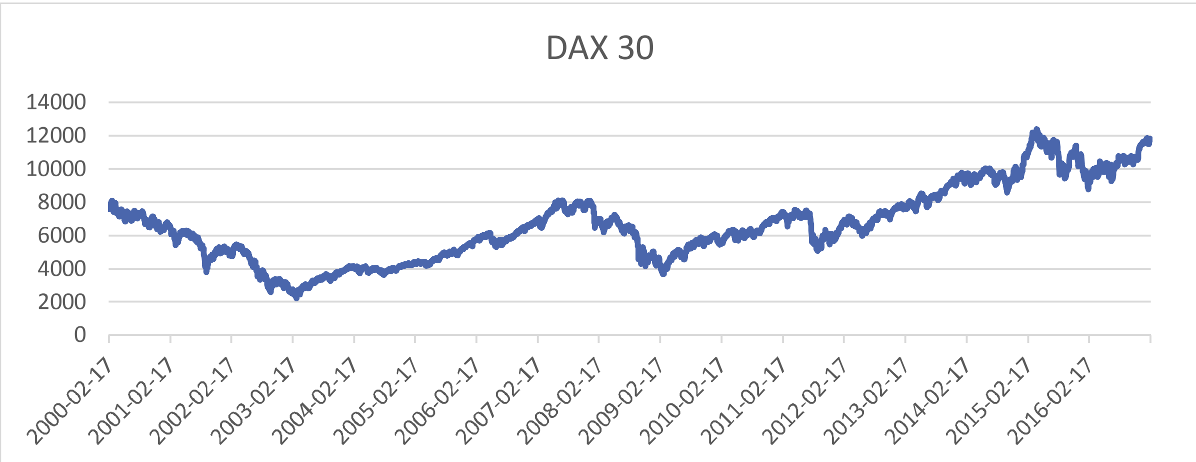
2016-02-17


DAX 30
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10000
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2000
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2001-02-17
2002-02-17
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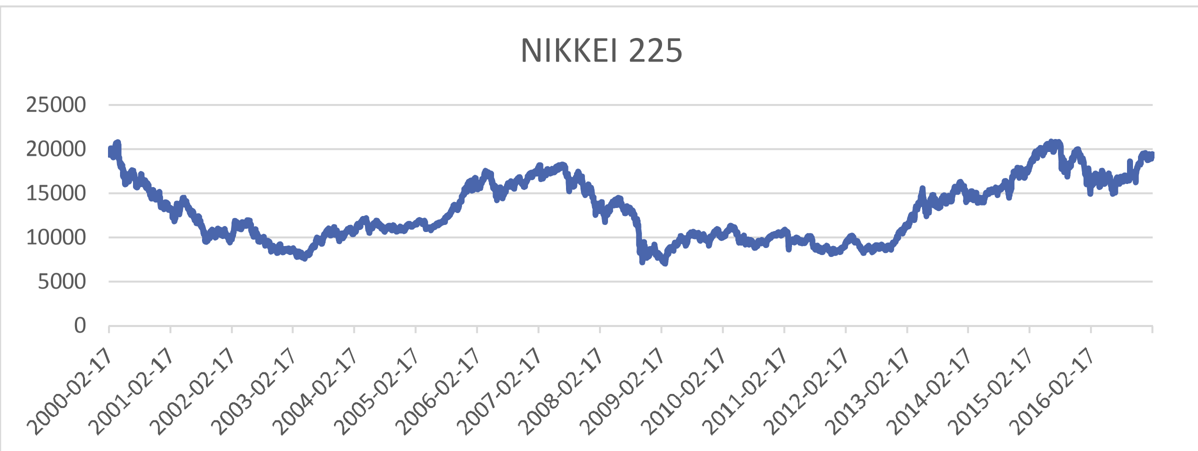
2016-02-17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2012-02-17
2013-02-17
2014-02-17
2015-02-17
2016-02-17


JAKARTA IDX
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4000
3000
2000
1000
0
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2001-02-17
2002-02-17
2003-02-17
2004-02-17
2005-02-17
2006-02-17
2007-02-17
2008-02-17
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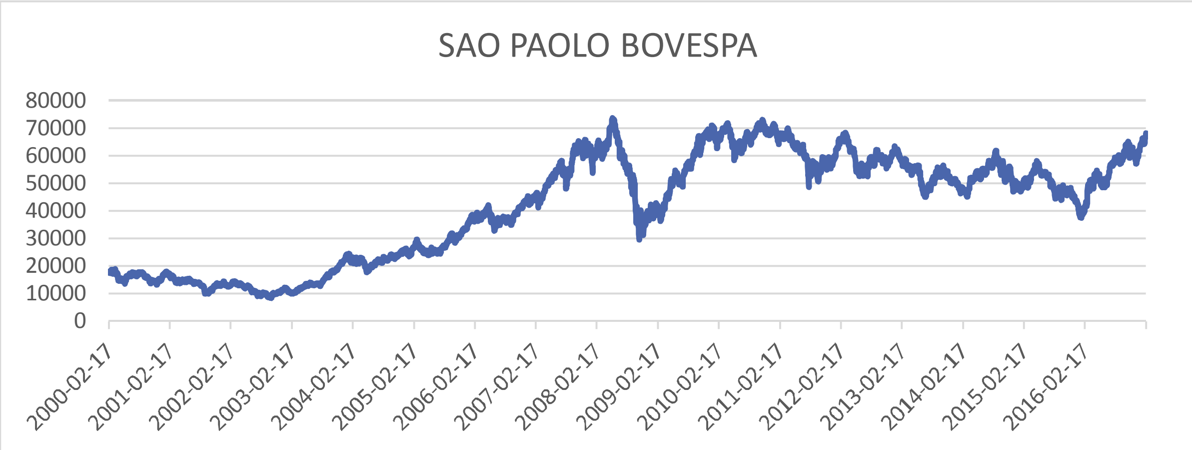
2016-02-17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2003-02-17
2004-02-17
2005-02-17
2006-02-17
2007-02-17
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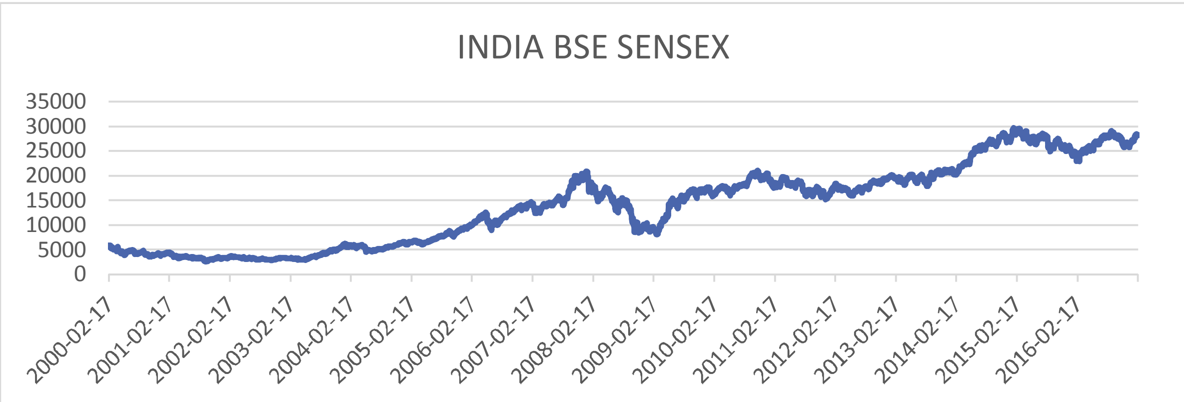
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2001-02-17
2002-02-17
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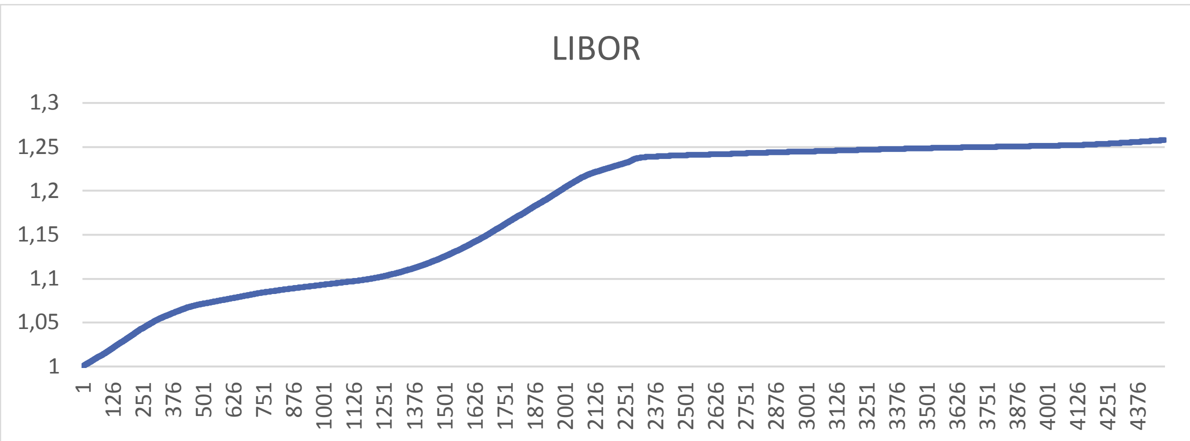
2015-02-17
2016-02-17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1,2
1,15
1,1
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1
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126
251
376
501
626
751
876
1001
1126
1251
1376
1501
1626
1751
1876
2001
2126
2251
2376
2501
2626
2751
2876
3001
3126
3251
3376
3501
3626
3751
3876
4001
4126
4251
4376

8.2 Correlation Matrix

Correlation Matrix	*COPPER*	*DAX*	*EUR_GBP*	*EUR_USD*	*GOLD*	*INDIA*	*IDX*	*NIKKEI*	*S_P*	*SAO_PAOLO*	*SILVER*	*USD_CHF*	*USD_JPY*	*WTI_OIL*
COPPER	1	0.026938	0.023884	-0.008	0.004973	0.041795	-0.00278	0.013083	-0.01192	-0.0245	0.007737	-0.01148	-0.03632	0.003601
DAX	0.026938	1	-0.012	0.00116	0.012793	0.040791	-0.01995	0.013765	0.03066	0.009413	0.011884	-0.00061	0.01337	0.037032
EUR_GBP	0.023884	-0.012	1	0.097263	-0.0185	0.033609	0.018964	0.009023	0.013977	-0.00284	-0.00826	-0.16537	-0.05213	0.015151
EUR_USD	-0.008	0.00116	0.097263	1	-0.00158	-0.02376	-0.01558	-0.00233	-0.01061	0.014222	0.00797	-0.09538	-0.02516	-0.01544
GOLD	0.004973	0.012793	-0.0185	-0.00158	1	-0.01305	0.002646	-0.00356	0.016254	-0.02019	0.045944	-0.01037	-0.02294	0.037161
INDIA	0.041795	0.040791	0.033609	-0.02376	-0.01305	1	0.001995	-0.04766	0.053738	-0.00714	0.053273	-0.00458	-0.01547	-0.01371
IDX	-0.00278	-0.01995	0.018964	-0.01558	0.002646	0.001995	1	0.010657	-0.0243	0.009616	-0.0354	0.002145	0.01077	-0.01425
NIKKEI	0.013083	0.013765	0.009023	-0.00233	-0.00356	-0.04766	0.010657	1	0.02823	0.062121	-0.00573	-0.0432	-0.03362	0.018217
S_P	-0.01192	0.03066	0.013977	-0.01061	0.016254	0.053738	-0.0243	0.02823	1	0.055721	0.042674	-0.02664	0.003353	-0.0263
SAO_PAOLO	-0.0245	0.009413	-0.00284	0.014222	-0.02019	-0.00714	0.009616	0.062121	0.055721	1	-0.02697	-0.01243	-0.00079	-0.00147
SILVER	0.007737	0.011884	-0.00826	0.00797	0.045944	0.053273	-0.0354	-0.00573	0.042674	-0.02697	1	0.035275	0.005	0.000807
USD_CHF	-0.01148	-0.00061	-0.16537	-0.09538	-0.01037	-0.00458	0.002145	-0.0432	-0.02664	-0.01243	0.035275	1	0.389871	-0.00206
USD_JPY	-0.03632	0.01337	-0.05213	-0.02516	-0.02294	-0.01547	0.01077	-0.03362	0.003353	-0.00079	0.005	0.389871	1	0.000665
WTI_OIL	0.003601	0.037032	0.015151	-0.01544	0.037161	-0.01371	-0.01425	0.018217	-0.0263	-0.00147	0.000807	-0.00206	0.000665	1

8.3 Results of Indicator Groups per Asset

S&P		*FMA 5*	*FMA 10*	*FMA 20*	*FMA 50*	*VMA*	*MACD*	*RSI*
>0	0.177778	0.155556	0.577778	0.422222	0.25	0	0.722222	
Mean Return	-0.00027	-0.00019	0.000103	-6.5E-05	-0.00022	-0.0002	7.28E-05	
> LIBOR	0.088889	0.111111	0.488889	0.4	0.194444	0	0.555556	
>B&H	0.066667	0.111111	0.377778	0.355556	0.083333	0	0.333333	
Sig. > B&H (10%)	0	0	0	0	0	0	0	
Sig. > B&H (5%)	0	0	0	0	0	0	0	
Sharpe>B&H	0.088889	0.111111	0.4	0.377778	0.138889	0	0.277778	

DAX	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.333333	0.466667	0.622222	0.533333	0.527778	0.666667	0.222222
Mean Return	-0.00012	-4.9E-05	0.000395	-7.3E-05	-1.4E-05	9.21E-05	-8.4E-05
> LIBOR	0.288889	0.377778	0.577778	0.466667	0.416667	0.666667	0.166667
>B&H	0.133333	0.311111	0.511111	0.444444	0.25	0.333333	0.111111
Sig. > B&H (10%)	0	0	0.088889	0.022222	0	0	0
Sig. > B&H (5%)	0	0	0.044444	0	0	0	0
Sharpe>B&H	0.133333	0.333333	0.533333	0.444444	0.333333	0.333333	0.055556

NIKKEI	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.511111	0.266667	0.311111	0.644444	0.25	0	0.388889
Mean Return	-4.9E-05	-0.0003	-0.00044	0.000369	-2.6E-05	-0.00023	2.21E-05
> LIBOR	0.377778	0.244444	0.2	0.644444	0.25	0	0.277778
>B&H	0.511111	0.333333	0.311111	0.644444	0.25	0	0.388889
Sig. > B&H (10%)	0	0.022222	0	0.111111	0	0	0
Sig. > B&H (5%)	0	0.022222	0	0.066667	0	0	0
Sharpe>B&H	0.511111	0.333333	0.311111	0.644444	0.25	0	0.388889

IDX	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.688889	0.8	0.822222	0.733333	0.861111	1	0.444444
Mean Return	0.000526	0.000606	0.000507	0.000553	0.000696	0.000661	-0.00016
> LIBOR	0.688889	0.777778	0.755556	0.733333	0.861111	1	0.333333
>B&H	0.488889	0.488889	0.511111	0.466667	0.638889	0.666667	0.166667

Sig. > B&H (10%)	0.244444	0.222222	0.111111	0.066667	0.277778	0.333333	0.055556
Sig. > B&H (5%)	0.2	0.177778	0.044444	0.044444	0.194444	0	0
Sharpe>B&H	0.511111	0.488889	0.511111	0.511111	0.611111	0.666667	0.166667
SENSEX	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.711111	0.777778	0.688889	0.666667	0.888889	0.666667	0.444444
Mean Return	0.000449	0.00072	0.000371	0.000379	0.000554	0.000339	-2.3E-05
> LIBOR	0.666667	0.733333	0.688889	0.644444	0.833333	0.666667	0.388889
>B&H	0.444444	0.622222	0.6	0.577778	0.694444	0.333333	0.277778
Sig. > B&H (10%)	0.222222	0.288889	0.155556	0.177778	0.194444	0	0
Sig. > B&H (5%)	0.133333	0.266667	0.111111	0.155556	0.083333	0	0
Sharpe>B&H	0.466667	0.666667	0.577778	0.6	0.638889	0.333333	0.222222
BOVESPA	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.511111	0.6	0.8	0.422222	0.666667	0.666667	0.333333
Mean Return	9.15E-05	0.000143	0.000539	-0.00043	0.000164	0.000282	-0.00018
> LIBOR	0.488889	0.6	0.755556	0.4	0.583333	0.666667	0.277778
>B&H	0.288889	0.4	0.555556	0.222222	0.305556	0.333333	0.111111
Sig. > B&H (10%)	0.022222	0	0.022222	0	0	0	0
Sig. > B&H (5%)	0.022222	0	0	0	0	0	0
Sharpe>B&H	0.288889	0.377778	0.555556	0.266667	0.361111	0.333333	0.111111
Gold	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.533333	0.511111	0.577778	0.333333	0.5	0.333333	0.611111
Mean Return	-3E-05	-4.4E-05	3.16E-05	-0.00014	-1.4E-05	-5.2E-05	4E-05
> LIBOR	0.444444	0.422222	0.533333	0.311111	0.416667	0.333333	0.333333
>B&H	0.2	0.066667	0.288889	0.088889	0.083333	0	0.277778
Sig. > B&H (10%)	0	0	0	0	0	0	0
Sig. > B&H (5%)	0	0	0	0	0	0	0
Sharpe>B&H	0.2	0.155556	0.311111	0.111111	0.138889	0	0.277778

WTI Oil	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.288889	0.444444	0.244444	0.533333	0.25	0.666667	0.444444
Mean Return	-0.00021	-0.00025	-0.00056	0.000685	-0.00017	8.38E-05	-3.2E-05
> LIBOR	0.222222	0.422222	0.244444	0.533333	0.166667	0.666667	0.277778
>B&H	0.222222	0.355556	0.177778	0.533333	0.138889	0.333333	0.166667
Sig. > B&H (10%)	0	0	0	0.088889	0	0	0
Sig. > B&H (5%)	0	0	0	0.044444	0	0	0
Sharpe>B&H	0.2	0.333333	0.177778	0.533333	0.138889	0.333333	0.111111
Copper	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.355556	0.311111	0.266667	0.422222	0.583333	1	0.166667
Mean Return	-0.00018	-4.8E-05	-0.00063	-0.00037	8.98E-05	0.000577	-0.00026
> LIBOR	0.288889	0.311111	0.155556	0.333333	0.444444	1	0.166667
>B&H	0.466667	0.4	0.377778	0.444444	0.722222	1	0.166667
Sig. > B&H (10%)	0.022222	0.022222	0	0.022222	0	0	0
Sig. > B&H (5%)	0	0	0	0	0	0	0
Sharpe>B&H	0.466667	0.4	0.355556	0.444444	0.722222	1	0.166667
Silver	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.311111	0.244444	0.355556	0.511111	0.388889	1	0.611111
Mean Return	-0.0004	-0.00055	-0.00056	-2.8E-05	-0.00011	0.000121	6.28E-05
> LIBOR	0.244444	0.222222	0.333333	0.466667	0.305556	0.666667	0.555556
>B&H	0.244444	0.222222	0.333333	0.466667	0.222222	0.666667	0.555556
Sig. > B&H (10%)	0	0	0.022222	0	0	0	0
Sig. > B&H (5%)	0	0	0.022222	0	0	0	0
Sharpe>B&H	0.244444	0.222222	0.333333	0.466667	0.277778	0.666667	0.555556
EUR-USD	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.4	0.444444	0.311111	0.488889	0.527778	1	0.611111
Mean Return	-3.8E-05	-3.9E-05	-0.00013	-7.1E-05	8.27E-06	6.63E-05	-5.1E-06
> LIBOR	0.311111	0.288889	0.2	0.422222	0.305556	1	0.166667
>B&H	0.377778	0.422222	0.266667	0.488889	0.472222	1	0.444444

Sig. > B&H (10%)	0	0	0	0	0	0	0
Sig. > B&H (5%)	0	0	0	0	0	0	0
Sharpe>B&H	0.377778	0.422222	0.266667	0.488889	0.472222	1	0.444444

USD-JPY	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.555556	0.444444	0.511111	0.288889	0.5	1	0.611111
Mean Return	4.55E-06	-4.7E-05	3.06E-05	7.76E-05	-8.8E-06	9.87E-05	3.41E-05
> LIBOR	0.4	0.311111	0.377778	0.288889	0.138889	1	0.333333
>B&H	0.511111	0.4	0.488889	0.288889	0.416667	1	0.5
Sig. > B&H (10%)	0	0	0	0.088889	0	0	0
Sig. > B&H (5%)	0	0	0	0.044444	0	0	0
Sharpe>B&H	0.511111	0.4	0.488889	0.288889	0.416667	1	0.5

EUR-GBP	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.666667	0.577778	0.422222	0.244444	0.333333	0.333333	0.611111
Mean Return	0.000119	5.39E-05	3.66E-05	-0.00013	-4.1E-05	-2.6E-05	2.22E-05
> LIBOR	0.488889	0.444444	0.355556	0.177778	0.194444	0	0.444444
>B&H	0.422222	0.355556	0.355556	0.133333	0.111111	0	0.277778
Sig. > B&H (10%)	0.133333	0.044444	0.022222	0	0	0	0
Sig. > B&H (5%)	0.066667	0	0.022222	0	0	0	0
Sharpe>B&H	0.422222	0.377778	0.355556	0.133333	0.111111	0	0.277778

USD-CHF	FMA 5	FMA 10	FMA 20	FMA 50	VMA	MACD	RSI
>0	0.311111	0.2	0.088889	0.555556	0.166667	0.333333	0.777778
Mean Return	-0.00011	-0.00017	-0.00025	0.000249	-0.00013	-7.5E-05	9.51E-05
> LIBOR	0.222222	0.155556	0.044444	0.488889	0.111111	0	0.722222
>B&H	0.555556	0.355556	0.288889	0.688889	0.416667	0.666667	0.888889
Sig. > B&H (10%)	0.022222	0	0	0.133333	0	0	0.388889
Sig. > B&H (5%)	0	0	0	0.088889	0	0	0.166667
Sharpe>B&H	0.466667	0.355556	0.222222	0.644444	0.416667	0.666667	0.888889

8.4 Volatility

TABLE 6. VOLATILITY	INDICATOR	SMA	DMA	EMA	RSI CROSS	RSI TOUCH	MACD	GRAND TOTAL
FMA (1)	σ(Sell)	0.000207	0.000249	0.000213				0.000223
	σ (Buy)	0.000192	0.000166	0.000192				0.000183
FMA (3)	σ(Sell)	0.000214	0.000226	0.000216				0.000219
	σ (Buy)	0.000192	0.000178	0.000195				0.000188
FMA (5)	σ(Sell)	0.000214	0.000216	0.000211				0.000214
	σ (Buy)	0.000193	0.000177	0.000193				0.000188
FMA (10)	σ(Sell)	0.000210	0.000214	0.000208				0.000211
	σ (Buy)	0.000199	0.000179	0.000200				0.000193
FMA (20)	σ(Sell)	0.000211	0.000213	0.000210				0.000211
	σ (Buy)	0.000202	0.000183	0.000200				0.000195
VMA	σ(Sell)	0.000274	0.000273	0.000278				0.000275
	σ (Buy)	0.000172	0.000175	0.000170				0.000172
RSI (70, 30)	σ(Sell)				0.000197	0.000171		0.000184
	σ (Buy)				0.000239	0.000284		0.000262
RSI (60, 40)	σ(Sell)				0.000174	0.000182		0.000178
	σ (Buy)				0.000275	0.000266		0.000271
RSI (50, 50)	σ(Sell)				0.000266	0.000173		0.000220
	σ (Buy)				0.000171	0.000276		0.000224
MACD	σ(Sell)						0.000248	0.000248
	σ (Buy)						0.000189	0.000189
TOTAL AVERAGE OF S(SELL)		0.000222	0.000232	0.000223	0.000212	0.000175	0.000248	0.000224
TOTAL AVERAGE OF S(BUY)		0.000191	0.000176	0.000192	0.000228	0.000276	0.000189	0.000192

8.4 Mean Return

Mean Return	***Average of RSI***	***Average of MACD***	***Average of VMA***	***Average of FMA 50***	***Average of FMA 20***	***Average of FMA 10***	***Average of FMA 5***
Copper	-0.000260465	0.000576821	8.98473E-05	-0.000370843	-0.000626314	-4.81034E-05	-0.000184681
DAGS	-8.40301E-05	9.21173E-05	-1.35978E-05	-7.3192E-05	0.000395033	-4.93574E-05	-0.000117614
EUR-GBP	2.22383E-05	-2.62837E-05	-4.10876E-05	-0.000132446	3.65524E-05	5.39268E-05	0.000119069
EUR-USD	-5.08491E-06	6.62793E-05	8.26938E-06	-7.09135E-05	-0.000127214	-3.92537E-05	-3.77773E-05
Gold	3.99504E-05	-5.15599E-05	-1.41601E-05	-0.000135858	3.15545E-05	-4.35503E-05	-2.97515E-05
IDX	-0.000159956	0.000660804	0.0006961	0.000553151	0.000507422	0.000606402	0.0005257
SENSEX	-2.28054E-05	0.00033857	0.000553646	0.000378994	0.00037096	0.000720222	0.000449177
NIKKEI	2.21149E-05	-0.000226092	-2.60659E-05	0.000368868	-0.000438065	-0.000301496	-4.91133E-05
S&P	7.27525E-05	-0.000203548	-0.000218131	-6.4608E-05	0.000102574	-0.000190274	-0.000270431
BOVESPA	-0.000177653	0.000282499	0.000163549	-0.000433657	0.000539108	0.000142944	9.1476E-05
Silver	6.28188E-05	0.000120688	-0.000111415	-2.81858E-05	-0.000563134	-0.000551144	-0.000402617
USD-CHF	9.50883E-05	-7.47183E-05	-0.000126603	0.000249111	-0.000252	-0.000167427	-0.000110612
USD-JPY	3.41352E-05	9.87153E-05	-8.76293E-06	7.76061E-05	3.06131E-05	-4.6644E-05	4.54675E-06
WTI Oil	-3.15358E-05	8.37849E-05	-0.000173541	0.00068473	-0.000555517	-0.000246671	-0.000209443
Grand Total	**-2.80308E-05**	**0.000124148**	**5.55747E-05**	**7.16255E-05**	**-3.91733E-05**	**-1.1459E-05**	**-1.58622E-05**

8.5 Share > B&H

	> B&H	Average of RSI	Average of MACD	Average of VMA	Average of FMA 50	Average of FMA 20	Average of FMA 10	Average of FMA 5
Equity New	**DAX**	0.111111111	0.333333333	0.25	0.444444444	0.511111111	0.311111111	0.133333333
Equity New	**NIKKEI**	0.388888889	0	0.25	0.644444444	0.311111111	0.333333333	0.511111111
Equity New	**S&P**	0.333333333	0	0.083333333	0.355555556	0.377777778	0.111111111	0.066666667
Equity Old	**SENSEX**	0.277777778	0.333333333	0.694444444	0.577777778	0.6	0.622222222	0.444444444
Equity Old	**IDX**	0.166666667	0.666666667	0.638888889	0.466666667	0.511111111	0.488888889	0.488888889
Equity Old	**BOVESPA**	0.111111111	0.333333333	0.305555556	0.222222222	0.555555556	0.4	0.288888889
Commodity	**Copper**	0.166666667	1	0.722222222	0.444444444	0.377777778	0.4	0.466666667
Commodity	**Gold**	0.277777778	0	0.083333333	0.088888889	0.288888889	0.066666667	0.2
Commodity	**Silver**	0.555555556	0.666666667	0.222222222	0.466666667	0.333333333	0.222222222	0.244444444
Commodity	**WTI Oil**	0.166666667	0.333333333	0.138888889	0.533333333	0.177777778	0.355555556	0.222222222
Currency	**USD-CHF**	0.888888889	0.666666667	0.416666667	0.688888889	0.288888889	0.355555556	0.555555556
Currency	**USD-JPY**	0.5	1	0.416666667	0.288888889	0.488888889	0.4	0.511111111
Currency	**EUR-USD**	0.444444444	1	0.472222222	0.488888889	0.266666667	0.422222222	0.377777778
Currency	**EUR-GBP**	0.277777778	0	0.111111111	0.133333333	0.355555556	0.355555556	0.422222222
	Grand Total	0.333333333	0.452380952	0.343253968	0.417460317	0.388888889	0.346031746	0.352380952

8.6 Share of Positive Significant Results at a 5% level

	SIG 5%	*Average of RSI*	*Average of MACD*	*Average of VMA*	*Average of FMA 50*	*Average of FMA 20*	*Average of FMA 10*	*Average of FMA 5*
Equity New	DAX	0	0	0	0	0.044444444	0	0
Equity New	NIKKEI	0	0	0	0.066666667	0	0.022222222	0
Equity New	S&P	0	0	0	0	0	0	0
Equity Old	SENSEX	0	0	0.083333333	0.155555556	0.111111111	0.266666667	0.133333333
Equity Old	IDX	0	0	0.194444444	0.044444444	0.044444444	0.177777778	0.2
Equity Old	BOVESPA	0	0	0	0	0	0	0.022222222
Commodity	Copper	0	0	0	0	0	0	0
Commodity	Gold	0	0	0	0	0	0	0
Commodity	Silver	0	0	0	0	0.022222222	0	0
Commodity	WTI Oil	0	0	0	0.044444444	0	0	0
Currency	USD-CHF	0.166666667	0	0	0.088888889	0	0	0
Currency	USD-JPY	0	0	0	0.044444444	0	0	0
Currency	EUR-USD	0	0	0	0	0	0	0
Currency	EUR-GBP	0	0	0	0	0.022222222	0	0.066666667
	Grand Total	**0.011904762**	**0**	**0.01984127**	**0.031746032**	**0.017460317**	**0.033333333**	**0.03015873**