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Technical Analysis

Testing the performance of five commonly used technical indicators

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Abstract

This thesis examines five commonly used technical indicators and their performance on five stocks listed at the Stockholm Stock Exchange during the time period January 2010 – March 2016. The research aims to see if the technical indicators can predict return in the upcoming period and also compare the profitability of the indicators versus the buy and hold strategy. Simple OLS regressions are used to analyze whether the different technical indicators are statistically significant for return in the upcoming period. The predictive ability of the technical indicators is overall quite poor as few of the indicators prove to be statistically significant. When comparing return per week invested between the examined technical indicators versus the buy and hold strategy, results find that the buy and hold strategy outperforms the Moving Average and the Moving Average Cross-Over indicator while the Moving Average Convergence Divergence and the Combined indicator provides higher average return per invested week for the majority of the stocks. These slightly contradictory results make it hard to determine whether weak form efficiency holds on Stockholm Stock Exchange and are much in line with the mixed results from earlier research made on other stock markets.

JEL classification: G14

Key Words: technical analysis, weak form efficiency, random walk, moving average, moving average cross-over, moving average convergence divergence

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Introduction

Purpose and contribution

This thesis examines five commonly used technical indicators and their performance on five stocks listed at the Stockholm Stock Exchange. Unlike much of previous research, which has been done on indices, this thesis concentrates on individual stocks.

Although the literature regarding technical analysis and the efficient market hypothesis is extensive, few studies test the individual performance of technical indicators on individual stocks listed on the Stockholm Stock Exchange. Five stocks have been selected, not only to increase the number of observations, but also to see if any results are consistent among all examined stocks. If so, results could give a hint on whether the Stockholm Stock Exchange is weak form efficient. The thesis will contribute to the already existing literature, testing the performance of individual technical indicators simultaneously resulting in conclusions, which has to be interpreted with caution, regarding the weak form efficiency on the Stockholm Stock Exchange. The empirical research conducted is based on the very latest data i.e. between the first of January 2010 until the eleventh of March 2016, contributing to previous research in the field of technical analysis and weak form market efficiency.

Background

Is it possible to consistently generate excess returns on the stock market? At least that is what thousands of investors believe and try every day. Some investors put great trust in fundamental analysis, others in technical analysis and some use the strategies as a complement to each other. Professionals have widely used technical analysis as a trading strategy for many years (Menkhoff 2010). It can be referred to as how an investor, by analyzing historical performance, charts and statistics for an asset, can predict future performance (Bodie et al. 2014).

Whether technical analysis can be used to predict future stock prices is something that has been heavily debated in the academia throughout the years. Supporters of the famous efficient market hypothesis believe that any form of technical analysis is fruitless, whereas many opponents to the theory see it as a fundamental part of a profitable investment strategy. For that reason a considerable amount of literature has been investigating the actual performance of technical analysis over the years, finding ambiguous results.

Research question

The main purpose of this thesis is to investigate the actual profitability and predictive ability of five commonly used technical indicators on five stocks listed on the Stockholm Stock Exchange. According to the efficient market hypothesis one should not be able to generate abnormal returns, nor predict future performance of an asset, by using technical analysis.

In order to see if any of the indicators are able to provide excess returns when investing according to the indicators, returns are manually computed and compared to the buy-and-hold strategy, which is used as a benchmark.

To test the predictive ability of each indicator five different null hypotheses is investigated, stating that none of the technical indicators are statistically significant for the return in the upcoming time period:

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$$

β_1 = Coefficient of MA10 indicator

β_2 = Coefficient of MA50 indicator

β_3 = Coefficient of MACO indicator

β_4 = Coefficient of MACD indicator

β_5 = Coefficient of a Combined indicator

Delimitations

The number of stocks investigated is limited to a manageable amount. If the sample included all stocks listed on the Stockholm stock exchange, the total sample size would be too large for a thesis of this magnitude. This makes any conclusions regarding the market efficiency on the Stockholm Stock Exchange as a whole hard to argue for.

Section description

The thesis consists of a theory section explaining the different theories underlying the empirical research. Next up is a literature review of previous research on weak form efficiency and technical indicators, followed by a section which presents the data and methodology used in the thesis. The continuing section presents and analyses the results whereas the final section concludes the thesis.

Literature Review

The literature regarding technical analysis and market efficiency is extensive. We have reviewed literature from the beginning of the 1950s until very up to date material. For the authors to achieve unbiasedness, literature with different findings for each theory and indicator has been reviewed. Earlier research on indicators has been done on their performance and profitability, both individually and combined with other indicators. As our thesis mainly examines indicators individual performance, this is the research we have primarily reviewed.

Market Efficiency

Ever since Maurice Kendall (1953) found no predictable patterns in stock prices, in one of the first empirical test of time series through the early adoption of computer technology in economics, a substantial amount of research on whether markets are efficient or not have been done. According to the efficient market hypothesis (Fama 1970), which have given rise to various theories within modern financial economics theory, pricing on the market always reflects all currently available information. The efficient market hypothesis is closely related to something called “random walk,” which Malkiel (1973) wrote extensively about in his book “A random walk down wall street.” He states that every following price fluctuation constitutes with random deviations from previous prices. The actual logic behind the random walk is that information flow is unrestricted, and that information is instantly reflected in stock prices while the price of tomorrow is an effect of only tomorrow’s news and will be undependable of the price fluctuations of today. Malkiel has several arguments that technical analysis is not working and states that the market is very close to effective. Although Malkiel does not reject the fact that price fluctuations have a memory, he believes that if they do exist they tend to be very limited.

During the late 1980s, American academics started to question the “random walk” and stated that the famous theory does not hold on the American stock market. One example is Brock, Lakonishok and Lebaron (1992) who found strong support for the power of several commonly used technical indicators to predict the Dow Jones Industrial Average Index. Jegadeesh and Titman (1993) observes that it is possible to consistently gain abnormal returns compared to the underlying market. The study examines the market efficiency by testing if it is possible to make profitable trades based upon previous returns. They conclude that this strategy proves to have significant abnormal returns over the period 1965-1989.

A rather recent review made by Park et al. (2007) finds evidence regarding the actual profitability of technical analysis. They find that among 95 modern studies, 56 find positive results, 20 negative results, and 19 mixed results when it comes to the profitability of technical analysis. Park et al. (2007) are rather critical to some of the studies validity and addresses further studies to be more detailed in their empirical research. An example of European market efficiency is Maria Rosa Borges (2010) test for weak-form market efficiency conducted on the France, German, UK, Greece, Portuguese and Spanish market indexes. She finds that France, Germany, UK and Spain shows signs of a random walk behavior, while Greece and Portugal obtain a high serial correlation.

Technical Indicators

Earlier studies on whether different indicators can be used to consistently outperform the market is ambiguous. Ellis and Parbery (2005) tested different Moving Average trading strategies on three indices. The research compared the performance of the 200-day Moving Average and the buy-and-hold strategy. Results found that the buy-and-hold strategy outperformed the Moving Average strategy on all three indices, especially when considering transaction costs. In more recent years, Paskalis Glabadanidis (2015) and Han et al. (2013) found that an empirically tested Moving Average-trading strategy provides excess returns, rather than if the underlying asset were bought and held on to. Glabadanidis (2015) examines returns, both from composed portfolios and individual stocks, while Han et al. (2013) focus solely on portfolios. The study done by Glabadanidis (2015) mainly focuses on the 24-Moving Average indicator, but also tests shorter lengths. Han et al. (2013) test several different averages, 10-day, 20-day, 50-day, 100-day and 200-day, where it is found that usage of shorter lengths seems to result in greater returns. Both Han et al. (2013) and Glabadanidis (2015) concludes that the examined strategy provides greater returns, after adjusting for transaction costs, than the buy-and-hold strategy.

Brock (1992) conducted an experiment to investigate whether the Moving Average Cross-Over indicator could be used to constantly gain abnormal returns. Brock tested both Variable Length Moving Average and Fixed Length Moving Average on the most commonly used lengths, (1/50), (1/150), (1/200, (2/200) and (5/150). Brock argued that earlier studies, which found technical analysis useless, might have been premature as he provides results that all examined indicators seem to outperform the underlying market. Camillo Lento (2008) later tested if the Moving Average Cross-Over indicator could be used to forecast asset pricing, note the difference from looking at the profitability of a technical indicator. Similar to Brock (1992),

Lento (2008) used both the Variable Length Moving Average and the Fixed Length Moving Average rule. Lento (2008) concludes that none of the examined indicators are significant as explanatory variables of pricing when using the Variable Length Moving Average rule. However the Fixed Length Moving Average rule found, when using averages of (1/50), (5/150), (1/200), that the examined indicators did explain part of future pricing, where R-squared ranged between 44.7% and 47,8%. The (5/150) indicator provided the highest R-squared percent and was therefore the indicator with the best forecasting ability.

The performance of the Moving Average Convergence Divergence indicator has been reviewed several times on different markets. Tanaka-Yamawaki and Tokuoka (2007) examined the effectiveness of the Moving Average Convergence Divergence applied on intraday and tick data. The study focuses on eight stocks listed on the New York Stock Exchange. The authors conclude that while the Moving Average Convergence Divergence is not a good predictor by itself, using it with the combination of other indicator gives additional predictive ability. Chong and Ng (2008) finds that the Moving Average Convergence and Divergence indicator can be used to generate significantly greater returns than the buy-and-hold strategy on the London Stock Exchange. Chong et al. (2014) then revisit the performance of the same indicator in five OECD countries markets. This paper finds that Moving Average Convergence Divergence indicator can be used to consistently gain excess returns in the Milan Comit General and the S&P/TSX Composite Index, while the performance of the indicator seems poor on DAX 30, Dow Jones Industrials, Nikkei 225. The fact that the indicator provides an advantage on the Italian stock market could be caused by the market being less developed than other OECD countries, therefore not being perfectly efficient (Chong et al. 2014). Similar to Chong et al. (2014) Rosillo (2013) presents mixed results of the indicator. While Chong et al. (2014) found the indicator to be profitable on specific markets, Rosillo found the indicator to generate abnormal returns on the Spanish stock market during certain time periods.

Theory

Efficient market hypothesis

The rise of the efficient market hypothesis (EMH) can be traced back to the mid-1950s when economists and statisticians started to analyze economic time series via the early adoption of computers. Maurice Kendall (1953) was one of the first who found no predictable patterns in stock prices when he examined the behavior of the stock market. Later Eugene Fama presented the theory based on the perquisites that on average, stock prices will fully reflect all available information (Fama 1965), often referred as the definition of the EMH.

Closely related with the EMH is the argument that stock prices should be totally random and unpredictable, a so called “random walk”, which Malkiel (1973) wrote extensively about in his book “A random walk down wall street”. It implies that when new information becomes available and indicates that a stock is underpriced, investors instantly buy the stock. This results in that the price of the stock reaches a fair level, where investors only can expect ordinary rates of return. “Ordinary rates” are reasonable rates of returns that come with the risk exposure of the stock. New information given to the investors is information that must be unpredictable, which means that stock prices that fluctuate in response to the information must therefore also move unpredictably (Bodie et al. 2014).

The efficient market hypothesis is often separated into three levels of efficiency: weak, semi-strong and strong. The different levels are separated by the view of the term “all available information”. This thesis primarily investigates the weak-form efficiency, which states that stock prices reflect all information that can be gathered by examining historical data e.g. historical prices and trading data. The weak-form level of EMH implies that any form of technical analysis i.e. analyzing historical prices is non-essential. Information regarding stocks are available for everyone, free and relatively easy to analyze. The weak form efficiency concludes that if any kind of data ever produced adequate information about future performance, investors would already have exploited the information. Therefore, adequate information immediately loses its value the moment it becomes publicly known (Bodie et al. 2014).

Technical indicators

Traders who embrace a technical approach when investing often rely on different *indicators*. The indicators are supposed to produce signals that tell the investor when to buy or sell an asset. This subsection explains and derives the indicators that are examined in this thesis.

Moving Average

As prices fluctuate and often differs each minute, many investors use averages to smoothen out otherwise volatile price action (Brock 1992). Instead of making investment decisions exclusively based on the current price of an asset, the Moving Average indicator emphasizes less volatile price action and focus on pricing over time. To obtain the Moving Average of an asset, pricing is averaged out over an equally weighted set number of periods. The calculation is illustrated below and provides the average price of n periods at time t (Han et al. 2013):

$$MA_{t,n} = \frac{P_{t-(n-1)} + P_{t-(n-2)} + \dots + P_{t-1} + P_t}{n} \quad (1)$$

n = Number of lags

P_t = Price at time t

t = Time period

Among investors who use technical analysis, the Moving Average is the most commonly used indicator (Brock et al. 1992, Han et al. 2013). Moving Average can be used to identify the current trend of a specific asset or market and used in a trend-following strategy. The idea is that an investor should invest and only hold the asset during an upward trend. When the trend interrupts, the asset should be sold (Han et al. 2013). During optimal market conditions, this allows the investor only to hold the asset during profitable periods.

Moving Average Cross-Over

Similar to the Moving Average this indicator is utilized in a trend following strategy. The indicator is primarily used to identify when a change in trend occurs. The Moving Average Cross-Over is derived from Moving Averages and consists of two different average lengths, a long-period average and short-period average. When the short-period average price closes above the long-period average, which would indicate that a positive trend emerges, this will trigger a buy signal. A sell signal will be produced contrariwise (Lento 2008, Brock et al. 1992).

There are two different ways of how the indicator can be used. Firstly, every given period produces a certain signal and the investor will act accordingly, *Variable Length Moving Average*. Secondly, when a signal is triggered this will be acted upon and other signals given for the next few days will be ignored, *Fixed Length Moving Average* (Lento 2008). The research done in this thesis is based on the Variable Length Moving Average and the mathematical calculation follows (Lento 2008):

(2)

$$\frac{P_{t-(S-1)} + P_{t-(S-2)} + \dots + P_{t-1} + P_t}{S} - \frac{P_{t-(L-1)} + P_{t-(L-2)} + \dots + P_{t-1} + P_t}{L} \Rightarrow 0 = Buy$$

$S = Short\ period\ lag$

$L = Long\ period\ lag$

$P_t = Price\ at\ time\ t$

Moving Average Convergence Divergence

This indicator is similar to the Moving Average Cross-Over used to identify changes in trends (Rosillo et al. 2013). The indicator is derived from the Exponential Moving Average, note the difference from the Moving Average, and consists of two different average lengths. Unlike the regular Moving Average this kind of average does not use equally weighted period, but instead puts more weight in recent pricing information. The Exponential Moving Average is calculated accordingly (Rosillo et al. 2013):

$$EMA_n(t) = \alpha * p_t + (1 - \alpha) * EMA_n(t - 1) \quad (3)$$

$n = Number\ of\ lags$

$p(t) = Asset\ price\ at\ time\ t$

Where α is calculated as follows:

$$\alpha = \frac{2}{1+n} \quad (4)$$

$n = number\ of\ periods$

$\alpha = Multiplier$

The Moving Average Convergence Divergence is then calculated by subtracting the longer Exponential Moving Average from the shorter Exponential Moving Average (Rosillo et al. 2013):

$$MACD(n) = EMA_k(i) - EMA_d(i) \quad (5)$$

Where:

$EMA_k(i) = Shorter\ Exponential\ Moving\ Average\ at\ period\ i$

$EMA_d(i) = Longer\ Exponential\ Moving\ Average\ at\ period\ i$

Usually, a signal line is included and calculated as either a Moving Average or Exponential Moving Average of the Moving Average Convergence Divergence line (Rosillo et al. 2013):

$$Sign(n) = MA_t(MACD(n)) \quad (6)$$

Similar to previous indicators there are different ways of using the Moving Average Divergence Convergence. Chong and Ng (2008) found it profitable to simply ignore the signal line and interpret a buy signal as:

$$Buy = MACD(t) > 0, MACD(t - 1) \leq 0 \quad (7)$$

In this thesis, a signal line will be included, which is also how the indicator was originally used (Rosillo et al. 2013). A buy signal is produced when the Moving Average Convergence Divergence is greater than the signal line (Appel 2003).

Econometric Theory

This subsection will briefly introduce the relevant econometric theory for the research conducted in this thesis. All concepts and ideas is presented more thoroughly in “Introduction to econometrics” (Wooldridge 2014)

Optimal Least Squares-regression (OLS)

Simple regression model

The OLS-regression can be used to create a model that describes a functional relationship between a dependent variable and explanatory variables. The model is computed as follows:

$$Y = \beta_0 + \beta_1 X_1 + U \quad (8)$$

Where:

$Y =$ *Dependent variable*

$\beta_0 =$ *Constant*

$\beta_1 =$ *Coefficient*

$X_1 =$ *Regressor*

$U =$ *Error term*

Where Y is the dependent variable of the model. β_1 equals the change in Y if X_1 is increased, while keeping everything else constant, where β_1 is called the causal effect if X_1 . β_0 is the model's constant and therefore the intercept. U , the so called error term, includes all explanatory power of Y , which is not explained by X_1 .

Significance level

The significance level is a chosen percentage that determines if a variable is considered statistically significant. A lower percentage level results in few significant results, but also interprets variables with a higher accuracy. The most commonly used significance level is 5%.

Dummy Variables

Dummy variables is a certain type of regressor that only takes a value of either “0” or “1”. The β -value of the X-variable equals the difference in output if the variable equals “1” rather than “0”.

Assumptions

In order for the OLS-regression to be a good estimator the model needs to be unbiased and consistent. Unbiasedness of the model indicates that it is a good estimator on average, while a consistent model predicts values close to the “true values” in large samples. To achieve unbiasedness of a regression where time-series data is used, assumptions 1-3 has to be fulfilled. To declare a model the best linear unbiased estimator two additional assumptions, 4 and 5, has to be made. Similar to previously described theory, the following assumptions and quotes are discussed further by Wooldridge (2014).

Assumption 1: Linear in parameters

“The stochastic process $(X_1 + X_2, \dots, X_n; t = 1, 2, \dots, n)$ follows the linear model” (Wooldridge 2014, p.279).

$$Y = \beta_0 + \beta_1 X_1 + U \tag{9}$$

Assumption 2: No perfect collinearity

“In the sample (and therefore in the underlying time series process), no independent variable is constant nor a perfect linear combination of the others” (Wooldridge 2014, p.280).

Assumption 3: Zero conditional mean

“For each t , the expected value of the error U_t , given the explanatory variables for *all* time periods is zero” (Wooldridge, 2014 p.280).

$$E[U_t|X] = 0, t = 1, 2, \dots, n \tag{10}$$

Assumption 4: Homoscedasticity

“Conditional on X, the variance of U_t , is the same for all t “(Wooldridge 2014, p.282).

$$\text{Var}[U_t|X] = \text{Var}(U_t) = \sigma^2, t = 1, 2, \dots, n \quad (11)$$

Assumption 5: No serial correlation

“Conditional on X, the errors in two different time periods are uncorrelated” (Wooldridge, 2014, p.283).

$$\text{Corr}[U_t, U_s|X] = 0, \text{ for all } t \neq s \quad (12)$$

Time series data

Data which is collected during a certain time period and in chronological order is called “Time series data”. When time series data is analyzed and used in an OLS-regression certain additional assumptions has to be considered. If data is constantly increasing or decreasing the regression might be affected by trending data. If data contains a trend, regardless if increasing or decreasing, this has to be accounted for. If not, the regressor might be biased and inconsistent.

Depending on the number of observations being examined, the model might require strict exogeneity, rather than the regular exogeneity assumption. If a large number of observations is used, the strict assumption is not necessary, however contemporary exogeneity still has to hold.

If the amount of observations is large enough, hence dropping the strict exogeneity assumption, highly persistent variables has to be considered instead. To determine whether the dependent variable is highly persistent the first order autocorrelation is calculated. Autocorrelation constitutes the correlation of a variable, amongst a given time series, and a lagged version of itself over a certain time. The purpose is to measure the correlation between two different time series, with the exception that one is in its original form and one variable is lagged. The time series is considered highly persistent if the correlation of the first difference is above 0.9, where 1 is perfect correlation. If highly persistent variables are found the OLS estimators might be inconsistent.

Data and Methodology

Data description

This subsection describes the data that is examined in this thesis. Weekly closing prices of the five following stocks have been extracted from *Bloomberg*:

Sandvik AB - A Swedish high-technology engineering company.

AB Volvo - A Swedish manufacturing company.

Telia Company AB - A Swedish telephone company and mobile network operator.

Investor AB - A Swedish investment firm

Nordea Bank AB - A Nordic financial institution.

Time series data is collected in chronological order from the first of January 2010 until eleventh of March 2016, which equals 324 observations for each stock. All historical prices have been adjusted for dividends. If prices were not adjusted for dividends, this would affect the return of the stock, thus resulting in an incomplete picture of the indicators performance.

Methodology

This subsection describes the methodology for how the research is conducted. Firstly the rule of how a buy- or sell signal is produced will be explained. Afterwards the econometric model will be specified along with the examined hypothesis. The last section describes how different assumptions, which are mentioned in the theory section, will be dealt with.

As discussed in the theory section, whether an indicator is statistically significant will be determined through OLS-regression. Also, a comparison in return between the buy-and-hold strategy and trading according to the indicators will be made. When an indicator triggers a buy signal, the stock will be bought at the start of the upcoming period and held until a sell signal is produced.

While not invested in stocks, a risk-free asset is bought. The risk-free rate is assumed to be 2% annually, which might seem high as interest rates in Sweden are currently relatively low. However, even though Sweden still has historically low interest rates, Avanza Bank and Klarna still offers a 1,2% risk-free rate, as the Swedish government guarantees deposits up to 100 000 euros (Riksgälden 2016). If the risk-free rate is averaged out over the years when the data is gathered from, an annual rate of 2% is a fair interpretation.

The fictitious portfolio will always be fully invested, whether a stock or risk-free asset is held, which allows for compounding returns. Total return is described with the following formula, which is also how Han et al. (2013) conducted their study;

$$R_{total} = R_{s,t} + R_{f,t} \quad (13)$$

R_{total} = Total return during given time period

$R_{s,t}$ = Return from days t where the stock is held upon a buy signal

$R_{f,t}$ = Return from days t where risk free asset is held upon a sell signal

Similar to previous research this thesis primarily focuses on a comparison in return between R_{total} and the buy-and-hold strategy i.e. holding the asset during the whole time period. The performance of the underlying asset versus the “market” is of less interest.

Trading rules

The indicators used in this thesis has found to gain excess returns on different markets in several previous studies, thus making it interesting if the same strategy can be applied on the Stockholm Stock Exchange. An illustration of different signals can be found in the appendix. No “short-selling” will be done, if the indicator produces a sell signal, the underlying asset will be sold and rebought upon next buy signal.

Trading rule 1 - Moving Averages

There are numerous ways of how Moving Averages can be used in trading. This thesis will use it in its most simple form, which is also how Glabadanidis (2015) and Han et al. (2013) found it profitable on the American stock market. If price close above the Moving Average this triggers a buy-signal, likewise, if price close below the Moving Average line this will produce a sell-signal (Glabadanidis 2015, Han et al. 2013). Two different periods, 10 day and 50 day averages, will be used in this thesis. By using two different lengths this also tests the hypothesis of Han et al. (2013), stating that using shorter averages increase returns.

$$Buy\ signal_t = Price_t > MA_{n,t} \quad (14)$$

$$Sell\ signal_t = Price_t < MA_{n,t} \quad (15)$$

Trading rule 2 - Moving Average Cross-Over

This indicator will use a 5-day and 150- average, the lengths which Lento (2008) found had the best forecasting ability for future pricing. Brock (1992) also names (5/150) as one of the most popular averages. A buy signal is produced when the 5-day average close above the 150-average, a sell signal contrariwise.

$$Buy\ signal_t = MA(5)_t > MA(150)_t \quad (16)$$

$$Sell\ signal_t = MA(5)_t < MA(150)_t \quad (17)$$

Trading rule 3 - Moving Average Convergence Divergence

This indicator will consist of a 12-day and 26 day exponential moving average. These averages are the most commonly used when computing Moving Average Convergence Divergence line (Chong 2008, Rosillo et al. 2013). As discussed in the theory section a signal line will be used and calculated from a 9-day average, which is how (Rosillo et al. 2013) conducted their research. A buy signal is produced when the Moving Average Convergence Divergence line close above the signal line:

$$Buy_t = MACD_t > Signal_t \quad (18)$$

$$Sell_t = MACD_t < Signal_t \quad (19)$$

Trading rule 4 - Combined indicator

This indicator will only trigger a buy signal when all of the previously described indicators produce buy signals.

$$Buy_t = X_1 + X_2 + X_3 + X_4 = 4 \quad (20)$$

$$Sell_t = X_1 + X_2 + X_3 + X_4 < 4 \quad (21)$$

Trading rule 5 – Buy-and-hold

The stock is bought in the first week of January 2010 and sold in March 2016. Returns are computed as the result of the entire period.

Transaction costs

To determine whether an investment strategy is profitable, transaction costs have to be considered. A highly competitive stockbroker market has led to relative small transaction costs.

For example (pricing information taken from Avanza Bank), if each trade is made with an amount of 1 000 000 SEK the transaction fee will be 99 SEK, which translates to around 0,01%. A transaction fee is paid both when buying and selling the asset. When calculating and adjusting returns for transaction costs, a fictitious portfolio of 1 000 000 SEK is assumed.

Risk

By holding an asset, of which the performance over a given time period is uncertain, the investor is exposed to risk. The amount of risk carried by the asset affects pricing. If an investor is exposed to a high amount of risk, the investor also expects an increase in return.

This thesis examines and compares the performance of different trading strategies used on the same stock. Since the same asset will be traded regardless of which strategy implemented, the risk can only be managed by holding the asset during a shorter period. When buying according to the buy-and-hold strategy, the investor is exposed to risk during the whole period, since only the risky asset i.e. the specific stock, is bought and held on to. If the same return can be accomplished through buying and selling the asset, thus reducing the time where the asset is held, it reduces the risk exposure. This makes it hard to compare risk-adjusted returns when using the buy-and-hold strategy compared to others, as this strategy exposes the investor to a higher amount of risk.

If average return per invested week of the stock is calculated, this accounts for risk exposure as the time period is constant and same for each strategy. On average, this way of computing returns, leads to the same amount of risk exposure of each strategy, thus enabling a fair comparison of return.

Econometric model specification

An OLS-regression is used to analyze whether the different indicators are statistically significant for return in the upcoming period. A *simple regression model* is used, where the indicators is used as explanatory variables of return in the following period for each stock. The simple model regression is used since the individual performance of each indicator is examined. If the regression were to include all indicators as dummy variables in the same model this would make them dependent of each other. The regression is computed as following:

$$\text{Return}_{t+1} = \beta_0 + \beta_{1,t}X_{1,t} + U_t \quad (22)$$

For each stock five regressions are done where X_1 is the regressor of the examined indicator. X_1 takes a value of “1”, when a buy signal is triggered, and “0” if a sell signal is produced.

Hypothesis

This thesis examines five different null hypothesis, which states that none of the indicators are statistically significant for return in the upcoming period:

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$$

$\beta_1 =$ Coefficient of MA10 indicator

$\beta_2 =$ Coefficient of MA50 indicator

$\beta_3 =$ Coefficient of MACO indicator

$\beta_4 =$ Coefficient of MACDindicator

$\beta_5 =$ Coefficient of a Combined indicator

Significance levels of either 10% or 5% will be assumed to determine the individual significance of the indicators.

Assumption tests

This subsection discusses the assumptions that require to be tested for, and how it is done, to achieve a constant and unbiased regressor. A significance level of 5% will be used to possibly reject the null hypothesis stated by the used tests.

Breusch-Godfrey

The Breusch-Godfrey test is used to test for serial correlation in the error term. The given null hypothesis states that there is no serial correlation. If rejected, robust standard errors is used in the OLS-regression (Wooldridge 2014)

Breusch-Pagan/Cook-Weisberg

The Breusch-Pagan/Cook-Weisberg test is used to test for heteroscedasticity. The given null hypothesis states that the error term is normally distributed. If rejected, robust standard errors is used in the OLS-regression (Wooldridge 2014).

Endogeneity

To test whether the model suffers from endogeneity the Durbin-Wu-Hausman test is used. The given null hypothesis states that the examined variable is uninformative about the error term. If this null-hypothesis were rejected this could indicate that the variable was endogenous. The test fails to reject the null-hypothesis in every regression conducted, so no endogeneity problems are assumed (Wooldridge 2014).

Highly persistent variables

To check whether the dependent variable is highly persistent the first order autocorrelation is tested. The correlation between the return variable and a lagged form of this variable is calculated. If the correlation exceeds 0.9 the variable is considered highly persistent (Wooldridge 2014).

Trend

Whether the data contain a trend can be observed by including a time variable in the regressor. The data is first set in chronologic order. Afterwards, a new variable is defined as time period, ranging between 1 and 324, and included in the regression. The variable is then observed as either significant or not. If the latter were the case the data would not contain a trend, therefore the time variable would not be included in the regression (Wooldridge 2014).

Results

This section is divided into individual- and aggregated results. In the first subsection results obtained from each individual indicator is presented. Outputs generated by each OLS-regression is displayed in tables, along with manually computed return data gained when investing according to the different strategies. Results for each stock, gained from the buy-and-hold strategy, will be used as a benchmark and compared to returns gained from investing according to the indicators.

All returns have been adjusted for transaction costs. When adjusting returns a portfolio of 1 000 000 SEK is assumed. As mentioned in the methodology section, mainly the average return per week invested of each strategy, has been compared. This is the only comparison in terms of returns that can be fairly interpreted as the risk exposure of the examined investment strategy is assumed on average, to be equal.

The tables will also include some of the different assumptions that are presented in the Theory section. If any of the assumptions has failed, it has been handled as described in the methodology section. None of the regressions has found any variable to be highly persistent, suffer from endogeneity nor contain a trend in the dependent variable. Therefore, the additional assumptions of whether the data contains a trend, endogeneity or highly persistent variables have been excluded in the tables. The last subsection will discuss aggregated results along with an answer to the examined hypothesis.

Individual results

Table 1: Results 10-Day Moving Average indicator

	<i>Sandvik</i>	<i>Volvo</i>	<i>Telia</i>	<i>Investor</i>	<i>Nordea</i>
β-value	-0,0080384	-0,0017043	-0,0062285	-0,0000637	-0,0017512
P-value	0,101	0,726	0,027**	0,985	0,645
Return (B&H)	13,3%	66,6%	15,9%	168,1%	58,0%
Avg.R/Week (B&H)	0,04%	0,21%	0,05%	0,52%	0,18%
Return	-40,0%	26,5%	-28,2%	102,2%	27,1%
Avg.R/week	-0,24%	0,16%	-0,16%	0,52%	0,15%
Weeks invested	164	165	179	196	180
# Trades	138	120	134	114	122
Heteroscedasticity	No	No	No	Yes	No
Serial Correlation	Yes	No	No	No	No

Notes: Results from 10-day Moving Average indicator where **Return (B&H)** denotes the total return, when holding the stock during the time period and **Return** denotes total return if investing according to the indicator during the time period. **Avg.R/week (B&H)** is the average return per week invested according to the Buy and Hold strategy, whereas **Avg.R/week** is the average return per week invested according to the indicator. **# Trades** is the number of trades conducted if investing according to the indicator. Results from OLS regression: $Return_{t+1} = \beta_0 + \beta_1 MA10 + U_t$ where ** = 5 % significance level, * = 10 % significance level

As shown in Table 1 the 10-Day Moving Average, at a 5% significance level, fails to predict the return for the following period for all stocks except Telia. The Telia stock shows significant results although with a negative β -value meaning one can, keeping everything else constant, on average expect a negative return when investing upon given buy signal by the 10-Day moving average. The Sandvik stock is very close to be statistically significant, at a 10% significance level, also with a negative β -value. The result shows that the average return per week for the Buy and Hold strategy outperforms investing according to the 10-day Moving Average for all stock except Investor, where it equals average return per week. Trading according to the 10-day Moving Average strategy will result in the highest total amount of trades, resulting in relatively large transaction costs, compared to all other indicators used in this thesis.

Table 2: Results 50-Day Moving Average indicator

	<i>Sandvik</i>	<i>Volvo</i>	<i>Telia</i>	<i>Investor</i>	<i>Nordea</i>
β-value	-0,0065303	0,0046966	-0,0038583	-0,0041746	-0,0037525
P-value	0,184	0,337	0,175	0,296	0,335
Return (B&H)	13,3%	66,6%	15,9%	168,1%	58,0%
Avg.R/week (B&H)	0,04%	0,21%	0,05%	0,52%	0,18%
Return	-31,2%	87,6%	-8,9%	68,0%	8,3%
Avg.R/week	-0,19%	0,49%	-0,05%	0,31%	0,05%
Weeks invested	164	180	172	220	177
# Trades	76	42	60	56	56
Heteroscedasticity	Yes	No	No	Yes	Yes
Serial Correlation	Yes	No	Yes	No	No

Notes: Results from 50-day Moving Average indicator where **Return (B&H)** denotes the total return, when holding the stock during the time period and **Return** denotes total return if investing according to the indicator during the time period. **Avg.R/week (B&H)** is the average return per week invested according to the Buy and Hold strategy, whereas **Avg.R/week** is the average return per week invested according to the indicator. **# Trades** is the number of trades conducted if investing according to the indicator. Results from OLS regression: $Return_{t+1} = \beta_0 + \beta_1 MA50 + U_t$ where ** = 5 % significance level, * = 10 % significance level

As shown in Table 2 the 50-Day Moving Average, at 5% significance level, fails to predict return in the upcoming period for all stocks, similar to the 10-Day Moving Average. The indicator is found to be statistically insignificant for all stocks during the examined time period, which implies that the predictive power of return in the upcoming period is poor.

When investing according to the 50-day Moving Average one could on average expect excess returns, compared to the buy-and-hold strategy when trading the Volvo stock. In all other cases the buy-and-hold strategy outperforms the 50-day Moving Average indicator.

Table 3: Results Moving Average Cross-Over indicator

	<i>Sandvik</i>	<i>Volvo</i>	<i>Telia</i>	<i>Investor</i>	<i>Nordea</i>
β-value	-0,0027950	-0,0012964	-0,0048433	-0,0037710	-0,0040972
P-value	0,585	0,803	0,115	0,421	0,356
Return (B&H)	13,3%	66,6%	15,9%	168,1%	58,0%
Avg.R/week (B&H)	0,04%	0,21%	0,05%	0,52%	0,18%
Return	2,3%	44,7%	-13,9%	92,6%	15,9%
Avg.R/week	0,01%	0,23%	-0,07%	0,37%	0,08%
Weeks invested	178	193	200	251	207
# Trades	32	24	34	20	32
Heteroscedasticity	Yes	Yes	Yes	Yes	Yes
Serial Correlation	Yes	No	Yes	No	No

Notes: Results from Moving Average Cross-Over indicator where **Return (B&H)** denotes the total return, when holding the stock during the time period and **Return** denotes total return if investing according to the indicator during the time period. **Avg.R/week (B&H)** is the average return per week invested according to the Buy and Hold strategy, whereas **Avg.R/week** is the average return per week invested according to the indicator. **# Trades** is the number of trades conducted if investing according to the indicator. Results from OLS regression: $Return_{t+1} = \beta_0 + \beta_1 MACO + U_t$ where ** = 5 % significance level, * = 10 % significance level

As shown in Table 3 the Moving Average Cross-Over, at a 5% significance level, fails to predict return in the upcoming period for all stocks. The indicator is found to be statistically insignificant for all stocks during the examined time period, which implies that the predictive power of return in the upcoming period is poor. However, the 50-Day Moving Average shows that investing according to the Moving Average Cross-Over provides excess return, on average when trading the Volvo stock, compared to the buy-and-hold strategy. This is in line with the results from the 50-Day Moving Average indicator. In all other cases, the buy-and-hold strategy outperforms the Moving Average Cross-Over indicator.

Table 4: Results Moving Average Convergence Divergence indicator

	<i>Sandvik</i>	<i>Volvo</i>	<i>Telia</i>	<i>Investor</i>	<i>Nordea</i>
β-value	0,0006664	0,0022592	-0,0049441	0,0010251	-0,0018681
P-value	0,892	0,642	0,078*	0,753	0,621
Return (B&H)	13,3%	66,6%	15,9%	168,1%	58,0%
Avg.R/week (B&H)	0,04%	0,21%	0,05%	0,52%	0,18%
Return	17,8%	78,2%	-20,3%	102,0%	30,0%
Avg.R/week	0,11%	0,48%	-0,13%	0,62%	0,18%
Weeks invested	157	162	161	165	166
# Trades	94	96	108	100	102
Heteroscedasticity	No	No	Yes	Yes	No
Serial Correlation	Yes	No	No	No	No

Notes: Results from Moving Average Convergence Divergence indicator where **Return (B&H)** denotes the total return, when holding the stock during the time period and **Return** denotes total return if investing according to the indicator during the time period. **Avg.R/week (B&H)** is the average return per week invested according to the Buy and Hold strategy, whereas **Avg.R/week** is the average return per week invested according to the indicator. **# Trades** is the number of trades conducted if investing according to the indicator. Results from OLS regression: $Return_{t+1} = \beta_0 + \beta_1 MACD + U_t$ where ** = 5 % significance level, * = 10 % significance level

As shown in Table 4 the Moving Average Convergence Divergence, at a 5% significance level, fails to predict return in the upcoming period for all stocks. The indicator is found to be statistically insignificant for all stocks during the examined time period, which implies that the predictive power of return in the upcoming period is poor. The indicator is significant when using on the Telia stock, at a 10% significant level, although a negative β-value which implies that when investing in the Telia stock upon given buy signal one can on average, keeping everything else constant, expect a negative return in the upcoming period.

Overall the return gained when investing according to the Moving Average Convergence Divergence is higher per invested week for Sandvik, Volvo and Investor, with an equal average return per week invested for Nordea. The Telia stock here once again proves to have a negative return per invested week when using the trading strategy for the indicator.

Table 5: Results Combined indicator

	<i>Sandvik</i>	<i>Volvo</i>	<i>Telia</i>	<i>Investor</i>	<i>Nordea</i>
β-value	-0,0012418	0,0010423	-0,0002862	0,0008383	0,0021895
P-value	0,815	0,853	0,917	0,781	0,548
Return (B&H)	13,3%	66,6%	15,9%	168,1%	58,0%
Avg.R/week (B&H)	0,04%	0,21%	0,05%	0,52%	0,18%
Return	8,4%	36,5%	14,70%	74,26%	3,49%
Avg.R/week	0,12%	0,46%	0,19%	0,65%	0,04%
Weeks invested	70	80	79	114	86
# Trades	64	66	66	88	66
Heteroscedasticity	No	No	Yes	Yes	Yes
Serial Correlation	Yes	No	Yes	No	No

Notes: Results from the Combined indicator where **Return (B&H)** denotes the total return, when holding the stock during the time period and **Return** denotes total return if investing according to the indicator during the time period. **Avg.R/week (B&H)** is the average return per week invested according to the Buy and Hold strategy, whereas **Avg.R/week** is the average return per week invested according to the indicator. **# Trades** is the number of trades conducted if investing according to the indicator. Results from OLS regression: $Return_{t+1} = \beta_0 + \beta_1 Combined + U_t$ where ** = 5 % significance level, * = 10 % significance level

As shown in Table 5 the Combined indicator, at a 5% significance level, fails to predict return of the upcoming period for all stocks. The indicator is found to be statistically insignificant for all stocks during the examined time period, which implies that the predictive power of return in the upcoming period is poor. The manually computed results find that trading according to the Combined indicator provides excess returns per week invested for Sandvik, Volvo, Telia and Investor compared to the buy-and-hold strategy. The buy-and-hold strategy outperforms usage of the indicator when trading the Nordea stock.

Aggregated results

As shown in previous tables the predictive ability of the indicators are overall quite poor. The indicators found to be statistically insignificant for the majority of the stocks examined. When the indicator proved to be statistically significant, the β -value was negative. Even though these findings could be useful if an investor were to short-sell a stock, one should never generate a hypothesis after analyzing a set of data. The hypothesis should be formulated before conducting the study, and since the methodology of this research ignores short-selling, this possibility will not be analyzed.

On the few occasions where the null-hypothesis is rejected, which might imply that the indicator can predict a return in the upcoming period, there does not seem to exist any pattern. Even though the Telia stock is statistically significant twice, this is when using two different indicators. When several OLS-regressions are conducted with the same explanatory variables, and as in this research found to be statistically significant in only one of the regressions, this could indicate that the rejection of the null-hypothesis might be a type-1 error. A type-1 error occurs when one incorrectly rejects a true null hypothesis, which could lead to a false conclusion being made. If using a 5% significance level, this also indicates that there is a 5% risk that the null-hypothesis is falsely rejected. Therefore, when many similar OLS-regressions are conducted without any pattern in the rejection of the null-hypothesis, as in this research, the results have to be interpreted with caution.

As mentioned in the literature review, Lento (2008) found that the Moving Average Cross-Over had poor predictive ability when interpreting signals according to the Variable Length Moving Average rule. While Lento (2008) did not test the performance of all indicators that are examined in this thesis, his conclusion is in line with results obtained from this research.

When analyzing returns from investing according to produced signals, unlike the predictive ability, the performance differs a lot between the indicators. When investing according to the Moving Average and Moving Average Cross Over indicators the buy-and-hold strategy outperforms both in terms of total return and average return per week on all stocks with a few exceptions. This contradicts the research done by Brock (1992), Glabadanidis (2015), and Han et al (2013), who all found that the Moving Average and Moving Average Cross Over indicators constantly provided excess returns. As there was no significant difference in return between the

two different Moving Average lengths, this also contradicts the findings of Han et al. (2013), which states that using shorter average lengths increase return. These results are in line with the conclusion made by Ellis and Parbery (2005) who, while using a different average length, found that the Moving Average could not be used to outperform the buy-and-hold strategy.

The Moving Average Convergence Divergence seems to perform quite well when calculated as average return per invested week. The indicator outperformed the buy-and-hold strategy on three stocks and had equal return when trading the Nordea stock. Results that are in line with the research made by Chong and Ng (2008), although they tested the indicator on the London Stock Exchange. The indicator seems to perform better at the stocks used in this research, compared to the asset examined in the research done by Rosillo et al. (2013) and Chong et al. (2014). Of all five examined indicators, the Combined indicator found to be most profitable. It outperformed the buy-and-hold strategy on four out of five stocks. Tanaka-Yamawaki and Tokuoka (2007) found that the Moving Average Convergence Divergence indicator could be combined with other indicators to provide additional predictive ability. Inspired by their research, the results of this thesis suggests that the combination of Moving Average Convergence Divergence along with other indicators could not increase predictive ability, but instead generate abnormal returns.

When comparing returns between the stocks, the Volvo stock stands out. Trading the Volvo stock according to four of the five examined indicators outperforms the buy-and-hold strategy. Explanations to why the indicators seem to perform better when trading the Volvo stock is hard to find. Therefore, the most feasible explanation would be that the result is a coincidence.

At first glance, the rather poor predictive ability of the examined indicators makes it hard to argue for any kind of weak form inefficiency. However, since both the Moving Average Convergence Divergence and the Combined indicator provides higher average return per invested week in the majority of the stocks examined, this questions the statement that any form of technical analysis is fruitless made by Malkiel (1973) and Bodie et al. (2014).

Conclusions

This thesis aims to test whether five commonly used indicators can be used to predict future returns on five individual stocks listed on the Stockholm Stock Exchange. The research also questions whether excess returns can be generated when investing according to the indicators. As a benchmark, in terms of risk and return, the buy-and-hold strategy is used. The predictive ability of each indicator is examined through an OLS-regression, while returns are manually computed. Weekly pricing data is gathered and analyzed from 2010 until 2016.

The predictive ability of the technical indicators is quite poor as few of the indicators proves to be statistically significant and when they are there does not seem to exist any pattern. These findings support the efficient market hypothesis, as the Stockholm Stock Exchange is considered a rather well-developed market and is therefore expected to be weak form efficient. If an indicator were constantly statistically significant at a 5% significance level, this would indicate that price action could be predicted with a 95% accuracy. If this were the case, traders would probably exploit this inefficiency instantly according to the efficient market hypothesis.

When computing returns of investing according to the indicators, this seems to question the efficient market hypothesis. The buy-and-hold strategy outperforms returns, adjusted for transaction cost, when investing according to the different Moving Average lengths and the Moving Average Cross-Over. However, the Moving Average Convergence Divergence and Combined indicator seem to generate abnormal returns. The performance of these two indicators appears to question the weak form efficiency, which states that previous pricing information cannot be used to predict future performance of an asset. These contradictory results, along with the small number of stocks that are examined in this thesis, makes it hard to argue whether the weak form efficiency holds or not.

As the results of this thesis are ambiguous, further research is suggested on the area. When testing the predictive ability of indicators, it is recommended that not every signal each day is acted upon. Both this thesis and Lento (2008) has found that when using the indicators according to the *Variable Length Moving Average*, the indicators have no predictive ability. Instead, the *Fixed Length Moving Average* rule is recommended.

To our knowledge, the Combined indicator, has not been tested on any market before. Therefore, additional testing of this indicator should be done, both on highly, and less so, developed markets. The apparent success of the Moving Average Convergence Divergence indicator should also be investigated further, both on stocks and indices. A recommendation to increase the accuracy of future research is to divide the gathered data into two different periods. If an indicator is found to be statistically significant or generates excess returns in both the first and second time period the credibility of the research would increase.

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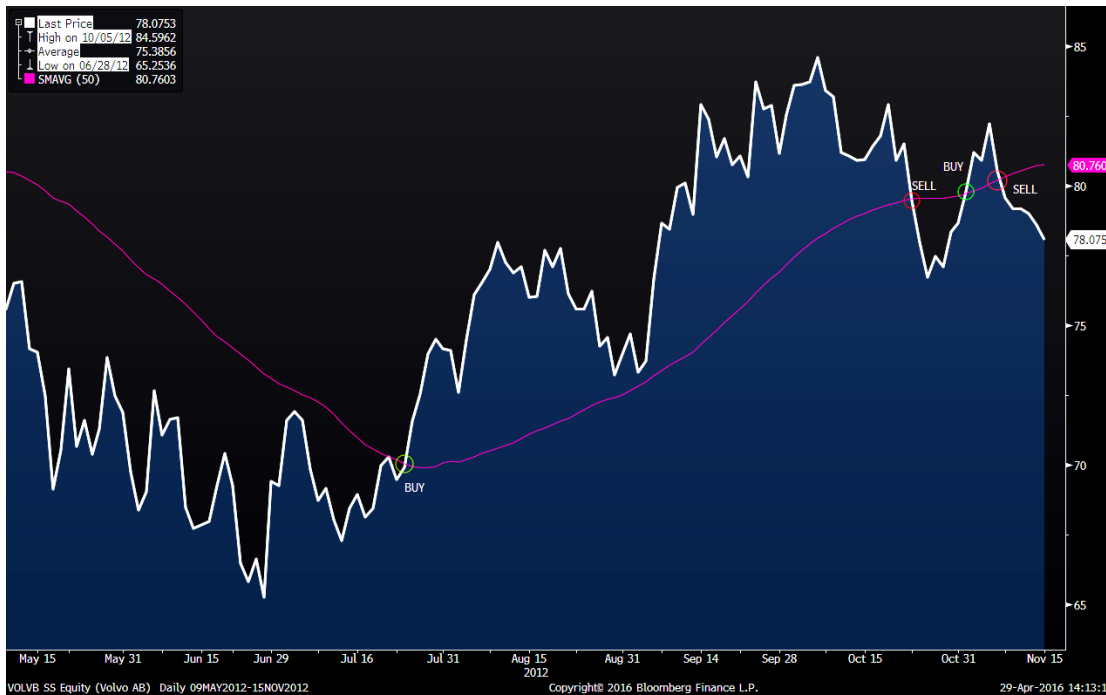
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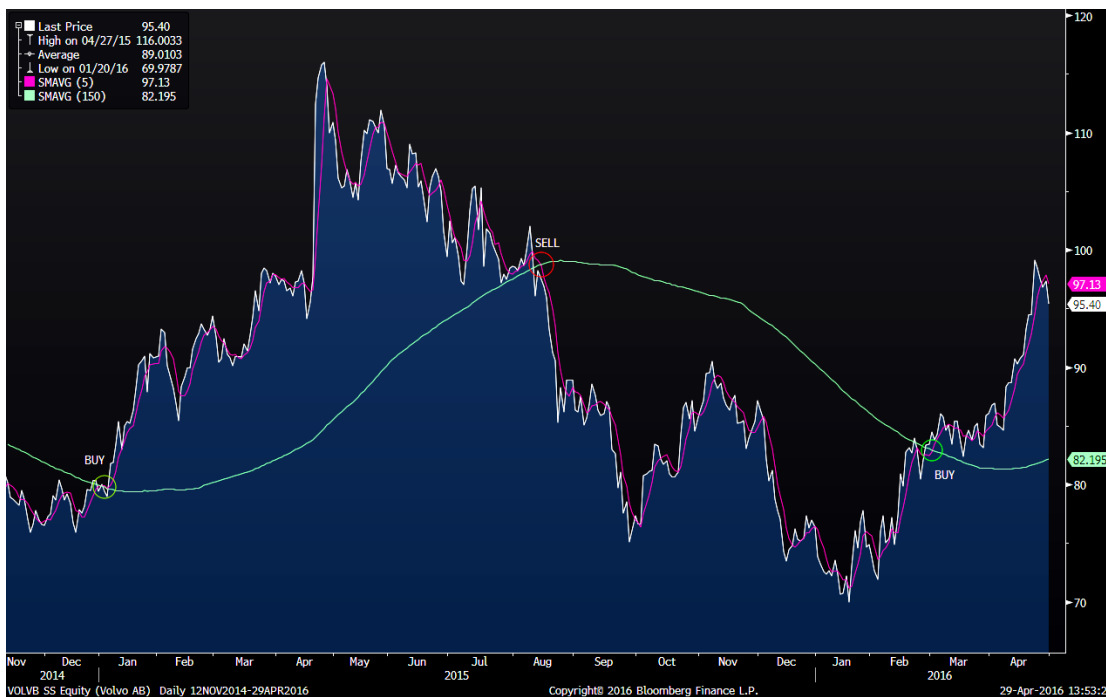
Appendix

Figure 1. Moving Average



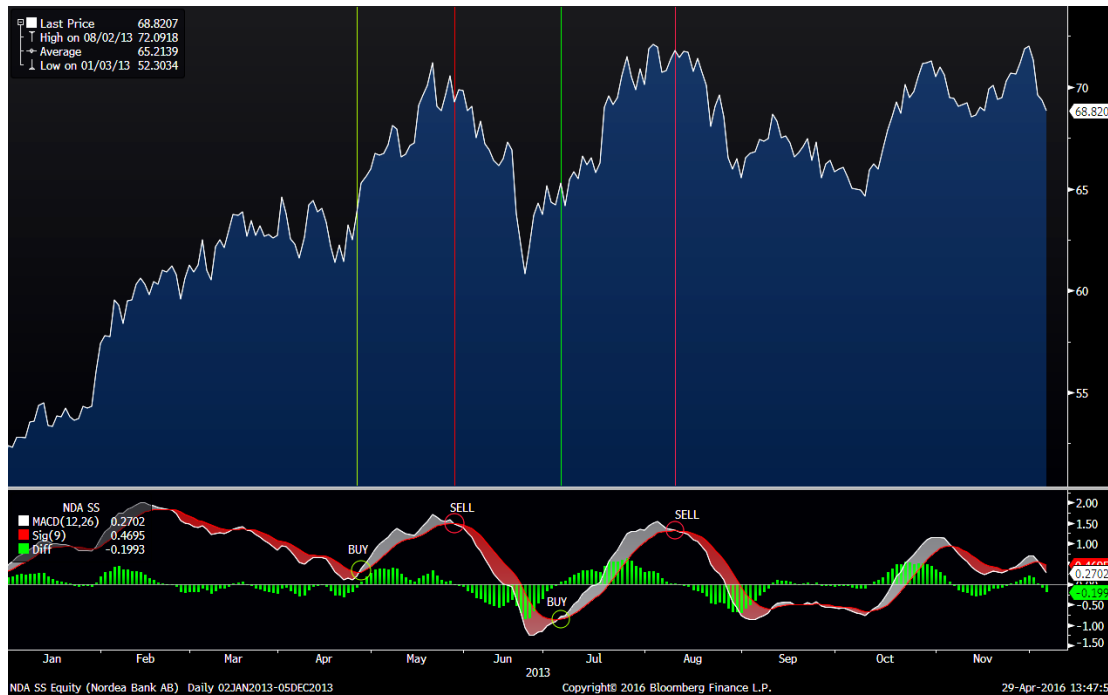
Note: Figure 1 is extracted from Bloomberg and illustrates produced buy and sell signals according to the Moving Average indicator the Volvo B stock

Figure 2. Moving Average Cross-Over



Note: Figure 2 is extracted from Bloomberg and illustrates produced buy and sell signals according to the Moving Average Corss-Over for the Volvo B stock

Figure 3. Moving Average Convergence Divergence



Note: Figure 3 is extracted from Bloomberg and illustrates produced buy and sell signals according to the Moving Average Convergence Divergence for the Nordea stock