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Applying Technical Trading Rules to Evaluate Weak-form Efficiency on the Swedish Stock Market

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I. Introduction

Having long been the predominant underlying theory of financial literature, the seeds of the Efficient Market Hypothesis (EMH) dates back to Bachelier (1900) and his work on financial speculation merely being a matter of stochastic processes. However, the EMH was more definitively proclaimed by Eugene Fama in 1970, who describes the core of the hypothesis as "a market in which prices always fully reflect available information is called efficient." (Fama, 1970, p.383). In accordance with the weak-form of the EMH, historical data are incorporated into current stock prices. This implies that future price movements cannot be derived from analysing historic price data. If the former is assumed to be true, then technical analysis (TA), which tries to identify patterns and trends from historical data, would prove useless. In a weak-form efficient stock market, the use of technical trading strategies should not yield returns that are significantly greater than those of the simple buy-and-hold strategy of the market itself.

Extensive research on efficiency and TA has been carried out on numerous financial markets. However, the consensual result of these studies remains indecisive. Following the outline of the EMH in the 1960s and 1970s, comprehensive research concluded TA rules to be useless. Studies by Fama and Blume (1966), Jensen and Bennington (1970), Van Horne and Parker (1967) and James (1968) find no significant returns in favour of the technical approach. In contrast to earlier studies, later research has found comprehensive returns from testing technical trading strategies on historical data. Studies by Brock et al. (1992), Levich and Thomas (1992) and Jiang et al. (2019) find significant profits when applying technical trading rules to US and Chinese stock markets. Studies by Lo et al. (2000), Blume et al. (1994), Treynor and Ferguson (1985), Brown and Jennings (1989), Pruitt and White (1988), Neely, Weller and Dittmar (1997) further support the efficiency of technical trading rules.

Although extensive research has been conducted applying technical trading rules to historical data, the cover of the Swedish stock market is in relation to other markets uncommonly meagre. The purpose of this paper is to examine weak-form efficiency on the Swedish stock market by evaluating the profitability of technical trading rules on historical price data. Variations of moving averages, relative strength index oscillators, and Bollinger bands have been constructed. These technical rules have then been applied to the information set OMX Stockholm 30 index over a period of 33 years to generate trading signals. The average returns of these rules are tested for significance with simple t-tests and compared to the unconditional mean of the buy-and-hold strategy of the raw index itself. To further analyse the technical rules, a portfolio of the top performing rules is endured for flat transaction costs of 0,5% and 1% per trade. The rules in the portfolio will also be applied to a Monte Carlo simulation of the underlying raw index, modelled by a geometric Brownian motion. The former is done to examine if the rules are able to produce significant profits when applied to simulated variations of the underlying raw index.

After conducting these tests, 142 unique technical trading rules have been constructed and a total of 146 561 trading signals have been generated. No rules generate average returns that are significantly greater than the buy-and-hold strategy of the raw index. In fact, 109 rules significantly underperform in comparison to the inherit returns of the raw index, even when not taking transaction costs into consideration. Michael Jensen defines an efficient market as: "A market is efficient with respect to information set θ_t, if it is impossible to make economic profits by trading on the basis of information set θ_t." (Jensen, 1978, p.3). Where information set θ_t refers to all historical data at present time, in this study the OMXS30 index data. The findings of this paper show that no rules based on θ_t are able to make significant returns when applied to the information set θ_t. When taking foot in Jensen's definition, the result of this paper cannot dismiss efficiency on the Swedish stock market. Furthermore, the cumulated returns of the portfolio consisting of the top performing rules underperforms against the raw index's return development. Undoubtedly and evidently, an inferior state of the former result is achieved when applying transaction costs. After running the Monte Carlo simulation, modelled with a geometric Brownian motion, efficiency cannot be dismissed. On 6 out of 5000 occasions the top performing technical rules generate significantly greater returns than the inherit buy-and-hold returns of the simulated indeces. Although these prominent rules occasionally appear, they are seemingly, due to their anomalous and irregular nature, merely a result of data snooping bias.

The content of the paper is divided into sections. In the above section I, an introduction and summary of the paper is given. In section II, the theoretical framework is outlined by further describing the EMH and TA. In section III, the method of how the research has been conducted is explained. In section IV, the empirical results are displayed and discussed. In section V, a conclusion of the study is given. Finally, in section VI, relevant references are reported.

II. Theoretical framework

A. Efficient market hypothesis

The EMH was definitively proclaimed by Eugene Fama in 1970. Fama describes a market in which prices always fully reflect available information as "efficient" (Fama, 1970, p.383). Efficiency is divided into three subsets, each level representing the amount of information nested in stock prices. In the weak-form, historical data is at present time incorporated in prices; in the semi-strong level, prices also adjust for all present time publicly available information (financial statements and announcements); in the strong-form, all private information is also considered. Each new level includes the conditions of the former. Fama's final remarks conclude the evidence in favour of the hypothesis as "extensive" and the evidence against it as "sparse" (Fama, 1970, p.416). The following years the EMH served as a bedrock for financial theory, described as a "fact of life" in economic literature (Jensen, 1978, p.3). However, the widely accepted view of the EMH has later come to be more shattered. Shiller (1989) argues that the idea of efficient markets seems implausible when considering the significant volatility strikes that periodically hit stock prices. A further critique of the hypothesis is the supposed predictability of markets. Malkiel (2003) points to price irregularity and predictable seasonal patterns such as the January effect as possible indicators of market inefficiency.

This study is primarily interested in the weak-form of efficiency. In a weakly efficient market, all historic data are reflected in asset prices. If the former is assumed to be true, then no additional information could be derived from analysis past data and patterns. As a result, applying TA to identify trends and patterns from historical data should not yield any significant returns. Michael Jensen defines the correspondence between efficiency and profits as: "A market is efficient with respect to information set θ_t, if it is impossible to make economic profits by trading on the basis of information set θ_t." (Jensen, 1978, p.3). In which, information set θ_t refers to all the available historical data at the present time.

B. Technical analysis

TA provides an alternative approach to the conventional way of fundamental stock picking. Levy (1967) describes TA as the recording of historical price movements and transactions to presuppose future trends. Technical rules generalise certain patterns in data and generates trading signals when those patterns reappear. There are many variations of technical rules, those most covered in past research are different types of volume and momentum indicators, moving averages, relative strength oscillators, and support and resistance levels. All rules vary in technique, but are all based on analysing and forming patterns from historical data. For this historical technical approach to be consistently reliable the behaviour of investors needs to be relatively constant through time. Pring (2002) expresses that investors rarely mirror their historic behaviour perfectly. However, he goes on to say that identifying that certain similar patterns amongst investors reappear is sufficient for technical analysts to derive future trends. By studying past behaviour, common characteristics can be observed and used to identify market turning points. These turning points can be exploited by technical analysts to generate profitable returns.

The efficiency of technical rules to produce profitable returns has been comprehensively covered since the 60s, with mixed results. Fama and Blume (1966) test variations of Alexander's filter rule on 30 Dow Jones Industrial Average (DIJA) securities. These rules are then compared to the return of a buy-and-hold strategy of DIJA itself. Fama and Blume conclude the rules to not appreciably increase expected returns. They also conclude their result to indicate that the market is working "rather efficiently" (Fama & Blume, 1966, p.240). Jensen and Bennington (1970) examine the use of a relative strength strategy. After introducing transaction costs, neither this approach produced significant returns over the buy-and-hold strategy. Research by Van Horne and Parker (1967) further supports the unpredictability of prices by mainly testing moving averages. Van Horne and Parker found no significant returns of these strategies; rather, they produce less profitable results on average than a simple buy-and-hold strategy. Built on the work of Van Horne and Parker, James (1968) further considers moving averages on NYSE securities to find no significant returns. Later research has come to challenge the early work consensus. Brock et al. (1992) use the DIJA over nearly 90 years to test 26 rules of moving averages and trading-range breaks. Although not considering transaction costs, the technical strategies constructed by Brock et al. (1992) show significant returns compared to the simple buy-and-hold strategy. Jiang et al. (2019) test several technical trading strategies in the Chinese stock market. The results from Jiang et al. (2019) once again show significant returns in favour of the technical approach, with moving averages dominating as the most prominent technical rule.

Levich and Thomas (1991) test similar strategies in foreign exchange markets, with findings that TA often produces significant profits. Neely et al. (1997) also consider foreign exchange markets. They use a genetic programming model to filter out efficient technical rules. In line with the conclusion of Levich and Thomas (1992), Neely et al. (1997) also find significant profits from this approach. Blume et al. (1994) display that investors who use technical market statistics outperform those who do not. They conclude TA as one of the fundamental ways for an agent to gather market information. Pruitt and White (1988) test the so called CRISMA trading system, which uses a combination of trade volume, relative strength and moving averages as technical rules. Pruitt and White (1988) find that the system outperforms the market over a comprehensive timespan, even when considering a constant transaction cost of 2% per trade. However, Marshall et al. (2006) review the CRISMA trading system for all securities in the CRSP database during a total of 27 years. They conclude the system to not be reliable in consistently generating profits, even before considering transaction costs. They consider the result of their studies to be consistent with weak-form market efficiency.

Many studies do not explicitly support the profitability of technical analyst; rather, they support the notion that the technical process helps in information analysis and investment decision making. Lo et al. (2000) examine the efficiency of TA using computational algorithms that recognize patterns in data. They do not explicitly find these patterns to be profitable when applied to US securities over a total period of 34 years; however, they conclude that the use of automated algorithms provides incremental and practical information for technical analysts. Brown and Jennings (1989) conclude that in certain equilibrium models, TA generally shapes the investment philosophies amongst investors heavily. Treynor and Ferguson (1985) propose that combining past price data with other valuable information can be helpful in generating uncommon profits; however, the analysis of past prices merely is not enough to generate significant profits.

The technical rules this study is concerned with are moving averages (MA), relative strength index oscillators (RSI) and Bollinger bands (BB). The methodology of these rules will be explained in the method section below. MAs have been thoroughly covered in US financial markets by, for instance, Van Horne and Parker (1967), Brock et al. (1992) and Lo et al. (2000). RSIs appear consistently in studies such as Jiang et al. (2019) and in the CRISMA trading system examined by Pruitt and White (1988) and Marshall et al. (2006), primarily concerned with US and Chinese stock markets. Due to its later recognition in the 1980s, BBs are not widely covered in major studies. This study will add on to previous work and test multiple variations of the technical rule on the Swedish stock market.

III. Method

The purpose of this study is to examine weak-form efficiency on the Swedish stock market by applying variations of technical trading rules on the OMXS30 index. If the market is weakly efficient, historical data are already incorporated into the present-day prices. Efficiency implies the impossibility of making profits by analysing and acting on past price information, and as a result, the technical trading rules in this study should not generate profits that are significantly greater than the buy-and-hold strategy of the market itself. The profitability of technical trading rules and its correspondence with the EMH has been comprehensively examined on primarily US and Chinese stock markets. This study will instead examine efficiency on the Swedish stock market, a market without previously having been exposed to this discussion. The conclusion of this study will add on to the discussion of the EMH and technical analysis. The following sections will describe the method of how this study has been conducted (section A), the construction of the technical trading rules (section B), the technical approach (section C) and the methods by which the comparative profits are measured (section D).

A. Data

The OMX Stockholm 30 index (OMXS30) has been used as the target sample. It displays the 30 most traded companies on the Stockholm Stock Exchange. The index will henceforth be denoted by the "raw index" or by "OMXS30". Data has been downloaded from the Nasdaq OMXS30 database (Nasdaq, 2019). The dataset consists of daily closing prices from 1986-09-30 to 2019-09-30 (33 years). The unconditional mean reflects the average performance of the buy-and-hold strategy of the raw index, this figure has been the comparative measure when the average daily returns of the technical rules have been examined. Taking foot in the definition provided by Jensen (1978), the OMXS30 raw price data between 1986 and 2019 is considered to be the information set θ_t. The index price at time t is henceforth denoted as I.

Table 1. Descriptive statistics: OMXS30

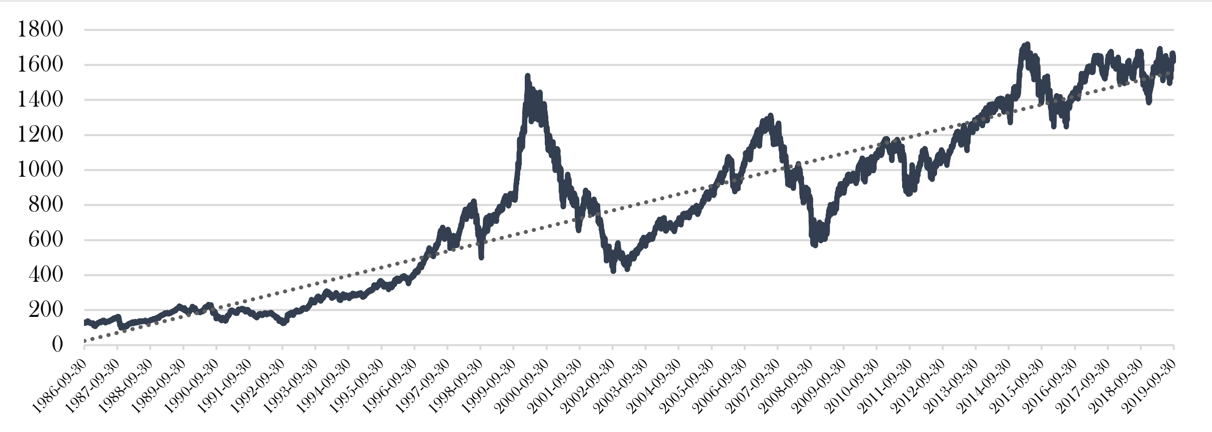
Table 1 shows the unconditional daily mean return, all-time daily low/high return, standard deviation, skewness, kurtosis and the number of observations for the cumulative returns of the OMXS30 during 1986-09-30 to 2019-09-30.

Mean	Low	High	Std	Skew	Kurt	N(observations)
0,04101%	-8,4242%	11,6533%	0,01416	0,1368	4,8627	8291

A total of 8291 daily returns are calculated from the dataset. The OMXS30 produce a daily mean return of 0,04101%. Lowest observed daily return amounts to -8,4242% and highest to 11,6533%.

The cumulative daily returns have a standard deviation of 0,01416. The positive skewness of 0,1368 is in line with the positive trend of the raw index that can be seen in Figure 1. The raw index also shows a kurtosis of 4,8627, which indicates relatively fat tails around the mean. Between 1986 and 2019, the OMXS30 displays a long-term positive trend. The overall positive trend seen in Figure 1 aligns with the positive daily mean and the positive skewness in Table 1.

Figure 1. Daily closing prices: OMXS30



B. Technical rules

Technical trading rules have been constructed using variations of (1) moving averages (MA), (2) relative strength index oscillators (RSI) and (3) Bollinger bands (BB). For each trading approach, arbitrary variations of variables and conditions need to be fulfilled for a trading signal to be generated. Trading signals will either be "buy" or "sell." A buy (sell) signal has resulted in a long (short) position in the raw index. After a signal has been generated, the position in the market has been held until a new signal has been generated or for a set number of days (holding period). For rules not containing a set holding period, an active position in the market has been held from the first trading signal until the end of the sample data.

(1) Moving averages

The MA rule compares the current price of the underlying security with the past average price over a number of days. Through the use of averages, the MA method is smoothing the data, which will partially eliminate short-term noise and display the overall trend. As a result, this method is a trend-following indicator. By constructing two MAs, one short-term and one long-term, buy and sell signals can be generated when the two averages cross. A buy signal is obtained when the short-term MA crosses the long-term MA from underneath, indicating positive trend momentum. Accordingly, a sell signals is obtained when the short-term MA crosses the long-term MA from above, indicating negative trend momentum. In other words, two conditions need to be present for a signal: (1) if short-term MA > long-term MA at the present time t, and (2) short-term MA < long-term MA at t_{-1}, then a buy signal is generated, and vice-versa. A hypothetical crossover example can be seen in Figure 2 below. The short-term MA crosses the long-term MA from above at point A and as a result a sell signal is generated. At point B, the short-term crosses the long-term from underneath, and a buy signals is generated. When no other conditions govern the creation of trading signals, then buy and sell signals will alternate for the entire data sample.

Figure 2. Hypothetical MA crossover

The short and long-term MA at time t is defined as the average of the closing prices of the OMXS30 index I during a number of d days.

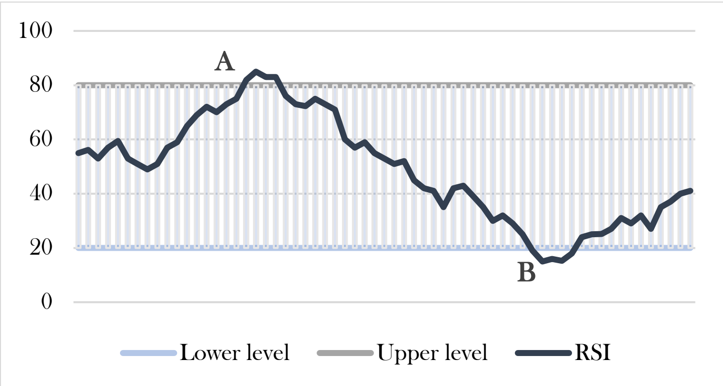
$$MA_t(d) = \frac{1}{d}\sum_{i=0}^{d} I_{t-i} \tag{1}$$

In this paper, the number of days in the MAs has varied with d_S = {1, 2, 5, 20, 50} in the short-term and d_L = {2, 5, 20, 50, 200} in the long-term. To eliminate potentially "false" trading signals during a crossover a so-called "band" has been introduced. A band determines the amount that the short-term MA needs to exceed or fall below the long-term MA before a signal can be produced. The band has varied with b = {0, 0,01, 0,02}. Each rule will be denoted by MA($d_S; d_L; b$). For instance, an MA with 1 day in the short-term, 2 days in the long-term and a 1% band will be denoted as MA(1,2,1). An MA with d_S = 1 is because of equation (1) simply the raw index. For MA rules, the position in the market has been held for a constant number of 5 days after a trading signal. When varying the MAs with d_{short}, d_{long} and a band b, a total of 45 different rules has been created.

(2) RSI oscillators

The RSI is a moderated index created by computing averages of previous positive and negative movements of the raw index. The RSI displays speed and change in the raw index's price movements. A daily RSI-value will always be ranged between 0-100. Since up and down movements are calculated using the raw index, the RSI will increase (decrease) when the averages of the raw index increases (decreases) day to day. Because of the former rationale, an RSI value above 50 indicates a market in which the past days have accumulated greater positive returns than negative, and vice versa. The RSI is then combined with one extreme support and resistance line in the same range. These lines will take two constant levels during the entire investment horizon for one specific rule. When the RSI crosses the lower (upper) constant level a buy (sell) signal is produced. The former methodology makes the RSI rule a mean reversion strategy. When the RSI gets above or below certain constant levels, the investor bets that it will reverse back towards the mean, theoretically the RSI value of 50. The procedure can be seen in the hypothetical breakthrough example in Figure 3. At point A the RSI breaks through the constant upper level of 80 to generate a sell signal. At point B the RSI breaks through the constant lower level of 20 to generate a sell signal. The constant upper and lower levels are placed an arbitrary distance above and below the mid-level of the 0-100 range.

Figure 3. Hypothetical RSI breakthrough



The RSI is calculated as the average positive and negative movements of the OMXS30 raw index I during a number of d days:

$$RSI_t = 100 - \left(\frac{100}{RS_t + 1}\right) \tag{2}$$

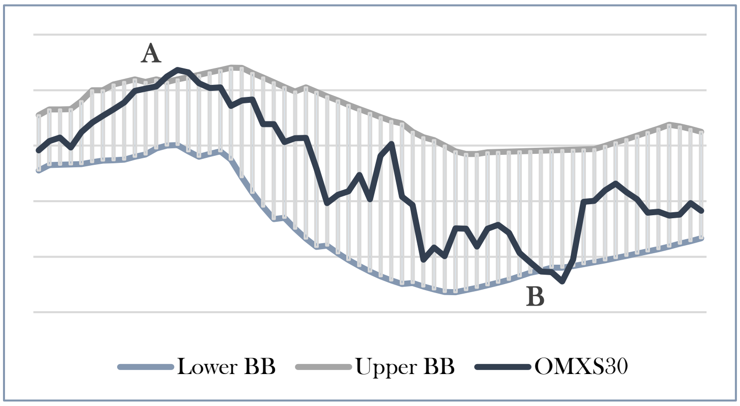
Where $RS_t = \frac{\frac{1}{d}\sum_{i=0}^{d} Up_{t-i}}{\frac{1}{d}\sum_{i=0}^{d} Down_{t-i}}$, with Up = max $(I_t - I_{t-1}, 0)$ and Down = max $(I_{t-1} - I_t, 0)$.

The days d in the average up and down movements has been varied with $d = \{5, 10\}$. The two fundamental indeces will be denoted by RSI(d), hence RSI(5) and RSI(10). The extreme constant lower level (C_L) and upper level (C_U) have varied with $(C_L) = \{20, 30\}$ and $(C_U) = \{70, 80\}$. To generate a signal, the RSI will have to be above or below the constant levels for K days. K has varied with $K = \{0, 5, 10\}$. Unlike the MA approach, the number of days in the holding period after a signal is generated has varied. The holding period H has varied with $H = \{\text{no}, 5\}$, where "no" denotes no holding period. By varying, d, (C_L), (C_U), K and H, a total of 48 rules have been created. Henceforth, each rule will be sorted into groups of (C_L, C_U) and denoted as RSI(d, K, H).

(3) Bollinger bands

Bollinger Bands (BB) are created calculating a continuous band around the raw index. Two extreme lines are constructed using MAs and the standard deviation of the raw index. The bands are positioned an arbitrary amount of standard deviations away from the moving average of the raw index. When the raw index breaks through the lower (upper) band a buy (sell) signals is created. The former methodology makes the BB rule a mean reversion strategy, much like the RSI rule. When the underlying index breaks through the upper or lower band, the investor bets on the index reverting back towards the mean, the midpoint between the bands. A hypothetical breakthrough can be seen in Figure 4. In point A the raw index breaks through the upper band limit and a sell signal is produced. In point B the raw index breaks through the lower band limit and a buy signal is produced. Since the bands are dependent on the standard deviation, they will widen when the volatility of the raw index increase, and vice versa.

Figure 4. Hypothetical Bollinger bands



The lower and upper bands at time t are calculated as:

$$Lower\ BB_t = MA_t(d) - \sigma_{I(d)} * n(std) \quad (3)$$

$$Upper\ BB_t = MA_t(d) + \sigma_{I(d)} * n(std) \quad (4)$$

Where $MA_t(d) = \frac{1}{d}\sum_{i=0}^{d} I_{t-i}$ (Equation 1), $\sigma_{I(d)}$ denotes the standard deviation of the raw index during d days and $n(std)$ the arbitrary number of standard deviations selected. The BB method takes foot in the MA method with the first parts of Equation 3 and 4 simply being the same as the computation of the MA rules. Lower and upper bands have then been created by adding on or taking away standard deviations of the raw index. The MA has been varied with d = {10, 20, 30}. The number of standard deviations has been varied with Std = {1, 1.5, 2, 2.5}. After a signal is generated, the position in the market has been held for H days, which has varied with H = {no, 5, 10}.

Table 2. Summary: Free variables

Table 2 shows a summary of the free variables governing the technical rules. C-lower and C-upper denote the lower and upper constant levels used in RSIs. If rules do not contain a certain variable they are marked with N/A.

Rule	Days in MAs	% band/K	Holding period	C-lower	C-upper	Std
MA	1, 2, 5, 20, 50, 200	0, 0.01, 0.02	5	N/A	N/A	N/A
RSI	5, 10	5, 10	no, 5	20, 30	70, 80	N/A
BB	10, 20, 30	N/A	no, 5, 10	N/A	N/A	1, 1.5, 2, 2.5

The variables governing each technical rule can be seen in Table 2 above. All variables are free in the sense that they are chosen after one's preference. There is limited coherence in past research when it comes to choosing these parameters. Accordingly, there is also limited coherence in which of these rules that produce continuous profitable results. According to Pring (2002) there is no optimal number of days for maximizing the reliability of the MAs. Brock et al. (1992), who comprehensively examine MAs, test for 1 and 2 days in the short-term and 50, 150 and 200 in the long-term MA. The number of days in the MA can be scaled up even more; however, the greater the range is set between short and long-term MA the less frequently trading signals will be generated. This study is not only considering 1 and 2 days in the short-term MA tested in Brock et al. (1992), but is also using 5, 20, 50 and 200 days.

The constant upper and lower levels for the RSIs can be adjusted depending on investors' macroeconomic view of the market. If investors believe in a positively trending market, then the constant lower level might be set closer to the mean of the RSI in relation to the constant upper level. This will raise the probability that the RSIs will break through the constant lower level more frequently and hence generate a greater number of buy signals. Vice versa would apply for a macroeconomic view of a negatively trending market. The standard deviation in the BBs has been ranged between 1 and 2,5 in this study. At a certain point, depending on the volatility of the raw data, a high std will position too far away from the raw index and not generate any breakthroughs and trading signals at all. Using standard deviations between 1 and 2,5 have tested a comprehensive range. The holding period has been added to certain rules to create a relatively even spread amongst the number of variations. This study has tested rules without any holding period, as well as using 5 and 10 days in the holding period. The days can be scaled up even more; however, at a certain point, several positions will be held at once because of the holding periods overlapping.

C. Technical approach

Raw data has been taken from the data source in Section A and inserted into Excel. Three distinct partially automated models have been programmed for each technical approach described in Section B. The former has been done using Excel VBA and Visual Basic 7 as the underlying programming language. The models have been constructed using the methodology described for each of the three technical approaches in Section B. Set parameters have governed the programmed models and have been manipulated by the free variables seen in Table 2. By automating the application of the technical rules to the raw data, a greater number of rules have been more efficiently and conveniently tested, rather than manually applying each rule. The methodology of measuring the performance of these rules is described in Section D below. After conducting these tests, the top five performing technical rules have also applied to a Monte Carlo simulation of the raw index's price dynamic. The simulation of the raw index's price dynamic has been realised 1000 times. The probabilities governing the approximation are described by a geometric Brownian motion (GBM):

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{5}$$

Where S_t is the simulated price, μ and σ is the underlying mean and standard deviation of the OMXS30 raw index and W the Brownian motion. The approximation of the raw index's price dynamic in Equation 5 can be rewritten to discrete time as:

$$S_{t+\Delta t} = S_t\left(1 + \mu\Delta t + \sigma\sqrt{\Delta t}\varepsilon_t\right) \tag{6}$$

Where ε_t is a stochastic variable from a standardised normal distribution with a probability density function of $\Phi(0,1)$ and Δt the size of the time interval. The stochastic variable has been randomized for a total of 10 000 days. The Monte Carlo GBM methodology has been repeated 1000 times and hence created 1000, 10 000-day simulations of the OMXS30 raw index price development. Each of the five top performing technical rules have then been applied to the simulated index and tested for significance against the inherit returns of the same index.

D. Performance measurement

This study is concerned with the performance of the technical trading rules compared to the performance of the raw index. The comparative measure for examining this subject has been the average daily returns. The average daily returns of the technical rules have been tested for significant difference to the average daily return of the buy-and-hold strategy of the raw index. The daily return of the raw index at time t and the average of these daily returns are simply:

$$r_t^{index} = \frac{P_t - P_{t-1}}{P_{t-1}} \quad (7)$$

$$\bar{r}_{index} = \frac{1}{d}\sum_{t=1}^{d} r_t^{index} \quad (8)$$

The daily returns of the technical rules are dependent on the generated trading signal. After a signal, every day has been divided into S = {buy day = 1, sell day = -1, no signal = 0}. The daily return and the average of these returns at time t are calculated as:

$$r_t^{rule} = S_t * r_t \quad (9)$$

$$\bar{r}_{rule} = \frac{1}{d}\sum_{t=1}^{d} r_t^{rule} \quad (10)$$

For strategies with a holding period, the return of a position has been calculated using Equation 4, though substituting P_t with the raw index price at the end of the holding period and P_{t-1} with the raw index price at the start of the holding period. For a sell signal, this procedure has been multiplied by -1. The average return has then been computed using Equation 10 in a normal fashion.

The returns of the technical rules have been tested for significance in relation to the daily returns of the buy-and-hold strategy of the raw index. These has been tested at a level of significance of $\alpha =$ 0,05. If the Swedish stock market is efficient in line with Jensen's definition, then the technical rules should not produce significant returns exceeding the buy-and-hold strategy of the raw index. To examine differences between the average returns produced by each technical rule and the buy-hold-strategy of the raw index, a two-tailed t-test has been used. The variance of the raw index and the technical rules have differed. Therefore, Welch's unequal variance t-test has been applied. The T-value and the degree of freedom are calculated as:

$$T\text{-}value = \frac{\bar{r}_{index} - \bar{r}_{rule}}{\sqrt{\frac{var_i^2}{n_i} + \frac{var_r^2}{n_r}}} \quad (11)$$

$$Df = \frac{\left(\frac{var_i^2}{n_i} + \frac{var_r^2}{n_r}\right)^2}{\frac{\left(\frac{var_i^2}{n_i}\right)^2}{n_i - 1} + \frac{\left(\frac{var_r^2}{n_r}\right)^2}{n_r - 1}} \tag{12}$$

Where $\bar{r}_{index}$ and $\bar{r}_{rule}$ capture the average daily return of the raw index and each strategy respectively, var_i^2 and var_r^2 capture the squared variance of the raw index's returns and respectively the technical rules' returns, and finally, n_i and n_r capture the number of daily returns for the raw index and the technical rules respectively. Since this study is concerned with technical rules that significantly differ from the raw index, the null- and alternative hypothesis are:

$$H_0: \bar{r}_{rule} = \bar{r}_{index} \tag{13}$$

$$H_1: \bar{r}_{rule} \neq \bar{r}_{index} \tag{14}$$

Rules that are significantly greater than the raw index are of interest because they will support the notion of inefficiency on the Swedish stock market. Rules that significantly underperform against the raw index are not signs of efficiency; rather, they may simply be an indication that the technical rules are flawed in their execution and actually worsen the profitability of trading the OMXS30 index during the selected time period 1986-2019. The latter result is also of interest because it would impair the capability and potential of the selected technical rules and undermine technical analysis in general.

IV. Empirical results

In this section, the empirical results of applying the selected technical rules will be presented. The summary outcomes from MAs, RSIs and BBs are presented respectively under section A. The general outcome of all rules and a joint analysis between the different technical techniques are discussed collectively in section B. The best performing rules across all three categories are then subject to flat transaction costs of 0,5% and 1%, and analysed further in section C. These rules are also applied to a Monte Carlo simulation of the underlying raw index in section D.

A. Technical rules

This section presents the outcome of applying moving averages, relative strength index oscillators and Bollinger bands on 33 years of the raw OMXS30 index daily price data. Following from the weak-form efficiency, historical data should be incorporated in stock prices. If the former is assumed to be true, then the technical rules should not yield returns that are significantly greater than the simple buy-and-hold strategy of the raw OMXS30 index. This study has constructed a number of 130 unique rules, 45 being moving averages, 48 relative strength index oscillators and 37 Bollinger bands. These rules have in total generated 146 561 trading signals between 1986 and 2019, 13 875 signals from MAs, 34 164 signals from RSIs and 98 523 signals from BBs. For each rule, the number of buy and sell signals and the buy-to-sell ratio have been displayed. The average daily returns for buy and sell signals are separately noted. The combined returns from both buy and sell signals are also noted and denoted as “buy-sell”. All returns are tested for significance against the unconditional daily mean return of the raw index (seen in Table 1) and discussed accordingly. The standard deviations of the daily returns are also presented. Some parameters are tested for correlation.

(1) Moving averages

The MA rules have varied with the number of days in the short and long-term averages and the band required to generate a signal. Specifically, d_S = {1, 2, 5, 20, 50} in the short-term, d_L = {2, 5, 20, 50, 200} in the long-term and b = {0, 0,01, 0,02} for the percentage band. After a signal has been generated, the position in the market has been held for a constant number of 5 days until the end of the data period. This approach has generated a total of 45 unique rules and 13875 trading signals during the 33 years of data. The number of rules with 1 day in the short-term MA (raw index) amounts to 15, 12 rules contain 2 days, 9 rules contain 5 days, 6 rules contain 20 days and 3 rules contain 50 days. General measures of the outcome can be seen in Table 3.

Table 3. MA: Outcome measurements

Table 3 shows all MA rules, denoted as $MA(d_S, d_L, b)$, (see section III.B.1). N(buy), N(sell) show the number of trading signals for buys and sells, and Buy/sell the ratio between them. $\bar{r}_r$ Buy (*) and $\bar{r}_r$ Sell (*) show the average daily return from buy and sell signals respectively. $\bar{r}_r$ B-S (*) display the combined return from both buy and sell signals. Significance is tested at $\alpha = 0{,}05$ against the unconditional mean of the raw index and denoted by (*). Std displays the standard deviation of the daily returns.

$MA(d_S, d_L, b)$	N(buy)	N(sell)	Buy/sell ratio	$\bar{r}_r$ Buy (*)	$\bar{r}_r$ Sell (*)	$\bar{r}_r$ B-S (*)	Std
MA(1,2)	2006	2004	0,5003/0,4997	0,05793	-0,01958*	0,03835	0,02151
MA(1,5)	1031	1031	0,5/0,5	0,02604	-0,01171*	0,01433	0,01554
MA(1,20)	430	430	0,5/0,5	0,00728	-0,00060*	0,00669	0,01007
MA(1,50)	238	238	0,5/0,5	0,01363	-0,00626*	0,00738	0,00703
MA(1,200)	117	117	0,5/0,5	0,00024*	0,00111*	0,00134*	0,00489
MA(1,2,1)	245	202	0,5481/4519	0,00860	-0,00789*	0,00070*	0,00984
MA(1,5,1)	250	220	0,5319/0,4681	-0,00657*	-0,00878*	-0,01535*	0,00911
MA(1,20,1)	120	122	0,4959/0,5041	0,00268*	-0,00613*	-0,00345*	0,00616
MA(1,50,1)	60	73	0,4511/0,5489	0,00346*	-0,00275*	0,00071*	0,00415
MA(1,200,1)	30	37	0,4478/0,5522	0,00051*	0,00349*	0,00400*	0,00300
MA(1,2,2)	43	27	0,6143/0,3857	-0,00227*	0,00013*	-0,00214*	0,00526
MA(1,5,2)	57	48	0,5429/0,4571	-0,00434*	-0,00167*	-0,00601*	0,00524
MA(1,20,2)	30	33	0,4762/0,5238	-0,00108*	-0,00892*	-0,01000*	0,00372
MA(1,50,2)	14	21	0,4/0,6	0,00009*	-0,00135*	-0,00126*	0,00265
MA(1,200,2)	12	13	0,48/0,52	-0,00044*	-0,00048*	-0,00092*	0,00188
Average	**312**	**308**	**0,5032/0,4968**	**0,00705**	**-0,00476**	**0,00229**	**0,00734**
MA(2,5)	879	879	0,5/0,5	0,01810	-0,02465*	-0,00656*	0,01439
MA(2,20)	330	330	0,5/0,5	0,00739*	-0,01147*	-0,00408*	0,00919
MA(2,50)	182	182	0,5/0,5	0,01088	-0,00484*	0,00604*	0,00617
MA(2,200)	91	91	0,5/0,5	0,00178*	-0,00333*	-0,00155*	0,00449
MA(2,5,1)	99	82	0,55/0,45	-0,00264*	-0,00785*	-0,01049*	0,00613
MA(2,20,1)	44	55	0,4680/0,5320	0,00423*	-0,00409*	0,00014*	0,00410
MA(2,50,1)	31	34	0,4769/0,5231	0,00073*	0,00046*	0,00119*	0,00346
MA(2,200,1)	12	23	0,3429/0,6571	0,00055*	-0,00211*	-0,00156*	0,00261
MA(2,5,2)	23	14	0,6216/0,3784	-0,00247*	-0,00338*	-0,00586*	0,00325
MA(2,20,2)	4	9	0,3077/0,6923	0,00048*	-0,00491*	-0,00443*	0,00194
MA(2,50,2)	5	6	0,4545/0,5455	0,00027*	0,00017*	0,00044*	0,00182
MA(2,200,2)	1	5	0,1667/0,8333	0,00069*	-0,00113*	-0,00044*	0,00134
Average	**142**	**143**	**0,4982/0,5018**	**0,00333**	**-0,00559**	**-0,00226**	**0,00491**
MA(5,20)	236	236	0,5/0,5	0,00245*	-0,00820*	-0,00574*	0,00688
MA(5,50)	125	125	0,5/0,5	0,00756*	-0,00203*	0,00553*	0,00512
MA(5,200)	62	62	0,5/0,5	0,00114*	-0,00080*	0,00034	0,00347
MA(5,20,1)	17	7	0,7083/0,2917	-0,00301*	0,00118*	-0,00183*	0,00229
MA(5,50,1)	8	5	0,6154/0,3846	-0,00110*	0,00024*	-0,00087*	0,00112
MA(5,200,1)	3	3	0,5/0,5	0,00054*	-0,00009*	0,00044	0,00120
MA(5,20,2)	2	0	1/0	-0,00117*	0,0	-0,00117*	0,00099
MA(5,50,2)	0	1	0/1	0,0	-0,00060*	-0,00060*	0,00055
MA(5,200,2)	0	0	0/0	0,0	0,0	0,0	0,0
Average	**50**	**49**	**0,5051/0,4949**	**0,00071**	**-0,00114**	**-0,00044**	**0,00240**
MA(20,50)	83	83	0,5/0,5	0,00094*	-0,00338*	-0,00244*	0,00396
MA(20,200)	32	32	0,5/0,5	-0,00076*	-0,00382*	-0,00458*	0,00249
MA(20,50,1)	0	0	0/0	0,0	0,0	0,0	0,0
MA(20,200,1)	0	0	0/0	0,0	0,0	0,0	0,0
MA(20,50,2)	0	0	0/0	0,0	0,0	0,0	0,0
MA(20,200,2)	0	0	0/0	0,0	0,0	0,0	0,0
Average	**19**	**19**	**0,5/0,5**	**0,00003**	**-0,00120**	**-0,00117**	**0,00108**
MA(50,200)	21	21	0,5/0,5	0,00141*	0,00337*	0,00478*	0,00212
MA(50,200,1)	0	0	0/0	0,0	0,0	0,0	0,0
MA(50,200,2)	0	0	0/0	0,0	0,0	0,0	0,0
Average	**7**	**7**	**0,5/0,5**	**0,00047**	**0,00112**	**0,00159**	**0,00070**
Total average	**155**	**153**	**0,5032/0,4968**	**0,00342**	**-0,00339**	**0,00002**	**0,00443**

Out of 45 MA rules, 15 have generated average returns above zero, 23 below zero and 7 generated no trading signals at all. Trading signals have been generated for all MA variations without a band; hence, the 1% and 2% bands are the reasons for the lack of trading signals amongst some of the rules at the lower end of Table 3. The average number of buy and sell signals for all rules are 155 and 153 respectively. On average, the MA rules generated approximately the same amount of buy and sell signals across all rules. Rules without a band will always tend towards 0,5/0,5 in a buy-to-sell ratio. The former follows since these rules can dismiss the precondition of having to remain a certain percentage above or below the long-term MA after a crossover. Crossovers can only happen if the short-term MA breaks the long-term MA from either underneath or from above. As a result, buy and sell signals will always alternate, and since this cannot be disrupted by a band these rules will always tend towards 0,5/0,5 with a large enough sample.

The average daily return from buy signals is positive of 0,00342% and for the sell signals negative of -0,00339. Buy-sell signals combined produce an average daily return of 0,00002%, with a standard deviation of 0,00443. Rules with a small range of days between the short-term and the long-term MAs (e.g. MA(1,2)) are naturally going to produce averages that are more alike than two MAs with a greater range (e.g. MA(1,200)). As a result, rules with a smaller range are generally more likely to cross and generate a greater number of trading signals. This can be seen in Table 3 where the number of trading signals decrease as the range between short- and long-term increase. There is also a strong positive correlation of $\rho_{N(total),\bar{\mathrm{r}}_{\mathrm{r}}} = 0{,}70934$ between the total trading signals generated and the average daily returns. The two former outcomes indicate that rules with a small range of days between short-term and long-term MAs, which will generate more trading signals, tend to outperform those with a larger range. A captivating and possible explanation might be that the market is less capable of processing market driving information when dealing with less time. If information incorporation is relatively slow, then the market will take longer time to incorporate information into prices. The former might lead to short-term under or overreaction that can be more efficiently exploited by MA rules with a shorter range, whilst MA rules with a greater range act on information that is, due to the time, already incorporated into prices. Accordingly, MA(1,2), MA(1,5), MA(1,20) and MA(2,50) are the most profitable ones amongst all MA rules. Also noteworthy is that the majority of the profitable rules keep 1 day (raw index) in the short-term MA. These rules also display a relatively higher standard deviation on average compared to those rules that do not include the raw index as the short-term MA. Correspondingly, there is a positive correlation of $\rho_{std,\bar{\mathrm{r}}_{\mathrm{r}}} = 0{,}480451$ between the standard deviation of the returns and the average daily returns.

For all categories of MA rules, the average return from buy signals outperform the average return from sell signals. Only 8 out of 48 categories of sell signals manage to produce average returns that are above zero, whilst 26 categories of buy signals produce average returns above zero. In many cases, trading solely based on the sell signals would generate negative returns. However, because of the slight positive average total return of 0,00002% from buy-sell signals across all MA rules, a portfolio with an equal share in each rule would yield slight positive returns over the time span of 33 years of data. When all rules are tested for significance against the unconditional daily average return of the raw index, 32 rules indicate significant difference at $\alpha = 0{,}05$. The null hypothesis states no significant difference between the technical strategies and the raw index and is therefore rejected. However, all 32 significantly different rules produce average returns that are significantly less than the raw index and worsen the profitability of trading the raw OMXS30 index during the selected time period. No single MA rule outperform the buy-and-hold strategy of the raw index itself (seen in Table 1); as a result, weak-form efficiency cannot be dismissed.

(2) RSI oscillators

The RSI rules have been varied with the number of days in the average up and down movements, the number of days above or below the constant levels before a signal is generated, the number of days in the holding period and the constant lower and upper levels. More specifically, d = {5, 10}, K = {0, 5, 10}, H = {0, 5}, (C_L) = {20, 30} and (C_U) = {70, 80}. Basic descriptive statistics of the indeces RSI(5) and RSI(10) can be seen in Table 4. The RSIs are also plotted in Figure 4 and 5. General measures of the outcome of all RSI rules can be seen in Table 5. The rules have been divided into the corresponding constant lower and upper levels (C_L) and (C_U). For each 4 combinations of (C_L) and (C_U), 12 rules have been generated. In total, the RSI approach has generated 48 different variations of RSI rules and 34 164 trading signals.

Table 4. Descriptive statistics: RSI(d)

Table 4 displays RSIs created using 5 respectively 10-day averages for up and down movements. Mean, standard deviation, the number of observations of RSI(5) and RSI(10) and the correlation between the RSIs and the raw index are also reported.

RSI(d)	Mean	Std	N(obs)
RSI(5)	54,0011	20,3942	8285
RSI(10)	53,6438	14,6372	8280

Both RSIs show means greater than 50. Theoretically, a stagnate underlying market should generate an RSI with a mean of 50. However, the underlying OMXS30 index is in positive trend over the time period (see Figure 1), which aligns with the RSIs showing means above 50. A positive trend will generate greater up than down movements in the long run and as a result the mean of the RSI will tend towards 100 rather than 0. The RSI value will move in some accordance with the raw index. The connection between the RSIs and the raw index can be seen by the positive correlation of $\rho_{RSI(5),index}$ = 0,4870 and $\rho_{RSI(10),index}$ = 0,3715. Using a greater number of days in the averages for up and down movements are likely to decrease the correlation between the RSI and the raw index. The former follows since including a greater number of days in the averages is likely to increase the difference between the outcome of the RSI and the raw index.

Figure 4. RSI(5-day)

Figure 4 shows a plot of the relative strength index using 5 days in the calculation of the average up and down movements.

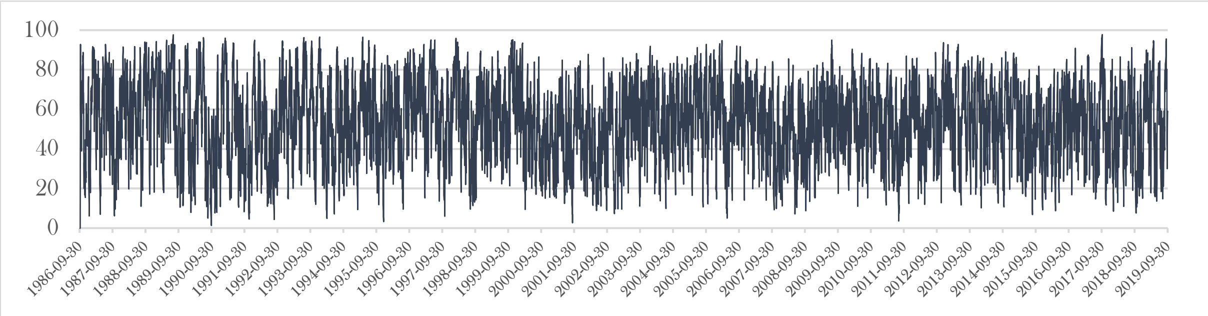
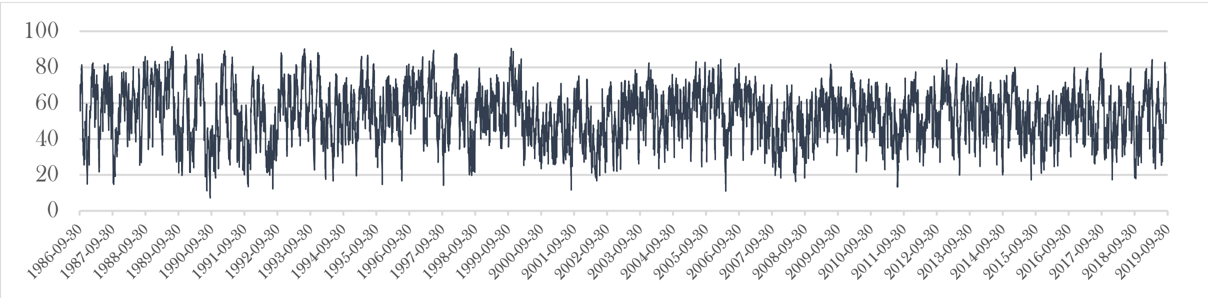


Figure 5. RSI(10-day)

Figure 5 shows a plot of the relative strength index using 10 days in calculation of the average up and down movements.



The difference in standard deviation between RSI(5) and RSI(10) shown in Table 4 can also be seen when plotting the indeces in Figure 4 and 5. Because of the higher standard deviation in RSI(5), it has extended further and more frequently towards the extreme levels of 0 and 100 than RSI(10). As a result, RSI(5) has been breaking through the constant lower and upper levels more frequently and generated a greater number of trading signals in general. The constant lower and upper levels have been set at $(C_L) = \{20, 30\}$ and $(C_U) = \{70, 80\}$. The constant levels could have been set beyond the parameters of this paper. Levels further towards 0 and 100 would have generated a smaller number of total trading signals since RSI(5) only occasionally extends below 10 or above 90, whilst RSI(10) barely extends beyond these levels at all. On the other hand, setting the constant levels closer to the mean of the RSIs would naturally generate a greater number of trading signals.

Table 5. RSI: Outcome measurements

Table 5 shows all RSI rules, denoted as RSI(d, K, H), (see section III.B.2). N(buy), N(sell) show the number of trading signals for buys and sells, and Buy/sell the ratio between them. $\bar{r}_r$ Buy (*) and $\bar{r}_r$ Sell (*) show the average daily return from buy and sell signals respectively. $\bar{r}_r$ B-S (*) display the combined return from both buy and sell signals. Significance is tested at $\alpha = 0{,}05$ against the unconditional mean of the raw index and denoted by (*). Std displays the standard deviation of the returns.

RSI(d, K, H)	N(buy)	N(sell)	Buy/sell ratio	$\bar{r}_r$ Buy (*)	$\bar{r}_r$ Sell (*)	$\bar{r}_r$ B-S (*)	Std
$C_L = 20$ $C_U = 80$							
RSI(5)	471	885	0,3473/0,6527	-0,02181*	-0,06237*	-0,08418*	0,01414
RSI(5,5)	35	199	0,1496/0,8504	0,02099	-0,01909*	0,00191	0,01415
RSI(5,10)	0	31	0/1	0,0	-0,06039*	-0,03654*	0,01362
RSI(5,0,5)	471	885	0,3473/0,6527	0,03352	-0,03687*	-0,00335*	0,01244
RSI(5,5,5)	35	199	0,1496/0,8504	0,01223	-0,00866*	0,00358*	0,00422
RSI(5,10,5)	0	31	0/1	0,0	-0,00214*	-0,00214*	0,00090
RSI(10)	70	229	0,2341/0,7659	0,01634	-0,02423*	-0,00789*	0,01416
RSI(10,5)	3	57	0,05/0,95	0,00075*	-0,03342*	0,02576*	0,01396
RSI(10,10)	0	16	0/1	0,0	-0,05942*	-0,03399*	0,01360
RSI(10,0,5	70	229	0,2341/0,7659	0,01434	-0,01153*	0,00280*	0,00613
RSI(10,5,5)	3	57	0,05/0,95	0,00250*	-0,00340*	0,01358*	0,00502
RSI(10,10,5)	0	16	0/1	0,0	-0,00108*	-0,00108*	0,00117
Average	**97**	**236**	**0,2913/0,7087**	**0,00657**	**-0,02688**	**-0,01013**	**0,00946**
$C_L = 20$ $C_U = 70$							
RSI(5)	471	2093	0,1837/0,8163	-0,04258*	-0,08315*	-0,12573*	0,01411
RSI(5,5)	35	635	0,0522/0,9478	0,00359*	-0,03648*	-0,03288*	0,01415
RSI(5,10)	0	164	0/1	0,0	-0,06418*	-0,04081*	0,01408
RSI(5,0,5)	471	2093	0,1837/0,8163	0,03352	-0,05924*	-0,02571*	0,01548
RSI(5,5,5)	35	635	0,0522/0,9478	0,01223	-0,02207*	-0,00983*	0,00651
RSI(5,10,5)	0	164	0/1	0,0	-0,01074*	-0,01074*	0,00306
RSI(10)	70	1111	0,0593/0,9407	-0,00430*	-0,04486*	-0,04916*	0,01415
RSI(10,5)	3	401	0,0074/0,9926	-0,00061*	-0,04067*	-0,04128*	0,01415
RSI(10,10)	0	139	0/1	0,0	-0,06414*	-0,04056*	0,01408
RSI(10,0,5	70	1111	0,0593/0,9407	0,01434	-0,05111*	-0,03675*	0,00955
RSI(10,5,5)	3	401	0,0074/0,9926	0,00250*	-0,01723*	-0,01473*	0,00485
RSI(10,10,5)	0	139	0/1	0,0	-0,00759*	-0,00759*	0,00288
Average	**97**	**757**	**0,1136/0,8854**	**0,00156**	**-0,04179**	**-0,03631**	**0,01059**
$C_L = 30$ $C_U = 80$							
RSI(5)	1200	885	0,5755/0,4245	-0,02430*	-0,06486*	-0,08916*	0,01413
RSI(5,5)	189	199	0,4871/0,5129	0,02055	-0,01953*	0,00102	0,01415
RSI(5,10)	16	31	0,3404/0,6596	0,01675	-0,04364*	-0,01656*	0,01363
RSI(5,0,5)	1200	885	0,5755/0,4245	0,06355	-0,03687*	0,02667	0,01690
RSI(5,5,5)	189	199	0,4871/0,5129	0,02384	-0,00866*	0,01518	0,00678
RSI(5,10,5)	16	31	0,3404/0,6596	0,00030*	-0,00214*	-0,00185*	0,00190
RSI(10)	493	229	0,6828/0,3172	0,00805	-0,03252*	-0,02447*	0,01416
RSI(10,5)	92	57	0,6174/0,3826	0,03307	-0,00730*	0,02576	0,01396
RSI(10,10)	12	16	0,4286/0,5714	0,03413	-0,02530*	-0,00120*	0,01360
RSI(10,0,5	493	229	0,6828/0,3172	0,03393	-0,01153*	0,02238	0,01230
RSI(10,5,5)	92	57	0,6174/0,3826	0,01699	-0,00340*	0,01358	0,00502
RSI(10,10,5)	12	16	0,4286/0,5714	-0,00183*	-0,00108*	-0,00291*	0,00183
Average	**334**	**236**	**0,5860/0,4140**	**0,01875**	**-0,02140**	**-0,00263**	**0,01070**
$C_L = 30$ $C_U = 70$							
RSI(5)	1200	2093	0,3644/0,6356	-0,06118*	-0,10175*	-0,16293*	0,01407
RSI(5,5)	189	635	0,2294/0,7706	0,00007*	-0,04000*	-0,03994*	0,01415
RSI(5,10)	16	164	0,0889/0,9111	0,00653*	-0,05765*	-0,03000*	0,01408
RSI(5,0,5)	1200	2093	0,3644/0,6356	0,06355	-0,05924*	0,00430	0,01925
RSI(5,5,5)	189	635	0,2294/0,7706	0,02384	-0,02207*	0,00178*	0,00840
RSI(5,10,5)	16	164	0,0889/0,9111	0,00030*	-0,01074*	-0,01044*	0,00349
RSI(10)	493	1111	0,3074/0,6926	-0,01453*	-0,05510*	-0,06963*	0,01414
RSI(10,5)	92	401	0,1866/0,8134	0,01090	-0,02916*	-0,01826*	0,01415
RSI(10,10)	12	139	0,0795/0,9205	0,02261	-0,04152*	-0,01386*	0,01409
RSI(10,0,5	493	1111	0,3074/0,6926	0,03393	-0,05111*	-0,01717*	0,01432
RSI(10,5,5)	92	401	0,1866/0,8134	0,01699	-0,01723*	-0,00024*	0,00657
RSI(10,10,5)	12	139	0,0795/0,9205	-0,00183*	-0,00759*	-0,00942*	0,00320
Average	**334**	**757**	**0,3061/0,6939**	**0,00843**	**-0,04100**	**-0,03048**	**0,01166**
Total average	**215**	**497**	**0,3020/0,6980**	**0,00883**	**-0,03280**	**-0,01989**	**0,01060**

The average return for RSI rules with a constant upper level of 80 generally outperform those with a constant upper level of 70. One explanation for the former might be that the means of the RSIs are above 50 and the underlying raw index being in positive trend. In a positively trending market, more buy signals are preferable since the probability of the market increasing in the long run is higher than decreasing. Also, when setting the constant upper level at 70 rather than 80, the number of sell signals are likely to increase since it gets closer to the means of the RSIs. Accordingly, the categories of rules that have the constant upper level set at 80 produce better average daily returns than those with it set at 70. The same reasoning is valid for the constant lower levels. In a positively trending market, buy signals are preferable, and the number of buy signals can be increased by setting the constant lower level closer to the means of the RSIs. It is apparent that the rules that produce the highest average returns are rules from the category C_L = 30 C_U = 80. This approach minimizes the distance from the constant lower level to the means of the RSIs and maximize the distance from the constant upper level to the means of the RSIs. Accordingly, these rules have the highest ratio of buy-to-sell signals.

On average, the RSI strategy produce a greater number of sell than buy signals, with approximately 215 buy, 497 sell signals and a buy-to-sell ratio of 0,3020/0,6980. The former follows since RSI(5) and RSI(10) show means above 50. With the RSI means above 50, they will both extend further towards 100 than 0, hence generating more sell signals on average. In general, rules with the condition of variable K perform better than those rules without variable K. If the RSI is breaking through the constant levels for less than 5 or 10 days, then a signal would not be generated if it were to governed by variable K. The former leads to a lower number of total trading signals for rules that include variable K. There is also a negative correlation of $\rho_{N(total),\bar{\mathrm{r}}_{\mathrm{r}}}$ = -0,54569 between total number of trading signals and average returns. Although this also may indicate that rules that generate less signals tend to produce higher returns, one should not forget that the presence of correlation is not enough to affirm an explanatory relationship. Nevertheless, only 13 rules generated average daily returns above zero; out of these, 9 produced total trading signals below the average number of total trading signals produced across all RSI rules. However, an exception to the reasoning of the negative correlation between trading signals and returns is the top performing rule in the entire RSI sample. RSI(5,0,5) produce an average daily return of 0,02667%, with a total of 2085 trading signals generated. An explanation to the profitability of this rule may simply be the overrepresentation of buy signals. With the constant levels at C_L = 30 and C_U = 80, RSI(5,0,5) generates 1200 buy and 885 sell signals, posing as an exception to the average buy-to-sell ratio of the RSI rules.

The average return is 0,00883% for buy signals and -0,03280% for sell signals. In general, trading solely on the buy signals would outperform trading on both buy and sell signals combined. In line with the reasoning in the former paragraph, one possible explanation may be the underlying market being in positive trend. However, since the correlations between the RSIs and the underlying raw index are not perfect, the possible explanation diminishes in potential. The average return for the combined buy-sell amounts to -0,01989%, which is less the 0,00002% produced by the MA rules. Out of 48 RSI rules, 13 generated average daily returns above zero and 35 below zero. When all RSI rules are tested for significance against the unconditional daily mean return of the raw index, 40 out of 48 rules indicate significant difference at $\alpha = 0{,}05$. The null hypothesis states no significant difference between the technical strategies and the raw index, and is therefore rejected. However, all 40 rules produce average returns that are significantly less than the raw index and significantly worsen the profitability of trading the raw OMXS30 index during the selected time period of 1986-2019. As well as the MA rules, no single RSI rule outperform the buy-and-hold strategy of the raw index itself (seen in Table 1); therefore, weak-form efficiency cannot be dismissed.

(3) Bollinger bands

The BB rules have been varied with the number of days in the MA of the raw index, the number of standard deviations added on to the MA and the holding period. More specifically, d = {10, 20, 30, 40}, Std = {1, 1.5, 2, 2.5} and H = {0, 5, 10}. General measures of the outcome of these rules can be seen in Table 6. The RSI rules have been split up and divided into categories of the number of days used in the MA. As a result, 12 rules are displayed for each variation of d. In total, the BB approach has generated 48 different variations of BB rules and 98 523 trading signals. The BB approach has generated considerably more trading signals in relation to the 13 875 and 34 164 trading signals generated by the MA and RSI approaches respectively. The former is likely to be a result of inconsistency in the effect of governing variables. For the BB approach, varying the number of days in the MA has not had the same effect on total signals generated as in the cases of MAs and RSIs. Table 6 shows that there is no considerable increase or decrease in the number of total trading signals generated when manipulating the number of days in the MA. For instance, BB(10,1), BB(20, 1), BB(30,1) and BB(40,1) all produce total signals in the range of 4420-4925. As a result, rules that generate many trading signals have reappeared in slightly different forms. However, MAs, RSIs and BBs are three different techniques governed by different computations. Hence, the technical rules cannot be expected to deliver similar outcomes in terms of generated trading signals.

Table 6. BB: Outcome measurements

Table 6 shows all BB rules, denoted as BB(d, Std, H), (see section III.B.3). N(buy), N(sell) show the number of trading signals for buys and sells, and Buy/sell the ratio between them. $\bar{r}_r$ Buy (*) and $\bar{r}_r$ Sell (*) show the average daily return from buy and sell signals respectively. $\bar{r}_r$ B-S (*) display the combined return from both buy and sell signals. Significance is tested at $\alpha = 0{,}05$ against the unconditional mean of the raw index and denoted by (*). Std displays the standard deviation of the returns.

RSI(d, Std, H)	N(buy)	N(sell)	Buy/sell ratio	$\bar{r}_r$ Buy (*)	$\bar{r}_r$ Sell (*)	$\bar{r}_r$ B-S (*)	Std
BB(10,1)	1794	2626	0,4059/0,5941	-0,11334*	-0,15434*	-0,26768*	0,01391
BB(10,1,5)	1794	2626	0,4059/0,5941	0,07726	-0,06298*	0,01428	0,02242
BB(10,1,10)	1794	2626	0,4059/0,5941	0,09291	-0,13226*	-0,03935*	0,03044
BB(10,1.5)	919	1149	0,4444/0,5556	-0,08015*	-0,12111*	-0,20127*	0,01402
BB(10,1.5,5)	919	1149	0,4444/0,5556	0,07100	-0,03450*	0,03650	0,01574
BB(10,1,5,10)	919	1149	0,4444/0,5556	0,07686	-0,05499*	0,02187	0,02123
BB(10,2)	234	219	0,5166/0,4834	-0,03019*	-0,07088*	-0,10108*	0,01412
BB(10,2,5)	234	219	0,5166/0,4834	0,00841	-0,00625*	0,00216*	0,00786
BB(10,2,10)	234	219	0,5166/0,4834	0,00170*	-0,00507*	-0,00337*	0,01006
BB(10,2.5)	12	9	0,5714/0,4286	0,00760	-0,03258*	-0,02498*	0,01415
BB(10,2.5,5)	12	9	0,5714/0,4286	-0,00092*	-0,00066*	-0,00158*	0,00248
BB(10,2.5,10)	12	9	0,5714/0,4286	-0,00294*	-0,00174*	-0,00469*	0,00348
Average	**740**	**1001**	**0,4250/0,5750**	**0,00902**	**-0,05645**	**-0,04743**	**0,01416**
BB(20,1)	1798	2923	0,3809/0,6191	-0,06407*	-0,10507*	-0,16915*	0,01406
BB(20,1,5)	1798	2923	0,3809/0,6191	0,04894	-0,07323*	-0,02429*	0,02317
BB(20,1,10)	1798	2923	0,3809/0,6191	0,07865	-0,18729*	-0,10864*	0,03120
BB(20,1.5)	1004	1503	0,4005/0,5995	-0,03788*	-0,07884*	-0,11672*	0,01411
BB(20,1.5,5)	1004	1503	0,4005/0,5995	0,05674	-0,03846*	0,01827	0,01735
BB(20,1,5,10)	1004	1503	0,4005/0,5995	0,05826	-0,08320*	-0,02494*	0,02329
BB(20,2)	418	435	0,4900/0,5100	-0,01878*	-0,05933*	-0,07811*	0,01414
BB(20,2,5)	418	435	0,49/0,51	0,03190	-0,01618*	0,01572	0,01027
BB(20,2,10)	418	435	0,49/0,51	0,02782	-0,02042*	0,00740	0,01389
BB(20,2.5)	106	59	0,6424/0,3576	0,00632	-0,03405*	-0,02772*	0,01415
BB(20,2.5,5)	106	59	0,6424/0,3576	0,00035*	-0,00370*	-0,00336*	0,00483
BB(20,2.5,10)	106	59	0,6424/0,3576	-0,00430*	-0,00361*	-0,00791*	0,00627
Average	**832**	**1230**	**0,4035/0,5965**	**0,01533**	**-0,05862**	**-0,04329**	**0,01556**
BB(30,1)	1794	3094	0,3670/0,6330	-0,03932*	-0,08032*	-0,11964*	0,01411
BB(30,1,5)	1794	3094	0,3670/0,6330	0,05277	-0,09771*	-0,04493*	0,02387
BB(30,1,10)	1794	3094	0,3670/0,6330	0,09097	-0,23274*	-0,14177*	0,03198
BB(30,1.5)	1027	1676	0,3799/0,6201	-0,02431*	-0,06528*	-0,08959*	0,01413
BB(30,1.5,5)	1027	1676	0,3799/0,6201	0,05904	-0,04210*	0,01694	0,01800
BB(30,1,5,10)	1027	1676	0,3799/0,6201	0,07378	-0,10333*	-0,02955*	0,02393
BB(30,2)	435	459	0,4866/0,5134	-0,01322*	-0,05376*	-0,06698*	0,01414
BB(30,2,5)	435	459	0,4866/0,5134	0,03306	-0,01951*	0,01355	0,01105
BB(30,2,10)	435	459	0,4866/0,5134	0,01731	-0,03727*	-0,01996*	0,01479
BB(30,2.5)	141	73	0,6589/0,3411	0,00313	-0,03807*	-0,03494*	0,01413
BB(30,2.5,5)	141	73	0,6589/0,3411	0,01099	-0,00707*	0,00391*	0,00571
BB(30,2.5,10)	141	73	0,6589/0,3411	-0,00143*	-0,01450*	-0,01593*	0,00760
Average	**849**	**1326**	**0,3903/0,6097**	**0,02190**	**-0,06597**	**-0,04407**	**0,01612**
BB(40,1)	1719	3206	0,3490/0,6510	-0,03170*	-0,07270*	-0,10440*	0,01412
BB(40,1,5)	1719	3206	0,3490/0,6510	0,02608	-0,10883*	-0,08275*	0,02423
BB(40,1,10)	1719	3206	0,3490/0,6510	0,04124	-0,24856*	-0,20732*	0,03275
BB(40,1.5)	1006	1756	0,3642/0,6358	-0,02124*	-0,06220*	-0,08343*	0,01414
BB(40,1.5,5)	1006	1756	0,3642/0,6358	0,05011	-0,04851*	0,00160	0,01844
BB(40,1,5,10)	1006	1756	0,3642/0,6358	0,05831	-0,11782*	-0,05951*	0,02405
BB(40,2)	453	538	0,4571/0,5429	-0,00984*	-0,05039*	-0,06024*	0,01414
BB(40,2,5)	453	538	0,4571/0,5429	0,02843	-0,02281*	0,00562	0,01215
BB(40,2,10)	453	538	0,4571/0,5429	0,01801	-0,04343*	-0,02542*	0,01574
BB(40,2.5)	158	98	0,6172/0,3828	0,00156	-0,04031*	-0,03875*	0,01412
BB(40,2.5,5)	158	98	0,6172/0,3828	0,00869	-0,01200*	-0,00331*	0,00637
BB(40,2.5,10)	158	98	0,6172/0,3828	-0,00996*	-0,02166*	-0,03162*	0,00883
Average	**834**	**1400**	**0,3733/0,6267**	**0,01331**	**-0,07077**	**-0,05746**	**0,01659**
Total average	**814**	**1239**	**0,3965/0,6035**	**0,01389**	**-0,06295**	**-0,04806**	**0,01561**

The 48 BB rules have generated an average number of 814 buy signals and 1239 sell signals per rule, which amounts to a 0,3965/0,6035 buy-to-sell ratio. Sell signals dominate the BB rules. When the standard deviation used in the governing variable Std = {1, 1.5, 2, 2.5} is increased, the number of total trading signals generated decrease. Using a high Std will push the BBs further away from the raw index, and as a result, less trading signals will be generated. When looking at the relatively small number of trading signals produced by the rules using 2,5 as Std, it is reasonable to believe that increasing the standard deviation beyond this point would yield close to or no trading signals at all. The former partly justifies the choosing of the range for Std. There is also a negative correlation of $\rho_{N(total),\bar{r}_r} =$ -0,52603 between the total trading signals generated and the average daily returns. On average, rules with less trading signals outperform those with more. However, the presence of correlation is not enough to affirm an explanatory relationship.

The average return from rules with 20 days in the MA outperform the others; however, the individually best performing rules come from the category with 10 days in the MA. BB(10,1.5,5) is the top performing BB rule with an average daily return of 0,03650%, slightly shy of the raw index's average daily return of 0,04101%. This rule generates 919 buy and 1149 sell signals. Interestingly enough, the return from buy signals solely amounts to 0,07100% and from sell signals to -0,03450%. A common theme for all BB rules is that trading solely based on buy signals generates average daily returns above zero, whilst trading solely based on sell signals does not. As for the RSI rules, one explanation might be the underlying raw index being in positive trend. The raw index pushes up towards the upper band more frequently than down towards the lower band. The former will result in a higher probability to generate sell signals. Accordingly, the buy-to-sell ratio is tilted towards a greater number of sell signals. An interesting topic for future research may be the possibility of using a relatively higher value in Std for the upper band, to mitigate some of the sell signals; and, at the same time keep the Std for the lower band relatively low.

When the BB rules are tested for significance against the unconditional daily average return of the raw index, 37 out of 48 rules indicate significant difference at $\alpha = 0{,}05$. The null hypothesis states no significant difference between the technical strategies and the raw index, and is therefore rejected. However, all 37 rules produce average returns that are significantly less than the raw index and therefore significantly worsen the profitability of trading the raw OMXS30 index during the selected time period. Just like the MA and RSI rules, no single BB rule outperforms the buy-and-hold strategy of the raw index itself by a significant margin; therefore, weak-form efficiency cannot be dismissed.

B. Joint analysis

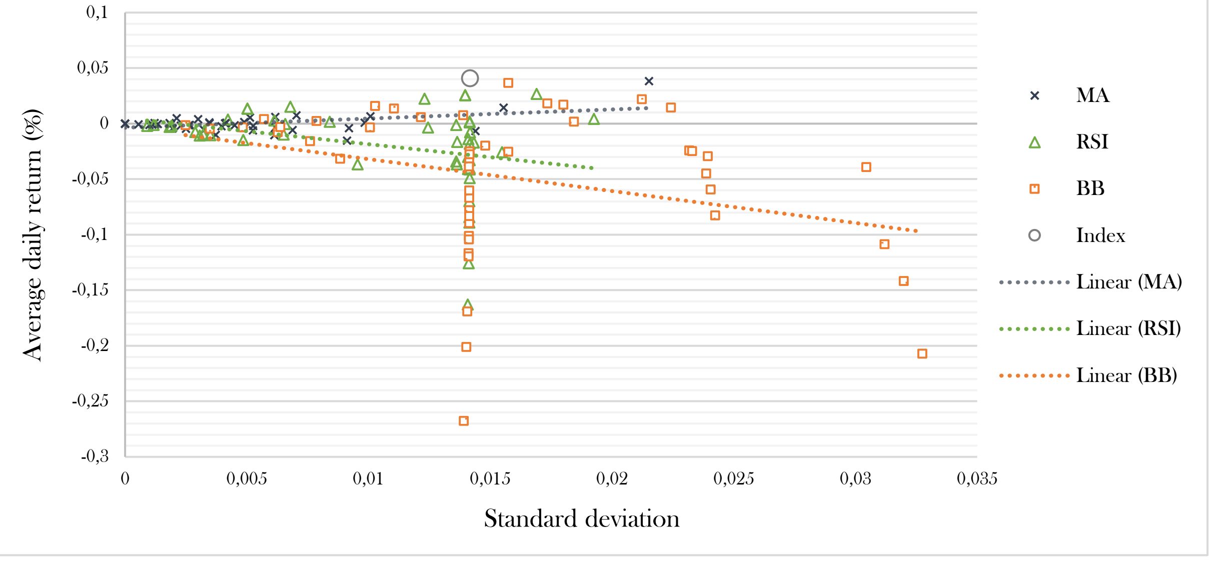
If all three technical categories are jointly considered, they differ considerably in outcome. The MA approach generates on average of 308 trading signals per rule and the buy-to-sell ratio amounts to 0,5032/0,4968. The same parameters for the RSI approach are 712 and 0,3020/0,6980, and for the BB approach 2053 and 0,3965/0,6035. The trading signals generated by the MA rules split approximately 0,5/0,5 into buy and sell. Unlike the MA approach, the RSI and BB rules generate a smaller number of buy than sell signals on average. For buy signals, the MA rules generated an average return of 0,00343%, the RSI rules 0,00883% and the BB rules 0,01389%. For sell signals the values are -0,00339%, -0,03280% and -0,06295%. No rules amongst RSIs and BBs generated average returns from sell signals that exceeded zero. The findings of buy signals outperforming sell signals also appear in studies such as Brock et al. (1992) and Bessembinder and Chan (1998). One explanation for the lack of profitability in sell signals might be the continuous positive trend of the underlying raw index during the selected time sample period. To confirm this explanation, the sell signals should produce positive returns during those occasional time periods where the market has been in negative trend. The former makes for interesting future research.

For the combined buy-sell, average daily returns are 0,00002% for the MA rules, -0,01989% for the RSI rules and -0,04806% for the BB rules. A scatter plot of the average returns from the combined buy-sell and their respective standard deviation can be seen in Figure 6. The average standard deviations for the rules' returns are 0,00443 for MAs, 0,01060 for RSIs and 0,01561 for BBs. The higher standard deviation amongst RSI and BB rules can be seen by the greater variation of returns illustrated in Figure 6. Also noteworthy in Figure 6 is that many rules bunch up around a standard deviation of 0,014. This is due to its proximity to the standard deviation of the raw index's returns of 0,01416. Technical rules that lack a great number of trading signals will tend towards the measures of the index itself. The plot in Figure 6 also shows the relationship between the rules' returns and their respective standard deviations. MA rules tend to display a slight positive relationship, whilst RSI and BB rules a negative one. Correspondingly, the MA rules show a strong positive correlation between average returns and trading rules generated, whilst RSI and BB rules show a negative correlation. A greater number of trading signals is likely to increase the variation of the returns.

Also, the MA, RSI and BB differ in technical approach. As noted in section III.A, The MA rule is a trend-following momentum indicator, whilst the RSI and BB rules are two different forms of mean reversion strategies. It might be the case that the slight positive relationship between average daily returns and the standard deviations of the MA rules is a consequence of the MA rule being a trend-following indicator. The slope of the linear relationship is positive in Figure 6 for the MA rules and negative for the RSI and BB rules. Betting on the raw index to follow an overall trend in momentum may simply be a less risk provoking strategy than betting on the raw index reverting back towards a previous mean level, as in the cases of the RSI and BB rules. It may also be the case that the MA rule is an overall easier concept to apply to the market. For instance, it is seemingly easier to identify the overall trend in index data rather than coming up with an appropriate mean for it. A seemingly admissible trend can be derived from plotting historical data. Coming up with an appropriate mean level poses as a greater challenge because it requires the mean to be justified by computing some sort of average over previous price movements, as in the cases of the RSI and BB rules. The former rationale makes the MA rule more compatible to use, and subsequently, may be the reason for the average performance being better across MA rules. It is also the case that in a positively trending market, as in the raw OMXS30 index, price levels may continue to reach overvalued levels multiple times in a row because of the positive trend. Hence, RSI and BB rules are triggered to generate unprofitable sell signals that contribute to the overall unprofitable performance of these rules. On that note, it should be noted that the outcomes of the MA, RSI and BB rules are not perfectly comparable because of the inconsistency in their technique. The three technical rules are also different in terms of their governing variables, which further weakens the comparison between them.

Figure 6. Average daily returns

Figure 6 displays a plot of the average daily returns of the technical rules and the index. The dotted lines display the relationships between average daily returns and standard deviation of the returns.

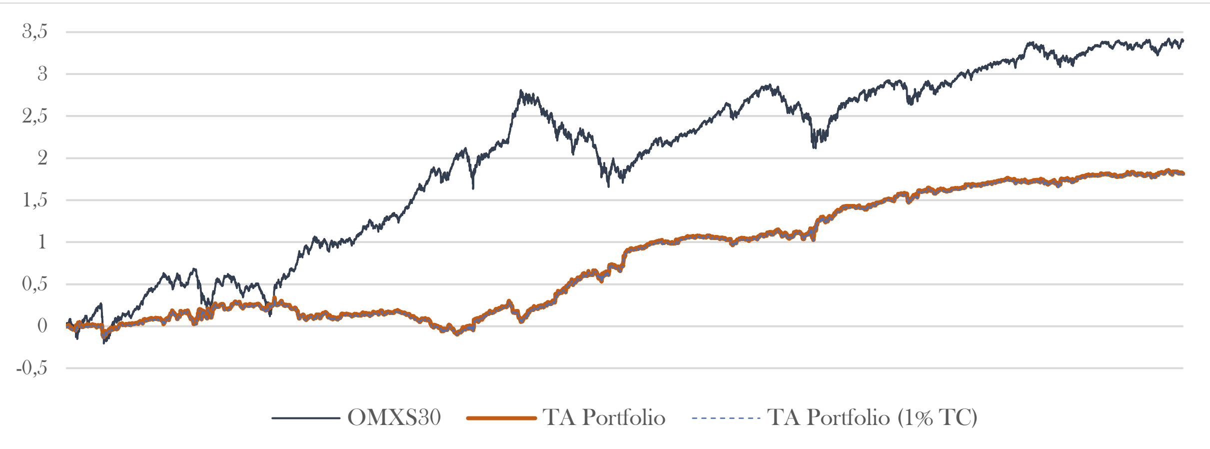


C. TA portfolio

The five best performing rules across all three technical categories are MA(1,2), BB(10,1.5,5), RSI(5,0,5) and RSI(10,5) with C_L = 30 and C_U = 80 and RSI(10,5) with C_L = 20 and C_U = 80. All five rules generated average daily returns above zero; however, none are significantly greater than the raw index itself. An equally weighted portfolio constructed of these five rules generate an average daily return of 0,02190% with a standard deviation of 0,006214. In comparison, the buy-and-hold strategy of the raw index amounts to an average daily return of 0,04101%. When the portfolio is adjusted for flat transaction costs of 0,5% and 1% per trade, the average daily return decreases to -0,49836% and -1,01862% respectively. The effects of the transaction costs on the average daily returns are considerable due to the total of 8627 trading signals this portfolio has produced in total. The development of the TA portfolio and the TA portfolio with a 1% per trade transaction cost (TC), compared to the development of the raw OMXS30 index can be seen in Figure 7. The transaction cost has been divided by the total number of trading signals from the five rules and then divided by the number of days in the sample data to achieve a continuous daily deduction. Although the raw index outperforms the TA portfolio from about 1993 and forwards, the TA portfolio shows consistent returns when the raw index is in negative trend during the millennium crisis and the 2007/08 crisis. However, there is a positive correlation of ρ_{r_i,r_r} = 0,84992 between the cumulated returns of the raw index and the TA portfolio. Although the TC has considerable effects to the average daily returns of the TA portfolio, the portfolio with TC considered is seen virtually shadowing slightly below the ordinary portfolio in Figure 7. The effect is not as visibly apparent because the flat TC has been multiplied with the number of trading signals and then split up equally amongst the days in the sample.

Figure 7. Cumulated daily returns: TA portfolio

Figure 7 shows the development of the daily returns of the raw OMXS30 index, the TA portfolio and the TA portfolio with a 1% per trade transaction cost deducted (1% TC). The comparison is made during the entirety of the data sample.



D. Monte Carlo simulation

The Monte Carlo simulation with a geometric Brownian motion have realised simulations of the raw index's price development. With the use of the mean and standard deviation of the raw OMXS30 index seen in Table 1, 1000 simulations of 10 000-day price developments have been generated. The top five performing rules displayed in the TA portfolio above have then individually been applied to the realisations. A total of 5000 technical rules have been applied on the 1000 simulations (5 per 1 simulation). The average daily return across all 5000 simulations can be seen in Table 7 below. For instance, applying the MA(1,2) rule to 1000 different simulations of the underlying index generated an average daily return of -0,00028%. The best performance is generated by the application of the RSI(5,0,5) rule, which generated an average daily return of 0,01932%. However, still shy of the buy-and-hold strategy of the raw index.

Table 7. Monte Carlo simulation: Top performing rules

Table 7 shows average daily return of the top five performing technical rules applied to the simulated indeces.

Rule	MA(1,2)	BB(10,1.5,5)	RSI(5,0,5)	RSI(10,5)	RSI(10,5)
Daily average	-0,00028%	-0,00929%	0,01932%	0,01783%	-0,01940%
				C_L = 30 and C_U = 80	C_L = 20 and C_U = 80

On only 6 occasions did the technical rules generate returns that were significantly greater than the inherit returns of the simulated indeces. In all cases, the average daily performances of the technical rules were worse in the Monte Carlo simulations than when they were when being applied to the actual raw index data. Since no continuous display of significant profitability can be identified, the result does not indicate continuity amongst the technical rules. A potential explanation for the anomalous findings of 6 significantly profitable rules may simply be the result of data snooping. Sullivan et al. (1999) describe data snooping as the possibility that suitable results are generated simply by chance rather than any inherit adequacy in the technical model. The former is at risk when a large number of technical rules are applied repeatedly at the same data set. In this study, the technical rules have been applied in the exact fashion described by Sullivan et al. (1999). The problem of data snooping has been acknowledged in previous studies and is for instance described as "immense" in Brock et al. (1992, p.1736) and as having considerable impact on identifying the number of profitable technical rules by Jiang et al. (2019). The anomalous findings of 6 rules that significantly outperform the index is not a sign of inefficiency, because data snooping cannot be ruled out. So, even after the Monte Carlo simulation, the dismissal of efficiency on the Swedish stock market is inconceivable.

V. Conclusion

The purpose of this study has been to examine weak-form efficiency on the Swedish stock market by evaluating the profitability of technical trading rules in comparison to the inherit returns of the underlying market index (OMXS30). Of the 142 variations of moving averages, relative strength index oscillators and Bollinger bands this study has examined, no rules generate average returns that are significantly greater than the buy-and-hold strategy of the raw index. In fact, 76,8% of rules significantly underperform, even when not taking transaction costs into consideration. Acknowledge Jensen's definition of an efficient market again: "A market is efficient with respect to information set θ_t, if it is impossible to make economic profits by trading on the basis of information set θ_t." (Jensen, 1978, p.3). This paper show that no technical rules based on the information OMXS30 are able to make significant profits when applied to that same the information set of OMXS30. If Jensen's definition is assumed to be adequate, then this paper cannot dismiss efficiency on the Swedish stock market.

Correspondingly, the development of the cumulated returns of the portfolio consisting of the top performing rules underperforms against the raw index's development. Evidently and undoubtedly, an inferior state of the former result is achieved when applying flat transaction costs of 0,5% and 1%. After running a Monte Carlo simulation, modelled by a geometric Brownian motion, non-dismissal of efficiency remains a valid conclusion. In 6 of 5000 cases the top performing technical rules generate significantly greater returns than the buy-and-hold returns of the simulated indeces. Although occasional profitable rules have been identified, they are, due to their anomalous and irregular nature, seemingly a result of mere data snooping bias. The topic of this paper can potentially be examined further by optimizing the efficiency of the technical trading rules by varying the governing variables through, for instance, machine learning processes. Although having been viciously researched, the topic of the efficient market hypothesis and its correspondence to technical analysis is not likely to be gratified in the near future.

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