SCHOOL OF ECONOMICS AND MANAGEMENT

Technical Analysis on the Swedish Stock Market

Evaluating the predictive ability of common technical trading rules

An Event Study Approach

Economics: Bachelor Essay, 15 credits

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Abstract

This paper investigates the predictive ability of technical trading rules (TTRs) on the Swedish stock market. Eight variations of two common TTRs—the relative strength index (RSI) and the moving average convergence/ divergence (MACD)—are applied on the constituent stocks of the OMX Stockholm 30 from January 2014 to December 2023. To evaluate forecasting ability, an event study is conducted. Abnormal returns are aggregated across stocks and across time and are tested for significance using a cross-sectional t-test. Results indicate that cumulative average abnormal returns (CAAR) are significant for some variations of the RSI and the MACD. However, since abnormal returns are inconsistent across trading signals and likely not large enough to offset transaction costs, this study cannot establish that conventional TTRs are appropriate tools to predict the future direction of the Swedish stock market.

Keywords: technical analysis, technical trading rules, Swedish stock market, event study

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1 Introduction

Technical analysis (TA) is a method used in financial markets to evaluate and predict future price movements by analyzing historical market data. It relies on the assumption that past price patterns and trends can provide valuable insights into potential future market behavior. Martin Pring (2002, p. 2), who has written several books on the subject, provides a more detailed explanation:

> The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed.

The notion that prices move in determined trends, however, directly challenges the core principles of the efficient market hypothesis (EMH), the long-dominant theory of asset price formation. Proposed by Eugene Fama in the 1960s, the EMH states that financial markets are efficient in processing and incorporating all available information into asset prices (Fama, 1970). Since this includes past market information, it should be impossible to consistently achieve above-average returns by using methods like technical analysis. Despite this, empirical research has found supporting evidence for the profitability of TA-based strategies. Studies by Lukac et al. (1988), Brock et al. (1992) and Chong and Ng (2008) found positive results when testing the ex-post performance of various technical trading strategies. Other studies, however, found that excess returns are confined to the early 1970s and mid-1980s, and that they have diminished since (Sullivan et al. 1999; Taylor 2013). This suggests that markets have become more effective following the 1990s.

Although the research on technical analysis is extensive, few studies have been conducted on the Swedish stock market. Furthermore, market conditions change, and keeping the literature updated is essential in ensuring its relevance and applicability. Thus, the purpose of this study is to test whether conventional technical trading rules (TTRs) can be used to make useful predictions on the Swedish stock market. To answer this question, eight variations of two popular TTRs—the relative strength index (RSI) and the moving average convergence/ divergence (MACD)—will be applied to the constituent stocks of the OMX Stockholm 30 from January 2014 to December 2023. To test their performance, an event study analysis will be performed, using the market model as a normal performance model and the OMXS30 index as the market proxy. Abnormal returns will be calculated separately for each individual stock and aggregated across events and across time. To test the significance of the abnormal performance, a cross-sectional t-test will be performed.

Results shows that the cumulative average abnormal returns (CAARs) are significantly different than zero for some variations of the RSI and the MACD. Results are however inconsistent between buy and sell signals, in which a rule can have significant CAARs for buy signals, but not for sell signals. Furthermore, CAARs are higher for the RSI than the MACD, although MACD is less volatile and has narrower confidence intervals. Finally, even though abnormal returns are statistically significant, they are likely not large enough to survive transaction costs. Thus, in conclusion, it cannot be stated that conventional technical trading rules can make reliable predictions on the Swedish Stock market. However, the study faces several limitations, such as not accounting for transaction costs and only evaluating a handful of rules.

The remainder of this paper is structured as follows: Section 2 makes an overview of the existing literature on EMH and TA. Section 3 discusses the TTRs, their formulas and the variations selected. Section 4 discusses the data and the event study procedure. Section 5 provides and discusses the results and Section 6 will be a brief conclusion of the study.

2 Literature Review

2.1 Efficient Market Hypothesis

In order to review the empirical research on the performance of TTRs it is important to have a basic understanding of the *efficient market hypothesis* (*EMH*), since it serves as the underlying theory on which the controversy of technical analysis rests. The EMH was popularized by Eugene Fama through his 1970 article in which he reviews the theory and empirical evidence on the efficiency of financial markets. According to his definition: “A market in which prices always ‘fully reflect’ available information is called ‘efficient’." (Fama, 1970, p. 383). To put it differently, if a financial market is efficient, asset prices quickly incorporate new information made publicly available and, in the absence of monopolistically held information (i.e. insider trading), it is impossible to systematically achieve risk-adjusted returns which are greater than that of the market average. Jensen (1978, p. 96) extended the definition of efficient markets: “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”. In other words, the market price always reflects its *fair value* at any time *t*, since all the information that is relevant in calculating the fair value available at time *t* is already incorporated in the price.

Fama also identified three levels of market efficiency, which Jensen (1978, p. 97) described with respect to information set θ_t:

(1) the *Weak Form* of the Efficient Market Hypothesis, in which the information set θ_t, is taken to be solely the information contained in the past price history of the market as of time *t*.
(2) the *Semistrong Form* of the Efficient Market Hypothesis, in which θ_t, is taken to be all information that is publicly available at time *t*. (This includes, of course, the past history of prices so the weak form is just a restricted version of this.)
(3) the *Strong Form* of the Efficient Market Hypothesis, in which θ_t is taken to be all information known to anyone at time *t*.

The weak form efficiency, also denoted as the *random walk theory*, suggests that all available market data (i.e. historical prices and volume) is already reflected in the current price, and implies that the future price is solely determined by the random emergence of new information. The semi-strong form also includes all publicly available information (e.g. financial statements and announcements), while the strong form further extends the definition to all available information, including undisclosed, privately held information. Since technical analysis relies on historical data to forecast the direction of future price movements, even at the weak form of efficiency the EMH suggests that technical analysis should not be possible.

In his review article, Fama (1970, p.416) reportedly found "extensive" evidence for the weak form of market efficiency and states that "contradictory evidence is sparse". This implies that TTRs should be fruitless in generating excess returns on the market. Nevertheless, since the article's publication, there have appeared numerous papers contesting the idea that markets are efficient, bringing attention to factors such as market anomalies and investor behavior. For instance, Lo and MacKinlay (1986) found positive serial correlation when investigating weekly returns on the American stock market, suggesting that prices do not follow a random walk as assumed in the weak form of the EMH. Another concern is raised by Shiller (1981), who argues that stock prices fluctuate more than can be justified by changes in their associated companies' fundamentals. This indicates that there exists noise that is not incorporated in the valuation process. In the 1990s, the emergence of behavioral finance led to new perspectives on the matter, challenging the idea that investors are rational decision-makers (Shiller, 2003). Common subjects were cognitive biases of individual investors and its aggregated effect on the market. For example, De Bondt and Thaler (1985) concluded that market participants tend to "overreact" when presented with important news, leading to stock prices temporarily deviating from their fundamental values before reverting to their long-term mean. Daniel and Titman (1999) came to similar conclusions, although their focus is primarily on behavioral biases caused by investor "overconfidence". Another aspect is that of herding behavior, were investors are influenced by other market participant's decisions. This can lead to an exponential effect on market volatility (Bikhchandani & Sharma, 2000). Thus, if investor sentiment systematically causes prices to overshoot and undershoot their fundamental value, betting against the market during strong trends (as suggested by some of the technical indicators reviewed in this paper) might be justified. However, despite having received a wide range of criticism over the years, the assumption that financial markets are efficient is still widely accepted in the academic literature.

2.2 Empirical Evidence on Technical Analysis

Another critique of the efficient market hypothesis is that research has found supporting evidence for the efficacy of technical analysis. Contrary to the assumptions of weak form market efficiency, technical analysis involves the manipulation of historical market data to gain insight into future price trends. Key components include trading rules, which use mathematical formulas to uncover potential entry and exit signals in the financial market. Consistent with the criticism of the EMH, technical trading strategies attempt to capture the anomalies caused by market conditions and investor sentiment in order to create arbitrage opportunities in speculative markets. Despite the aforementioned positive findings, TTRs are viewed with skepticism by many academics, who remain convinced that markets are efficient (Park & Irwin, 2007). Nevertheless, they are still popular among institutional investors (Menkhoff, 2010). To provide insight into this discussion, the following section will examine the empirical literature on the performance of technical trading strategies.

Park and Irwin (2007) made a comprehensive review of the empirical research testing the profitability of TTRs. In their survey, they identify two key periods based on the thoroughness of testing procedures: "early" studies conducted between 1960 and 1987, and "modern" studies carried out between 1988 and 2004. Early studies generally found positive results on foreign exchange markets and futures markets, while negative results on stock markets. This implies that stock markets were more efficient than forex markets or futures markets prior to the mid-1980s. However, as noted by the authors, early studies lack elements such as statistical significance tests, cross-validation, parameter-optimization, and adjustments for risk and transaction costs. Furthermore, they only account for a handful of trading rules and are prone to data snooping. While modern studies are said to have improved in this regard, the authors still observe notable differences across papers. Out of the 95 modern studies examined, the results were as follows: 56 were positive, 20 were negative, and 19 were mixed in regard to the profitability of TTRs. Although these results seem to be in favor of technical analysis, an important caveat is that modern studies only found excess profits in the stock market until the late 1980s, but not thereafter. In forex and futures markets, TTRs were profitable until the early 1990s and mid-1980s, respectively.

According to Park and Irwin (2007, p. 789), the work by Lukac et al. (1988) can be viewed as representative of the modern literature as it is the first to significantly improve upon the limitations of the early studies. In their study they test 12 technical trading systems on 12 commodity futures from 1978 to 1984. They include a parameter-optimization technique, in which the best-performing variations of each trading system during a rolling 3-year period is selected for next year's trading. Statistical inference testing is also included. Out of the 12 optimized trading systems, 7 provided significant gross returns and 4 produced significant risk-adjusted net returns.

Brock et al. (1992) further addresses the problems using t-tests to make inferences on time series data by adopting a modified bootstrap approach. Since t-tests assume normally distributed, stationary, homoscedastic and serially uncorrelated data, and stock returns tend to violate these assumptions (e.g. leptokurtosis and autocorrelation), inferences made on the conditional buy (sell) returns may be inaccurate. By resampling the original data using appropriate time series models, inferences can be made without relying on any background assumptions. In Brock et al.'s study, they test variations of moving averages and trading-range breaks on the Dow Jones Industrial Average (DIJA) index between 1897 to 1986. Out of the 26 TTRs reviewed, all showed positive (negative) conditional buy (sell) returns. As a consequence, all buy-sell differences overperformed the benchmark buy-and-hold strategy. Moreover, buy signals generally yielded higher absolute returns than sell signals, and returns following buy signals were generally less volatile than returns following sell signals. However, these results do not account for transaction costs, and drawing conclusions about the profitability of TTRs might be premature.

Sullivan et al. (1999) extend Brock et al.'s study by considering substantially more rules and performing out-of-sample tests. They use the same index and sample period as Brock et al. but include an additional ten years (1987-1996) for out-of-sample validation. They also employ a bootstrap reality check method, in which a simulation selects the best rule out of 7,846 rules based on two performance measures (mean return and Sharpe ratio). For the in-sample data, the best rule was a 5-day moving average with an annualized average return of 17.2%. When applying the same rule on the out-of-sample data, however, the annual mean return is only 2.8% and thus insignificant. The authors suggest that this might be because stock markets have become more efficient over time.

A more recent comprehensive study is made by Taylor (2013), who test 900 variants of the same trading rules examined in Brock et al. (1992). Contrary to Brock et al., Taylor uses individual stocks on the DIJA and not the index. He examines the period 1928 to 2012 and includes a tuning procedure, in which portfolios of stock positions are updated each month based on the previous net performance of TTRs. To test risk-adjusted returns, two econometric models are employed, which allow the estimation of risk to change over time. Policies on short-selling is also recorded, with the hope of providing more insight. Taylor distinguishes three important results. First, positive risk-adjusted returns are restricted to the mid-1960s to the mid-1980s, peaking in the early 1970s. Second, profits coincide with low market liquidity. Third, profits are mostly driven by the variation of returns conditional on sell signals. The last result is inconsistent with the findings by Brock et al., who reported higher excess returns following buy signals. It also implies that the profitability of TTRs is positively correlated with the ability to short-sell stocks. An explanation put forth by the author is that the prevailing market inefficiencies around the 1970s allowed for the success of TTR strategies. As these became more well known, profits were eventually driven down. This compels Taylor to title his work *The rise and fall of technical trading rule success*.

Finally, Chong and Ng (2008) investigated two of the TTR's explored in this paper: namely, the relative strength index (RSI) and the moving average convergence divergence (MACD). They test the rules on a U.K. stock market index from 1935 to 1994 and subdivide the data into three periods in order to avoid data snooping issues. For both the RSI and the MACD, the conditional buy (sell) mean returns were significantly higher (lower) than the unconditional sample mean returns. The trading rules also outperformed the reference buy-and-hold strategy. However, the authors neither account for risk nor transaction costs.

In conclusion, the empirical evidence on technical analysis remains inconclusive. Trading profits seem to vary across markets and appear to have diminished over time. Furthermore, it is unclear whether excess returns survive the presence of transaction costs. While the research conducted in this paper will not accomplish the same level of sophistication or comprehensiveness as the established literature, it will provide a relatively unexplored approach to address the issue of technical analysis. Utilizing the event study methodology, this study will attempt to assess the impact that buy (sell) signals have on stock returns.

3 Technical Trading Rules

Technical trading rules (*TTRs*) form an essential part of technical analysis. Simply put, they are mathematical formulas that use past market data to generate signals indicating whether an asset should be bought or sold. Although the literature varies on the classification of different TTRs, they are usually distinguished based on what they input (e.g. price, volume or open interest), what they measure (e.g. trend, momentum or volatility) and the underlying strategy that they follow (trend-following or counter-trend) (Murphy, 1999; Pring, 2002).

The TTRs reviewed in this paper are variations of the *relative strength index* (*RSI*) and the *moving average convergence/ divergence* (*MACD*). These are simple and intuitive trading rules that are included because they are frequently mentioned in the technical analysis literature. Moreover, they are incorporated in the online charts of some of the biggest stockbrokers in Sweden (e.g. Avanza and Nordnet). Although more sophisticated technical trading systems would improve the robustness of the study, these are difficult to obtain since they are often personalized and undisclosed. Besides, Gerritsen (2017, p.180) found that investment recommendations issued by technical analysts were closely related to the signals generated by common TTRs. Therefore, for practical reasons, this study will only address simple trading rules. The formulas and general procedures of each TTR will be discussed below.

3.1 Relative Strength Index

The *relative strength index* (*RSI*) is a counter-trend momentum indicator originally proposed by J. Wells Wilder in the late 1970's. It was first published in his book *New Concepts in Technical Trading Systems* (1978) and has since become one of the most popular indicators used in technical analysis. As the term implies, momentum indicators are concerned with the rate of change of price. If the asset price rises very rapidly, it has high, positive momentum; if the asset falls very rapidly, it has high, negative momentum. Apart from being a momentum indicator, RSI is also a counter-trend indicator. Counter-trend, or contrarian, strategies assume that financial markets tend to revert to their long-term mean after experiencing strong trends. This is supported by the assumption that market participants tend to overreact when presented with new information, causing prices to temporarily deviate from their intrinsic values (De Bondt & Thaler, 1985). Therefore, if momentum is highly positive, the asset is considered *overbought*, and its price is expected to fall. Conversely, if momentum is highly negative, the asset is considered *oversold*, and its price is expected to rise.

The formula and general procedure of calculating the RSI is described below:

$$RSI = 100 - \left[\frac{100}{1 + RS}\right] \tag{1}$$

$$RS = \frac{Average\ UP}{Average\ DOWN} \tag{2}$$

For each trading day:

(1) Calculate the difference between the current day's close and the previous day's close.
   a. An *up*-period is defined when the current day's close is higher than the previous day's close: If $P_t - P_{t-1} > 0,\ UP = |P_t - P_{t-1}|$ and $DOWN = 0$.
   b. A *down*-period is defined when the current day's close is lower than the previous day's close: If $P_t - P_{t-1} < 0, UP = 0$ and $DOWN = |P_t - P_{t-1}|$.

(2) Calculate the 14-day moving average of the *UP* and *DOWN* values. Wilder uses a modified version of a simple moving average:
   a. The first day, sum the 14 previous *UP* and *DOWN* values respectively and divide them by 14.
   b. The second day, multiply the previous (first) day's average by 13 and add the current (second) day's value. Divide the total by 14.
   c. Repeat Step b. for the following days.

(3) Calculate the *relative strength factor (RS)* as in Eq. (2).

(4) Calculate RSI as in Eq. (1).

If the rate of change is positive, the *Average UP* will be high, and the *Average DOWN* will be low, which causes the $RS > 1$ in Eq. (2) and the $RSI > 50$ in Eq. (1). The opposite is true if the rate of change is negative. By construction, the RSI ranges from 0 to 100 (see Eq. [1]). If the RSI moves above 70, a top is signified, and the asset is considered overbought. If the RSI moves below 30, a bottom is indicated, and the asset is considered oversold (Wilder, 1978, pp. 63-70).

In this paper, four variations of the RSI are considered. The standard variant proposed by Wilder uses an upper threshold (T_U) of 70, a lower threshold (T_L) of 30, and a smoothing period (n) of 14. If the thresholds are expanded, the RSI becomes less sensitive, since a higher momentum reading is needed to trigger an overbought (oversold) signal. If the smoothing period is decreased, the momentum reading becomes more volatile, and the RSI becomes more sensitive. Common adjustments include thresholds of (T_U, T_L) = (80, 20) and a smoothing period of n = 9 (Murphy 1999, pp. 239-246). Therefore, the four variations selected are combinations of the thresholds T = {(70, 30), (80, 20)} and the smoothing periods n = {14, 9}. The variation are denoted as RSI(T_U, T_L, n) and are displayed along with the conditions for the trading signals in Table 1.

Table 1 Variations of the RSI and their corresponding conditions for generating buy (sell) signals.

Variant	**Signal**
RSI(70, 30, 14)	$signal = \begin{cases} Buy, & RSI < 30 \\ Sell, & RSI > 70 \end{cases}$
RSI(70, 30, 9)	
RSI(80, 20, 14)	$signal = \begin{cases} Buy, & RSI < 20 \\ Sell, & RSI > 80 \end{cases}$
RSI(80, 20, 9)	

3.2 Moving Average Convergence/ Divergence

The *moving average convergence/ divergence (MACD)* is a momentum indicator that is defined by the difference between two exponential moving averages (EMA) of the asset price. By subtracting a longer-term EMA from a shorter-term EMA, the MACD attempts to measure the direction and strength of a trend. If the trend is quickly rising, the shorter-term EMA will rise faster than the longer-term EMA. If the trend is quickly falling, the shorter-term EMA will fall faster than the longer-term EMA. Although the standard form of the MACD is generally described as a trend-following indicator in technical analysis literature, the inventor of the MACD rule, Gerard Appel, additionally proposed an alternative version which more closely conforms to a contrarian strategy (Appel, 2005). Both variants will be discussed below.

To calculate the MACD requires two exponential moving averages of different lengths. An EMA is a type of moving average that gives more weight on recent prices. This is in contrast to a simple moving average (SMA), which puts equal weights across all entries. The formula for the EMA is shown in Eq. (3).

$$EMA_{t,n} = \left[P_t \times \left(\frac{2}{n+1}\right)\right] + EMA_{t-1,\mathrm{n}} \times \left[1 - \left(\frac{2}{n+1}\right)\right] \quad (3)$$

The multiplier $(\frac{2}{n+1})$ consists of the smoothing factor (s = 2) and the EMA-period (n) and is what gives recent prices higher weighting. The weighting is higher for short-term EMAs than long-term EMAs, since there is a negative relationship between the length of the EMA-period and the multiplier. In order to obtain the first observation of the EMA, an n-period SMA is used.

Appel originally used periods of 12 and 26 for the short and long EMA, respectively. According to Murphy(1999, p. 253) this is the most common setting for the MACD. To calculate the *MACD* (also called the *MACD-line* to avoid confusion with the MACD strategy), the 26-period EMA is subtracted from the 12-period EMA (see Eq. [4]). Moreover, a 9-period EMA of the MACD-line, called the *signal-line*, is also calculated. The signal-line serves as a further smoothening of the MACD rule, which intends to make it less sensitive to noise.

$$MACD_{t,12,26} = EMA_{t,12} - EMA_{t,26} \quad (4)$$

In the standard variant of the MACD, a buy signal is produced when the (faster) MACD-line crosses the (slower) signal-line from below, and a sell signal is produced when the MACD-line crossed the signal-line from above. This adheres to a trend-following strategy since the trading signals are positively related to the direction of the market trend. However, Appel (2005, p. 170) also introduces an additional condition to the MACD, in which a buy (sell) signal also requires the MACD-line to be below (above) the zero-line. This is justified by the assumption that a highly negative (positive) MACD-line indicates a market bottom (top), and in alignment with the overreaction hypothesis (De Bondt & Thaler, 1985), a trend reversal is expected. Thus, Appel argues that the best buy signals are produced when the MACD-line crosses the signal-line from below and the MACD-line is negative. Conversely, the best sell signals are generated when the MACD-line crosses the signal-line from above and the MACD-line is positive.

Accordingly, both the standard and the adjusted versions of the MACD will be reviewed in this paper. Additionally, two sets of varying parameters will be considered. This generates four MACD rules in total, which will be denoted MACD-I(n_S, n_L, n_{Sig}) for the standard variant and MACD-II(n_S, n_L, n_{Sig}) for the adjusted variant. Here, n_S, n_L and n_{Sig} stands for the periods of the short-term EMA, the long-term EMA and the signal-line, respectively. The two sets of parameters are n = {(12, 26, 9), (19, 39, 9)}. To simplify the conditional formulas of the trading signals, the cross-overs of the MACD are expressed in Eq. (5).

$$\mathrm{C} = \begin{cases} C_{Above}, & [MACD_{\boldsymbol{t-1},nS,nL} > SigLin_{\boldsymbol{t-1},nSig}] \; AND \; [MACD_{\boldsymbol{t},nS,nL} < SigLin_{\boldsymbol{t},nSig}] \\ C_{Below}, & [MACD_{\boldsymbol{t-1},nS,nL} < SigLin_{\boldsymbol{t-1},nSig}] \; AND \; [MACD_{\boldsymbol{t},nS,nL} > SigLin_{\boldsymbol{t},nSig}] \end{cases} \tag{5}$$

This says that if the MACD-line is greater than the signal-line in the previous period, and smaller than the signal-line in the current period, an above crossing (C_{Above}) has occurred. The opposite is true for a below crossing (C_{Below}). All MACD variations are summarized in Table 2.

Table 2 Variations of the MACD and their corresponding conditions for generating buy (sell) signals.

Variant	Signal
MACD-I(12, 26, 9) MACD-I(19, 39, 9)	$signal = \begin{cases} Buy, & C = C_{Below} \\ Sell, & C = C_{Above} \end{cases}$
MACD-II(12, 26, 9) MACD-II(19, 39, 9)	$signal = \begin{cases} Buy, & C = C_{Below} \; AND \; [MACD_{\boldsymbol{t}} < 0] \\ Sell, & C = C_{Above} \; AND \; [MACD_{\boldsymbol{t}} > 0] \end{cases}$

4 Data and Methodology

4.1 Data

The data used for this study is the daily adjusted closing prices of the OMX Stockholm 30 (OMXS30) index and its constituent stocks. The OMXS30 is a capitalization-weighted stock market index containing the 30 most traded stocks in the Stockholm

Stock Exchange. The series spans a 10-year period from January 2014 to December 2023. Prices are adjusted for splits, dividends and capital gain distributions, which are retrieved from the Nasdaq Nordic database. The index is plotted in Figure 1, highlighting notable periods such as the upturn in 2015, the downturn in 2020 caused by the COVID-19 pandemic and the subsequent upward trend. The long-term trend of the OMXS30 is positive.

Figure 1. Plot of the adjusted closing index values of OMXS30 from 2014-01-02 to 2023-12-29.

The returns for the index and stocks are calculated using the log differences between the current period's price and the previous period's price. The formula is shown in Eq.(6).

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{6}$$

Summary statistics of the daily returns for OMXS30 are shown in Table 3. The standard deviation is 1.15%, with a minimum of -11.17% and a maximum of 6.85%.

The distribution of the returns is negatively skewed (-0.6615), indicating that highly negative returns are more common than highly positive returns. This is also shown by the minimum and maximum values, where the minimum value is almost twice the size of the maximum value. Since the overall trend of the OMXS30 is positive, this suggests large, but more occasional negative price movements, and small, but more frequent positive price movements. Moreover, the distribution of returns are leptokurtic (kurtosis > 3), implying that the returns are more concentrated around the mean (≈ 0). This is to be expected of security returns. The correlation coefficient $\varrho(i)$ shows the estimated autocorrelation at lag i, ranging from 1 to 5 days. The short-term autocorrelation is relatively small, with the most deviating value being at -0.0552 for lag 1, indicating that returns are marginally negatively correlated with the returns of the previous trading day.

Table 3 shows the summary statistics of the stock returns for each constituent stock of the OMXS30. The cross-sectional average of all statistics is listed at the bottom. Since the composition of OMXS30 is updated twice per year, some of the stocks are listed at a later period than the beginning of the sample period. Thus Essity, Evolution, SBB and Sinch have fewer observations than the OMXS30. In total, the sample size for all 30 stocks of the OMXS30 is 73 383. Among all stocks, SBB, Evolution and Sinch are the most volatile, which could be explained by the fact that the period after they got listed was more uncertain as seen in Figure 1. The average skewness and kurtosis have the same sign as for the OMXS30, although kurtosis is higher (12.9588), which suggest that more extreme returns occur for the individual stocks than the weighted index. This is particularly evident for Kinvik, with a kurtosis of 116.6.

Table 3 Descriptive statistics for daily returns of the OMXS30. N is the number of observations and $\varrho(i)$ is the estimated autocorrelation at lag i.

Index	*N*	*Mean*	*SD*	*Min*	*Max*	*Skew*	*Kurt*	*ρ(1)*	*ρ(2)*	*ρ(3)*	*ρ(4)*	*ρ(5)*
OMXS30	2507	0.0002	0.0115	-0.1117	0.0685	-0.6615	6.7899	-0.0552	-0.0131	0.0292	-0.0008	-0.0144

Table 4 Descriptive statistics for daily returns of each constituent stock of the OMXS30. *N* is the number of observations and ϱ(*i*) is the estimated autocorrelation at lag *i* for each stock return series. The cross-sectional average of all stocks is shown in the last row.

Stock	*N*	*Mean*	*SD*	*Min*	*Max*	*Skew*	*Kurt*	*ρ(1)*	*ρ(2)*	*ρ(3)*	*ρ(4)*	*ρ(5)*
ABB	2507	0.0004	0.0137	-0.1116	0.0897	-0.4793	5.1745	0.0153	-0.0089	0.0153	-0.0052	0.0282
ALFA	2507	0.0004	0.0181	-0.1267	0.1177	-0.2734	6.4219	-0.0369	-0.0175	-0.0175	-0.0270	0.0006
ALIV SDB	2507	0.0003	0.0201	-0.3098	0.1532	-1.5605	27.2828	0.0114	0.0009	-0.0195	0.0154	0.0165
ASSA B	2507	0.0004	0.0154	-0.1027	0.0800	-0.2851	3.3529	-0.0482	-0.0328	0.0295	-0.0045	-0.0554
ATCO A	2507	0.0008	0.0179	-0.1043	0.1350	0.0740	4.2230	-0.0633	-0.0381	0.0160	-0.0112	-0.0234
ATCO B	2507	0.0008	0.0180	-0.1008	0.1206	0.0359	3.5164	-0.0613	-0.0444	0.0234	0.0002	-0.0400
AZN	2507	0.0005	0.0154	-0.1633	0.1235	-0.3838	10.3798	-0.0227	-0.0206	0.0183	-0.0013	-0.0131
BOL	2507	0.0006	0.0225	-0.1799	0.1213	-0.6269	7.0477	-0.0358	-0.0356	0.0446	-0.0264	0.0003
ELUX B	2507	0.0000	0.0203	-0.2269	0.1442	-1.2684	16.2832	0.0103	0.0047	0.0157	-0.0022	0.0157
ERIC B	2507	0.0000	0.0200	-0.2258	0.1612	-1.4949	18.1734	-0.0050	-0.0225	0.0231	-0.0051	-0.0202
ESSITY B	1642	0.0001	0.0143	-0.0899	0.1329	0.3632	9.2294	-0.0835	-0.0031	-0.0135	-0.0136	-0.0071
EVO	2204	0.0019	0.0283	-0.1742	0.2431	0.4929	9.5452	0.0084	0.0400	-0.0063	-0.0355	0.0164
GETI B	2507	0.0002	0.0222	-0.2414	0.1729	-1.5118	20.2679	-0.0132	0.0228	-0.0200	-0.0264	0.0114
HEXA B	2507	0.0006	0.0181	-0.1259	0.1044	-0.1299	5.3786	-0.0320	-0.0182	0.0010	-0.0133	-0.0011
HM B	2507	0.0000	0.0205	-0.1390	0.1670	0.3168	9.9596	0.0002	-0.0302	0.0228	0.0291	-0.0172
INVE B	2507	0.0007	0.0136	-0.1238	0.0915	-0.4825	5.3485	-0.0351	0.0011	0.0223	0.0107	-0.0120
KINV B	2507	-0.0003	0.0243	-0.5587	0.1591	-5.3971	116.5977	-0.0303	0.0092	-0.0268	-0.0048	-0.0134
NDA SE	2507	0.0002	0.0161	-0.1381	0.0842	-0.7878	6.7793	0.0299	-0.0136	0.0209	-0.0027	-0.0048
NIBE B	2507	0.0009	0.0204	-0.1489	0.1316	-0.1000	5.1721	-0.0041	0.0349	0.0079	0.0199	-0.0153
SAND	2507	0.0005	0.0184	-0.1149	0.1031	-0.1403	2.8956	-0.0406	-0.0233	0.0209	-0.0057	0.0001
SBB B	2290	0.0002	0.0384	-0.3343	0.4272	0.0765	15.1471	-0.0135	-0.0173	-0.0148	0.0677	-0.0081
SCA B	2507	0.0008	0.0166	-0.0985	0.1147	0.3694	5.1541	-0.0422	-0.0060	0.0165	0.0017	-0.0172
SEB A	2507	0.0004	0.0161	-0.1496	0.1474	-0.5491	11.3733	-0.0294	-0.0069	0.0025	0.0211	0.0136
SHB A	2507	0.0002	0.0154	-0.1283	0.0872	-0.5549	6.6452	-0.0119	0.0005	-0.0130	0.0065	-0.0192
SINCH	2065	0.0009	0.0377	-0.3220	0.3218	-0.0452	11.4865	0.0075	0.0024	0.0397	-0.0143	0.0133
SKF B	2507	0.0002	0.0186	-0.1270	0.1096	-0.2966	3.6345	-0.0193	-0.0105	-0.0120	-0.0110	0.0058
SWED A	2507	0.0003	0.0160	-0.1507	0.0974	-1.4236	12.3158	0.0169	-0.0172	0.0144	0.0027	-0.0161
TEL2 B	2507	0.0004	0.0151	-0.1192	0.1260	-0.3859	9.6925	-0.0257	0.0262	-0.0094	-0.0319	-0.0330
TELIA	2507	0.0000	0.0129	-0.1368	0.1100	-0.6080	13.7874	-0.0590	-0.0108	0.0004	-0.0097	-0.0378
VOLV B	2507	0.0006	0.0175	-0.1570	0.1399	-0.1500	6.4980	-0.0165	0.0167	0.0047	-0.0077	-0.0308
Average	***2446.1***	**0.0004**	**0.0194**	**-0.1743**	**0.1439**	**-0.5736**	**12.9588**	**-0.0210**	**-0.0073**	**0.0069**	**-0.0028**	**-0.0088**

4.2 Methodology

An event study approach is adopted to measure the information value of the trading signals emitted by each rule. An event study is a statistical analysis method used to assess the impact of a specific *event* on the value of a financial asset or market. It involves examining the *abnormal returns* (deviations from *expected returns*) of the asset or market around the time of the event. The goal is to determine whether the event had a significant and measurable effect on the financial variables being studied. For this study, the event will be defined as the trading signals generated by each TTR, and the expected returns will be estimated using the *market model* with the OMXS30 index as the market proxy. The abnormal returns will be aggregated across all events and stocks, and a cross-sectional t-test will be conducted to assess their significance. The event study procedure employed in this paper is primarily based on the methodology proposed by MacKinlay (1997).

4.2.1 Event Study Methodology

In an event study, an event refers to a specific occurrence that is believed to have a significant impact on the value of the assets in the financial market. To quantify the potential impact associated with the event, abnormal returns must be estimated. Abnormal returns are defined as the difference between actual returns and expected returns (see Eq.[7]).

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t) \tag{7}$$

Here, $AR_{i,\tau}$, $R_{i,\tau}$, and $E(R_{i,\tau} \mid X_\tau)$ are the abnormal returns, the actual returns and the expected returns, respectively.

Various models exist to estimate the expected returns, adhering to different theoretical frameworks and exhibiting varying levels of sophistication. The one applied in this study will be *OLS market model*. The OLS market model, also known simply as the market model, uses a simple linear regression between past stock returns and past market returns to estimate the expected returns of a given security (see Eq.[8] and Eq.[9]) .

$$\begin{gathered} R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \\ E(\varepsilon_{i,t}) = 0 \\ var(\varepsilon_{i,t}) = \sigma^2_{\varepsilon_i} \end{gathered} \tag{8}$$

$$E(R_{i,t}|R_{m,t}) = \alpha_i + \beta_i R_{m,t} \tag{9}$$

Here, $R_{i,t}$ and $R_{m,t}$ are the individual security and market returns at time t. $\varepsilon_{i,t}$ is the error term, which under the exogeneity assumption is expected to be zero. α_i, β_i, and $\sigma^2_{\varepsilon i}$ are the parameters of the linear regression model and are estimated using ordinary least squares (OLS). Although more complicated normal performance models exists (e.g. multifactor models or economic models), MacKinlay mentions that they only provide limited improvements compared to the market model (1997, p.18-19).

There are two main timeframes over which the event study analysis is performed: the *event window* and the *estimation window*. The event window is the time period surrounding the event day, and it is during this window that the abnormal returns are examined. Although the length of the event window depends on the characteristics of the event being studied, usually it includes an interval before and an interval after the event day. The *estimation window* is the period during which the parameters for the market model are estimated and is defined as the time span leading up to the event window. The estimated parameters are then used to calculate the abnormal returns in the event window. Together, the estimation window and the event window constitute the *observation window*. If time is denoted as τ in the observation window, the event day occurs at time τ = 0, the estimation window spans from $\tau = T_0$ to $\tau = T_1$ and the event window ranges from $\tau = T_1$ to $\tau = T_2$. Moreover, the length of the estimation window and the length of the event window are denoted as $L_1 = T_1 - T_0$ and $L_2 = T_2 - T_1$, respectively (see Figure 2.).

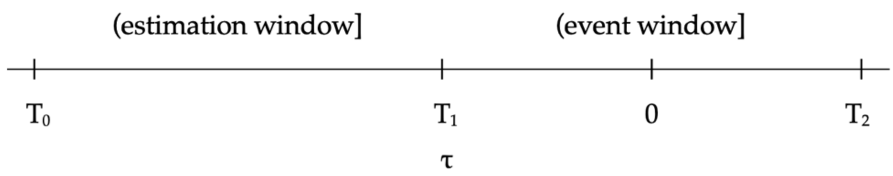

Figure 2. Timeline for the event study

To calculate the abnormal returns at time τ using the market model, the expected return retrieved from the estimated parameters of the linear regression is subtracted from the actual returns:

$$AR_{i,\tau} = R_{i,\tau} - \alpha_i - \beta_i R_{m,\tau} \tag{10}$$

Examining the formula provided in Eq. (10), it becomes evident that the abnormal returns for each day τ are simply the residuals of the linear regression, but on an out-of-sample basis. The variance of the abnormal returns is thus the same as the variance of the error term in Eq.(8), plus a disturbance component that accounts for sampling error (see Eq.[11]).

$$var(AR_{i,\tau}) = \sigma^2_{\varepsilon_i} + \frac{1}{L_1}\left[1 + \frac{(R_{m,\tau} - \mu_m)^2}{\sigma^2_m}\right] \tag{11}$$

If the length of the estimation window (L_1) is long enough, the disturbance component approaches zero and the variance of the abnormal returns ($var[AR_{i,\tau}]$) approaches the variance of the error term ($\sigma^2_{\varepsilon\iota}$).

To evaluate the impact that the event has on the broader market, the ARs must be aggregated across securities and across time. To aggregate the ARs across securities for each event period in the event window ($\tau = T_1 + 1, \ldots, T_2$) the average abnormal return (AAR) is calculated:

$$AAR_\tau = \sum_{\iota=1}^{N} AR_{i,\tau} \tag{12}$$

N stands for the number of securities examined. If the there are multiple occurrences of the event per security, N, is instead the number of occurrences across all securities. If L_1 is large, the variance of the AAR is:

$$var(AAR_\tau) = \frac{1}{N^2}\sum_{\iota=1}^{N} \sigma^2_{\varepsilon_i} \tag{13}$$

To aggregate the AARs across the event window, the average cumulative abnormal return (CAAR) is calculated as:

$$CAAR(\tau_1, \tau_2) = \sum_{\tau=1}^{2} AAR_\tau \tag{14}$$

If τ_1 and τ_2 are two subsequent periods inside the span of event window, the CAAR is simply the cumulative sums of the AARs from period τ_1 to τ_2. The variance of the CAAR is then:

$$var(CAAR[\tau_1, \tau_2]) = \sum_{\tau=1}^{2} var(AAR_\tau) \tag{15}$$

To test if the CAAR is statistically significant, a cross-sectional t-test is performed. The null hypothesis states that CAAR from period τ_1 to period τ_2 is not significantly different from zero:

$$\begin{aligned} H_0&: CAAR(\tau_1, \tau_2) = 0 \\ H_1&: CAAR(\tau_1, \tau_2) \neq 0 \end{aligned} \tag{16}$$

The test statistic to test the null hypothesis is:

$$\theta_1 = \frac{CAAR(\tau_1, \tau_2)}{\sqrt{var(CAAR[\tau_1, \tau_2])}} \tag{17}$$

There are two main assumptions associated with the t-test. The first is that raw asset returns are assumed to be jointly multivariate normal. The second is that they are independently and identically distributed. Typically, asset returns tend to violate these assumptions due to the presence of leptokurtosis and autocorrelation (Brock et al., 1992). Nevertheless, MacKinlay (1999, p. 17) asserts that t-tests remain robust in the face of such violations. Another problem associated with performing t-tests on ARs aggregated across securities is that of clustering. Clustering refers to the events of the different securities occurring closely in time. This poses a problem since it might cause dependencies across the included security's returns, making inferences unreliable (Kothari & Warner, 2004).

4.2.2 Specifications

As mentioned earlier, the events studied in this paper will be the buy (sell) signals generated by each variation of the RSI and the MACD. The conditional formulas of each rule are summarized in Table 5. The *event day* will be defined as the date the signals are emitted. However, since closing prices are used as the underlying data, the potential impact of each trading signal is not expected to be observed until the day after the signal is generated. Moreover, as TTRs often generate signals clustered in time, an additional selection criterion will be applied to avoid overlapping event windows. This criterion specifies that a buy(sell) signal will be coded as an event only if no other signal has been generated in the last L_2 trading days.

Table 5 The variations of the RSI and MACD, and their corresponding conditions for generating buy (sell) signals.

Variant	Signal
RSI(70, 30, 14)	$signal = \begin{cases} Buy, & RSI < 30 \\ Sell, & RSI > 70 \end{cases}$
RSI(70, 30, 9)	
RSI(80, 20, 14)	$signal = \begin{cases} Buy, & RSI < 20 \\ Sell, & RSI > 80 \end{cases}$
RSI(80, 20, 9)	
MACD-I(12, 26, 9)	$signal = \begin{cases} Buy, & C = C_{Below} \\ Sell, & C = C_{Above} \end{cases}$
MACD-I(19, 39, 9)	
MACD-II(12, 26, 9)	$signal = \begin{cases} Buy, & C = C_{Below}\ AND\ [MACD_t < 0] \\ Sell, & C = C_{Above}\ AND\ [MACD_t > 0] \end{cases}$
MACD-II(19, 39, 9)	

Next, the window parameters will be specified. For the estimation window, MacKinlay (1999) suggest approximately 120 days prior to the event. Thus, the estimation window in this study will be of length L_1 = 150 days. This is enough to minimize the disturbance component of Eq.(11). The event window will span L_2 = 14 days. This includes 3 pre-event days and 10 post-event days. The advantage of using a short event window is that it reduces the biases caused by event clustering (Cowan & Sergeant, 2001). Furthermore, a shorter event window also leads to fewer events being filtered out by the criterion that ignores overlapping trading signals (described above). In contrast, the disadvantage of short event windows is that the analysis becomes limited to a short-term horizon. The complete observation window is illustrated in Figure 3.

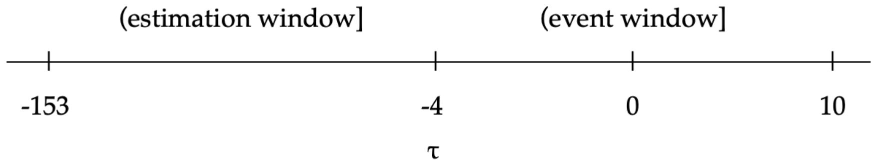

Figure 3. Timeline for the event study including the specified window parameters

The event study analysis will be conducted separately for each constituent stock of the OMXS30 and then the abnormal returns will be aggregated. For each event of a given security, the T_0 = -154 to T_1 = -4 days prior to the event will be used to estimate the parameters of the market model. As mentioned earlier, the OMXS30 index returns will be used as the representation of market returns (R_m) in the market model, and the returns of each constituent stock as R_i. The returns are calculated according to Eq.(6). The abnormal returns that result from the market model will be grouped by the sign of the signal (i.e. either buy or sell), and then averaged across securities by event period τ = -3, …,10 as in Eq.(12). Then the CAAR will be calculated using Eq.(14) and be tested for significance using Eq.(17). The CAARs will be calculated for five different intervals of the event window: [-3, 10], [-3, 0], [1, 3], [1, 6] and [1, 10].

4.3 Limitations

There are some notable limitations of the study which could affect the importance of the results. First, prices are not adjusted for transaction costs following buy and sell and which restricts the discussion of the TTRs' profitability. The scope of the research will therefore be limited to only assess the general direction of excess returns following buy and sell signals. The second limitation is that only eight rules are tested. Optimally, more rules should be tested to make justifiable conclusions about the effectiveness of TTRs. Parameter-optimization techniques used by Lukac (1988), Brock et al. (1992) and Sullivan et al. (1999) are recommended. The final limitation that will be mentioned is that the test statistic is not adjusted to account for non-normal and possibly autocorrelated data. Although MacKinlay (1997) assures that the t-test is robust to violations, and that errors from miscalculating the risk is likely to be small for short-horizon tests (Korthari & Warner, 2004), Brown and Warner (1985) found that adjustment to the residual variance ($\sigma^2_{\varepsilon\iota}$) did improve the accuracy of estimating abnormal returns.

5 Empirical Results

This section presents the results associated with each TTR. Section 5.1 contains the results for the relative strength index (RSI), and Section 5.2 presents the results for the moving average convergence/divergence (MACD).

5.1 Relative Strength Index

Table 6 shows the distribution of the trading signals associated with each variant of the RSI. First, it is evident that sell signals occur more frequently than buy signals for all variations of the RSI. This is slightly surprising, considering that RSI generates sell signals when prices rise very fast, and the overall skewness of each stock is negative (see Table 4). However, since the overall trend of the market is positive, this distribution could be explained by the fact that positive returns occur more frequently than negative returns and that the sell signals require large, but not extreme, movements in price to be triggered. Second, the RSI rule that produced the most signals is RSI(70,30,9) and the rule that generated the fewest signals is RSI(80,20,14). This is expected, because the wider thresholds and the longer smoothing period of RSI(80,20,14) makes it less sensitive to price movements. The opposite is true for RSI(70,30,9). Comparing the number of conditional observations to the total sample size of 73 383, the percentage of trading signals to the total number of trading days ranges between 0.28% to 2.13%.

Table 6 Number of buy (sell) signals generated by each variant of the RSI. Relative frequency is shown in parenthesis.

Signal	**RSI(70,30,14)**	**RSI(70,30,9)**	**RSI(80,20,14)**	**RSI(80,20,9)**
Buy	412 (37.8%)	662 (42.3%)	73 (35.1%)	284 (37.1%)
Sell	679 (62.2%)	904 (57.7%)	135 (64.9%)	481 (62.9%)
Total	1091 (100.0%)	1566 (100.0%)	208 (100.0%)	765 (100.0%)

The results of the analysis for the CAARs is presented in Table 7. The intervals [1, 3], [1, 6] and [1, 10] denote different spans of the post-event window (i.e. after event day

0), while [-3, 0] denotes the pre-event window and [-3, 10] the full event window. Additionally, the CAAR for each variant are plotted in Figure 4, and the AARs for the full event window are plotted in Table 10 in the Appendix.

Table 7 Cumulative average abnormal returns (CAAR) conditioned on RSI buy (sell) signals for different time intervals. Note that ***, ** and * denote significance levels 0.1%, 1% and 5%, respectively, for the test statistic.

	RSI(70,30,14)		**RSI(70,30,9)**		**RSI(80,20,14)**		**RSI(80,20,9)**	
Period	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**
[1, 3]	0.19% (1.29)	-0.18% (-1.68)	0.12% (1.09)	0.08% (0.86)	1.31%*** (3.94)	-0.51%* (-2.01)	0.10% (0.57)	-0.27%* (-2.13)
[1, 6]	0.22% (1.08)	-0.43%** (-2.86)	0.10% (0.62)	-0.09% (-0.68)	1.67%*** (3.56)	-1.02%** (-2.86)	0.37% (1.49)	-0.57%** (-3.14)
[1, 10]	0.40% (1.52)	-0.42%* (-2.2)	-0.09% (-0.45)	-0.04% (-0.23)	1.96%** (3.24)	-1.11%* (-2.41)	0.23% (0.72)	-0.55%* (-2.36)
[-3, 0]	-4.87%*** (-29.18)	4.13%*** (33.92)	-3.54%*** (-28.22)	3.40%*** (33.08)	-8.79%*** (-22.96)	6.19%*** (21.29)	-5.64%*** (-27.83)	4.67%*** (31.47)
[-3, 10]	-4.47%*** (-14.31)	3.71%*** (16.27)	-3.63%*** (-15.46)	3.36%*** (17.49)	-6.83%*** (-9.53)	5.09%*** (9.34)	-5.41%*** (-14.27)	4.12%*** (14.83)

First, the abnormal returns show high momentum leading up to the post-event window (in the interval [-3, 0]), and diminishes after the event day (in the interval [1, 10]). This is seen both in the CAARs in Figure 4 and in Table 10 in the Appendix. Furthermore, the trends before the post-event window are negative for the buy signals and positive for the buy signals. This causes the CAARs to be highly significant for the pre-event window [-3,0] and thus for the full event window [-3, 10], albeit with the "wrong" sign (see Table 7). Second, sell signals generally perform better than the buy signals in the post-event window. Out of all 4 RSI rules being tested, 3 out of the 4 RSI rules show significant CAARs associated with sell signals, while only 1 out of the 4 RSI rules show significant CAARs for the buy signals. Sell signals are also followed by CAARs with "correct" (negative) signs. This could imply that markets tend to reverse slightly faster in short-term rising markets than in short-term falling markets. Third, the best performing RSI rule is the RSI(80,20,14), which is the only rule to have significant CAARs for both buy and sell signals. Buy signals are also followed by highly significant CAARs for this rule. While this rule does produce highly significant results, it has only produced 208 signals out of the 73 383 trading days in the sample. It does however raise the question whether higher thresholds for oversold conditions should be employed, since it is the only rule that produces significant CAARs for buy signals. Fourth, the interval for which the CAARs are most significant is [1,6], i.e. six days after the event day. After the sixth day, the CAARs loose significance for all rules.

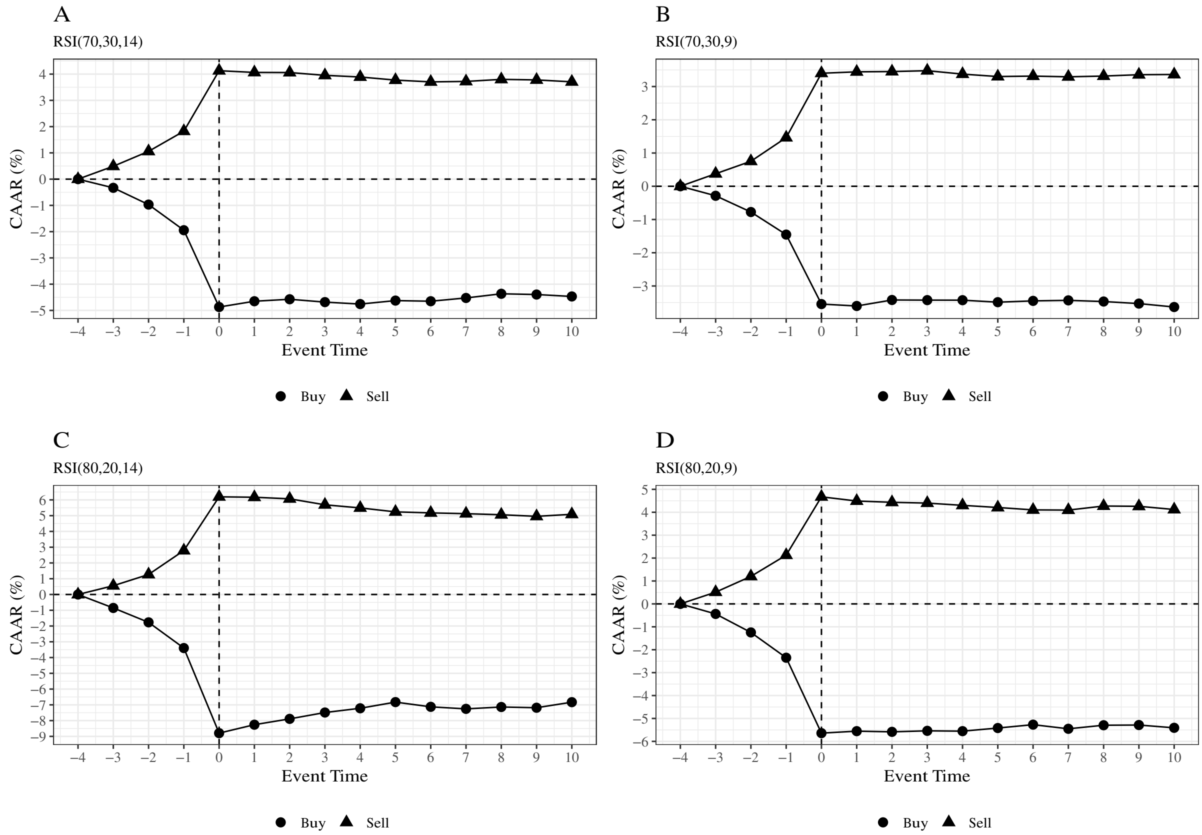

Figure 4. Plot of cumulative average abnormal returns (CAAR) for RSI from event day -3 to 10. Panel A and Panel B shows RSI with the thresholds of 70 and 30, and with a 14 and 9-period moving average, respectively. Panel C and Panel D shows RSI with the thresholds of 80 and 20.

The overall interpretation of the results is that, overall, RSI seems to do an adequate job of identifying weakening trends for both buy and sell signals. This is apparent in Figure 4, where there seems to be an abrupt flattening in the abnormal returns. It also appears to predict short-lived trend reversals for sell signals. However, comparing the slight negative CAARs after the sell signals, to the highly negative CAARs leading up to the buy signals, suggests that RSI fails to capture the largest price movements. Furthermore, it is not certain whether the positive returns resulting from a short position will survive transaction costs. Significant CAARs in the full post-event window [1,10] range from -0.42% to 1.11%. This study does not adjust for transaction costs, which would be meaningful. Thus, in conclusion, the RSI might have some predictive ability in the short run, but results are probably not economically significant. Also, RSI appears to perform better in rising markets, than in falling.

5.2 Moving Average Convergence/ Divergence

Table 9 shows the number of trading signals generated by each MACD rule. Compared to the RSI, the generation of buy (sell) signals by the MACD is more evenly distributed. However, the adjusted variant of MACD (MACD-II) generates slightly more sell signals than buy signals compared to the standard version (MACD I). This could be due to the fact that the MACD-II has the characteristics of a contrarian strategy, and that positive returns are more common than negative returns. The MACD rules also produces more trading signals than the RSI and there isn't as much variation across rules on the number of signals produced. Compared to the full sample, the ratio of signals emitted to the number of observations ranges from 2.8% for MACD-I(19,39,9) to 3.3% for MACD-II(12,26,9).

Table 8 Number of buy (sell) signals generated by each variant of the MACD. Relative frequency is shown in parenthesis.

Signal	**MACD-I(12,26,9)**	**MACD-I(19,39,9)**	**MACD-II(12,26,9)**	**MACD-II(19,39,9)**
Buy	1088 (51.0%)	1044 (51.3%)	1063 (44.0%)	905 (43.3%)
Sell	1045 (49.0%)	992 (48.7%)	1355 (56.0%)	1184 (56.7%)
Total	2133 (100.0%)	2036 (100.0%)	2418 (100.0%)	2089 (100.0%)

In Table 9 are the CAARs for each MACD rule, and for each trading signal and event window interval. In Figure 5 are the plots of the CAARs for the full event-window. In Table 11 in the Appendix are the AARs for each rule.

Table 9 Cumulative average abnormal returns (CAAR) conditioned on MACD buy (sell) signals for different time intervals. Note that ***, ** and * denote significance levels 0.1%, 1% and 5%, respectively, for the test statistic.

	MACD-I(12,26,9)		**MACD-I(19,39,9)**		**MACD-II(12,26,9)**		**MACD-II(19,39,9)**	
Period	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**
[1, 3]	0.05% (0.56)	0.08% (0.92)	0.05% (0.52)	-0.03% (-0.35)	0.19%* (2.17)	-0.08% (-1.13)	0.20%* (2.12)	-0.13% (-1.72)
[1, 6]	0.10% (0.82)	0.19% (1.54)	0.02% (0.14)	-0.08% (-0.63)	0.34%** (2.74)	-0.08% (-0.74)	0.24% (1.76)	-0.27%* (-2.43)
[1, 10]	0.07% (0.45)	-0.13% (-0.80)	-0.07% (-0.43)	-0.21% (-1.33)	0.45%** (2.83)	-0.34%* (-2.55)	0.35%* (2.02)	-0.50%*** (-3.55)
[-3, 0]	1.87%*** (19.2)	-2.01%*** (-19.78)	1.94%*** (19.50)	-2.17%*** (-21.25)	1.79%*** (17.64)	-1.85%*** (-21.63)	1.82%*** (16.4)	-2.14%*** (-23.91)
[-3, 10]	1.94%*** (10.65)	-2.13%*** (-11.25)	1.87%*** (10.06)	-2.38%*** (-12.48)	2.24%*** (11.82)	-2.19%*** (-13.71)	2.17%*** (10.47)	-2.64%*** (-15.78)

First, abnormal returns increase (decrease) exponentially before a buy (sell) signal and plateaus after the event day. This is opposite to the RSI, where trends are positive before a sell signal and negative before a buy signal and could be explained that the MACD in essence is a trend-following indicator. Even the counter-trend-inspired, adjusted MACD rule (MACD-II) follows this pattern, which is probably because the MACD-line is only required be either negative or positive and is not bound by any thresholds like the RSI (see Table 5). This indicates that trends do not always persist after the MACD rules issue a signal. This is also evident when comparing the pre-event CAARs [-3,0] to the 3-day post-event CAARs [1,3] in Table 9. Second, when comparing the different variants of the MACD, the adjusted MACD-II performs better than the standard MACD variant. The CAARs of the standard variant is not significant for either buy or sell signals in the post-event window. In the standard variant with 12-period and 26-period EMAs, CAARs are even positive after sell signals. Of the adjusted MACD rules, the MACD-II with 12-period and 26-period EMAs have higher CAARs following buy signals, while the longer-horizon MACD-II, with 19-period and 39-period EMAs have higher CAARs following sell signals. The third important result is that CAARs that are significant for the MACD rules are lower compared to the CAARs significant for the RSI rules for the same time interval. This suggests that the variance of the CAARs are smaller for MACD than for RSI, which in turn indicates that markets are more stable preceding signals emitted by MACD. Third, abnormal returns following trading signals generated by the MACD are less volatile than abnormal returns following trading signals emitted by the RSI (see Table 11 in the Appendix).

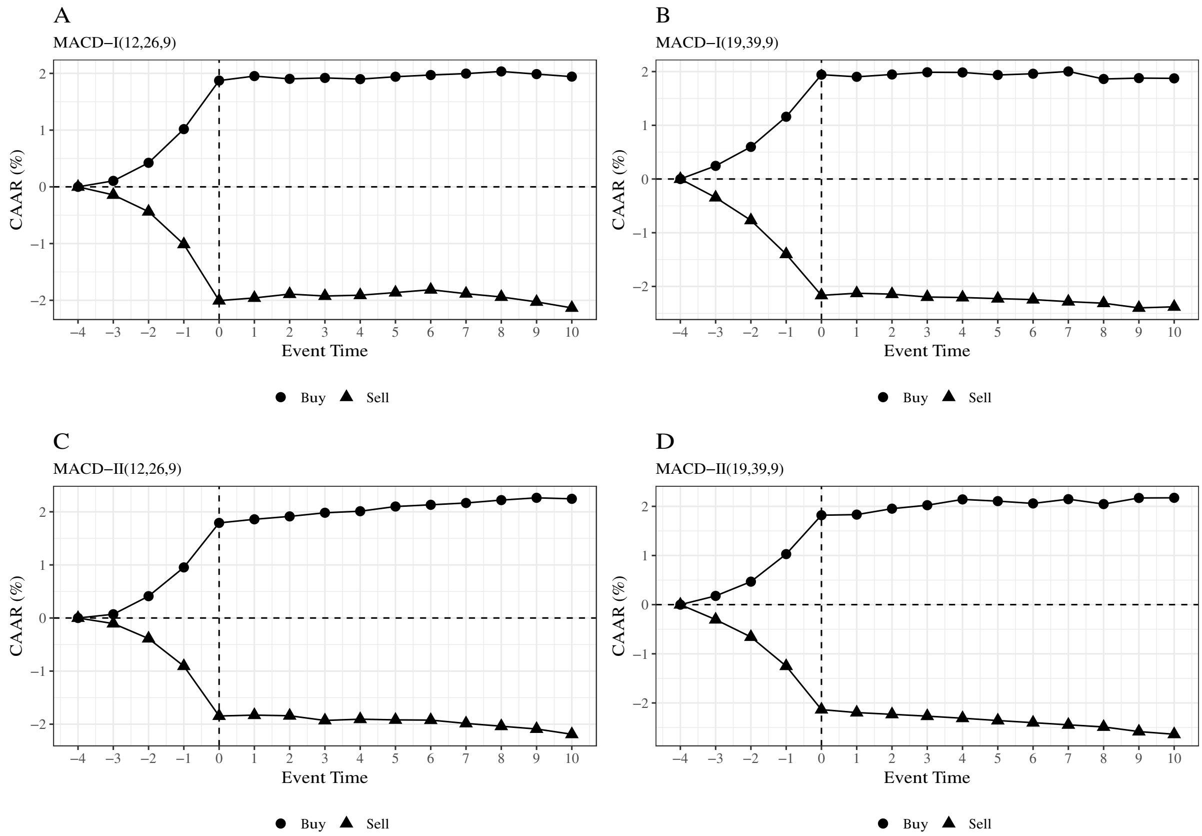

Figure 5. Plot of cumulative average abnormal returns (CAAR) for MACD from event day -3 to 10. Panel A and B shows the two variations of the standard MACD rule varied with exponential moving averages of different lengths. Panel C and D shows the two variations of the adjusted MACD rule.

Overall, MACD does appear to have some predictive ability in the adjusted version, however returns are probably not economically significant. In fact, there appears to be an almost even distribution of rising and falling prices following a trading signal emitted by the MACD (see Figure 5). Moreover, results are inconsistent regarding buy and sell signals for different rules. One of the adjusted MACD rule makes better predictions for sell signals, while the other makes better predictions for buy signals. Therefore, in general, MACD is not a reliable tool in predicting future price movements.

6 Conclusion

The purpose of this study was to evaluate the predictive ability of conventional technical trading rules on the Swedish stock market. Eight variations of the relative strength index (RSI) and the moving average convergence/ divergence (MACD) were applied on the constituent stock of the OMX Stockholm 30 between January 2014 and December 2023. To test the performance of the buy and sell recommendations issued by each rule, an event study analysis was conducted. Results show significant cumulative abnormal returns (CAAR) for some variations of the RSI and MACD. However, few variations show significant CAARs for both buy and sell signals, making them inconsistent. Abnormal returns that are significant are also not likely to survive transaction costs. Thus, the results of this study suggest that the trading rules are not able to make reliable predictions about the future direction of stock price movements. Nevertheless, it is important to acknowledge that this study is subject to several limitations. These include a small amount of trading rules being tested, the absence of transaction costs in the analysis and bias in the test statistic. Further analysis is thus recommended.

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Appendix A

Average Abnormal Returns (AAR) for RSI and MACD

Table 10 Average abnormal returns (AAR) conditioned on RSI buy (sell) signals.

	RSI(70,30,14)		RSI(70,30,9)		RSI(80,20,14)		RSI(80,20,9)	
Day	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**
-3	-0.33%	0.49%	-0.29%	0.38%	-0.85%	0.56%	-0.44%	0.51%
-2	-0.64%	0.57%	-0.49%	0.38%	-0.91%	0.71%	-0.81%	0.69%
-1	-0.98%	0.77%	-0.68%	0.71%	-1.63%	1.52%	-1.10%	0.93%
0	-2.93%	2.30%	-2.09%	1.94%	-5.40%	3.41%	-3.29%	2.55%
1	0.22%	-0.07%	-0.06%	0.04%	0.53%	-0.03%	0.09%	-0.18%
2	0.08%	0.00%	0.18%	0.01%	0.37%	-0.10%	-0.03%	-0.06%
3	-0.11%	-0.11%	0.00%	0.03%	0.40%	-0.38%	0.04%	-0.03%
4	-0.07%	-0.06%	0.00%	-0.10%	0.27%	-0.20%	-0.01%	-0.10%
5	0.13%	-0.12%	-0.06%	-0.07%	0.39%	-0.25%	0.14%	-0.09%
6	-0.02%	-0.07%	0.04%	0.01%	-0.30%	-0.06%	0.15%	-0.11%
7	0.12%	0.02%	0.02%	-0.02%	-0.13%	-0.05%	-0.18%	-0.01%
8	0.16%	0.08%	-0.04%	0.02%	0.12%	-0.07%	0.16%	0.18%
9	-0.03%	-0.02%	-0.06%	0.04%	-0.05%	-0.10%	0.01%	-0.01%
10	-0.07%	-0.07%	-0.10%	0.01%	0.35%	0.13%	-0.12%	-0.14%

Table 11 Average abnormal returns (AAR) conditioned on MACD buy (sell) signals.

	MACD-I(12,26,9)		MACD-I(19,39,9)		MACD-II(12,26,9)		MACD-II(19,39,9)	
Day	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**	**Buy**	**Sell**
-3	0.10%	-0.14%	0.24%	-0.35%	0.07%	-0.10%	0.18%	-0.30%
-2	0.32%	-0.30%	0.35%	-0.42%	0.34%	-0.28%	0.29%	-0.35%
-1	0.59%	-0.58%	0.56%	-0.63%	0.54%	-0.52%	0.56%	-0.59%
0	0.86%	-0.99%	0.78%	-0.77%	0.84%	-0.94%	0.79%	-0.88%
1	0.08%	0.05%	-0.04%	0.04%	0.07%	0.02%	0.01%	-0.06%
2	-0.05%	0.07%	0.04%	-0.02%	0.05%	-0.01%	0.12%	-0.04%
3	0.02%	-0.03%	0.04%	-0.05%	0.07%	-0.09%	0.07%	-0.04%
4	-0.02%	0.01%	0.00%	-0.01%	0.03%	0.02%	0.12%	-0.04%
5	0.04%	0.05%	-0.05%	-0.02%	0.09%	-0.01%	-0.04%	-0.05%
6	0.03%	0.05%	0.02%	-0.02%	0.03%	0.00%	-0.05%	-0.04%
7	0.02%	-0.07%	0.04%	-0.04%	0.03%	-0.06%	0.09%	-0.04%
8	0.04%	-0.06%	-0.14%	-0.03%	0.05%	-0.05%	-0.10%	-0.04%
9	-0.05%	-0.09%	0.02%	-0.09%	0.04%	-0.05%	0.12%	-0.09%
10	-0.04%	-0.11%	0.00%	0.02%	-0.02%	-0.10%	0.00%	-0.05%