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AN EMPIRICAL TEST OF A 14-DAY MONEY FLOW INDEX AND RELATIVE STRENGTH INDEX HYBRID'S PREDICTIVE ABILITIES ON HELSINKI, OSLO AND STOCKHOLM STOCK EXCHANGES

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ABSTRACT

Technical analysis has been used in stock market forecasts for more than a century and it is one of the basic applications of the modern day finance. However these methods have for decades raised conflicting opinions in the science community, leaving the field a subject of disdain by academics. The purpose of this thesis is to test whether a hybrid of money flow index (MFI) and relative strength index (RSI) yields abnormal returns on Helsinki, Oslo and Stockholm stock exchanges. The hybrid of MFI and RSI is a volume weighted RSI, which' predictive power is solely based on utilization of historical stock prices and trading volumes. MFI-RSI hybrid measures market momentum and indicates 'oversold' and 'overbought' levels on the market oscillating between 0 and 100.

The predictability of the market will be studied by applying the MFI-RSI vehicle on equally weighted country indices and a combined portfolio of the 450 stocks. The results indicate that MFI-RSI hybrid has trend predicting abilities at 5 % significance level on a bear market, but the transaction costs erode the profits on a bull market. The results suggest market efficiency in Finland, Norway and Sweden, yet the predictive power under distress market condition signals of a change in the investor sentiment during financial crisis. In addition to the excess returns, an insight is taken on the strategy's risk reducing properties.

KEYWORDS: Technical analysis, relative strength index, money flow index, predictive ability

1. INTRODUCTION

The purpose of technical analysis is to extract recurring and predictable price patterns from the historical data with the help of price and volume information. The history of this type of analysis dates back to commodity markets of 1600^{th} century, as the Japanese rice traders traded on the Dojima Rice Exchange in Osaka (Wong, Manzur & Chew, 2003). Technical analysis has been one of the basic financial practices for decades, but the applications based on the historical price and volume data has never enjoyed similar trust and acceptance as fundamental analysis. One of the most important reasons for questioning the technical methods as a true science is that it has been difficult to show undisputed evidence on the efficiency of technical analysis.

As several technical methods are also based on visual identification of patterns, technical analysis is also known as “charting” and is often considered by academics to be highly subjective. Visual pattern identification is however likely to be a common practice due it’s conductivity for human cognition (Lo, Mamaysky & Wang, 2000), and majority of the technical tools are based on purely quantitative methods aiming to extract predictable price components. Wong et al. (2003) suggest that recent applications on computational science could mean that upcoming concepts in technical analysis would include chaos theory, fuzzy logic and genetic algorithms.

Majority of the studies discussing the information content of stock price and volume data, including Fama’s and Blume’s (1966), support the market efficiency hypothesis, claiming that past prices and volume can’t contain information, giving that weak form efficiency is fulfilled. However a substantial amount of literature has collected evidence (e.g. Brock, Lakonishok and LeBaron, 1992; Sullivan, Timmerman and White, 1999) suggesting that technical analysis in fact captures predictable components in stock prices. Moreover, Menkhoff (2010) explains how a vast majority of fund managers apply technical analysis in their investment decisions and that in case of short horizon investments the technical aspects are even greater than those of fundamental analysis. The science community has also gone some length in order to find evidence from technical analysis profitability in markets other than US and UK stock exchanges. These markets include emerging stock exchanges such as Malaysia, Thailand, Taiwan (Bessembinder & Chan, 1995), India (Sehgal & Garhyan, 2002) and Mexico (Garza-Gomez, Metghalchi & Chen, 2010). The amount of academic literature about technical analysis has risen in the recent years, and it is noteworthy that approximately half of the empirical studies performed after 1960 date between 1995 and 2004 (Park & Irwin, 2007).

Among the mentioned studies there have been conclusions for and against the predictive power of technical analysis, and the results will be reviewed in the third section of the thesis. The theoretical basis of technical methods has in a way been strengthened due to discoveries of stock returns such as market anomaly returns that can not be explained by common risk (e.g. Bernard & Thomas, 1990). An explanation for the results in contrast with random walk hypothesis can be market inefficiency, as the prices shift from the fundamental values. Brock et al. (1992) note that according to another theory the markets are efficient and the predictability is a result of time-varying equilibrium returns. The authors mention that short horizon returns have been also tried to explain by market microstructure, that is, price reversals stemming from bid-ask movements. Brock et al. suggest the latter explanation to be implausible.

The strategy used in the thesis employs past price and volume data, using the 14-day data to extract ‘oversold’ and ‘overbought’ market levels on short time horizon. For the tests in this study only one parameter set for one technical indicator is used in order to avoid data snooping, a very common phenomena attributed to technical analysis. A single technical method can be altered with statistical methods enough to find a fitting pattern for a historical time series and to invalidate the results. For instance Jensen and Benington (1970) note that if they are given enough computer time, they are able to create trading rules on any table of random numbers, given that they are allowed to use the same table of numbers. The rules used in other tables would turn out to be useless.

1.1 Purpose of the study

The purpose of this study is to test a combination of money flow index (MFI) and relative strength index (RSI) on stocks of Helsinki, Oslo and Stockholm stock exchanges and to seek evidence on whether the possibilities of earning abnormal returns exist. Thus, the contribution for technical analysis research is to answer the main research question of the thesis; does MFI-RSI yield statistically significant abnormal returns during the observation period? The combination of MFI and RSI oscillators (hereafter referred as MFI-RSI) is a form of hybrid, also called a volume-weighted RSI (Yen & Hsu, 2010). In order to avoid data snooping bias, a single oscillator parameter length and strategy is under investigation. The observation period will be divided into three subperiods in order to extract the predictive abilities under different market conditions. In terms of market efficiency, it is sensible to examine market phases separately in order to determine what effects the market sentiment has on the predictability.

MFI-RSI is a measure of momentum, thus it assumes values between 0 and 100. The aim of this thesis is not to identify the optimal parameter set for the strategy by data mining, but a brief insight is taken on the risk ratio sensitivity for the parameter adjustment.

1.2 Structure of the study

The rest of the paper is organized as follows. Section 2 discusses the market efficiency and the basic assumptions related to the information content of stock prices. Section 3 explains background, basic assumptions and theoretical foundations of technical analysis. Section 4 will present an overview of the technical indicators studied in academic literature and applied by practitioners. Section 5 introduces the data set, methods and the hypothesis and in section 6 the results are examined. Finally, section 7 provides my conclusions and suggestions for further research.

1.3 Limitations of the study

There are three important limitations in this study, the most considerable one being the relatively short observation period. The theoretical foundations of technical analysis are disputed, as serial correlations can even be extracted as a cause of a subtle data-snooping bias. Thus, it is highly probable that a reoccurring price patterns can be found for any length of period and the findings can be supported by models that are in fact capturing an arbitrary chance. Brock et al. (1992) use 60 years of data in their study in order to reduce the effects of data-snooping. However, the settings of the testing vehicle in this study are simplified and only one investment strategy is utilized, which is to avoid mining for self-fulfilling selection of parameter sets.

Another limitation is the construction of the tested indices. The stocks are weighted equally, which generally is far less common approach on empirical testing of investment strategies. Also, equal weighting as such allows a fluctuation of a single stock to have an unnaturally powerful effect on the market index. This must be acknowledged, as it has been shown by for instance Fama and French (2008) that anomalies are emphasized when observing equal weight indices.

The third limitation to be considered is the sample-selection bias, as in order to be included in the final sample a time series of a stock has to contain a sufficient amount of data. This eliminates the firms that have been listed during the observation period as well as the bankrupted firms or the firms that for other reasons are no longer listed in the observed stock exchanges. The high number of eliminated firms combined with previously mentioned artificial construction of indices might have a negative effect on the significance of the results, as these weaken the test reproducibility. However, as the indices are weighted equally, removing the above named firms as possible outliers can be expected to have a stabilizing effect on the daily returns.

2. MARKET EFFICIENCY AND RANDOM WALK

The very essence of questioning the profitability of technical trading rules lies within the fact that a said efficient market has at any given moment discounted the information at hand in the prices. Having been unable to identify predictable patterns in stock prices, Kendall (1953) shook the grounds of financial analysis at his time by concluding that the data was behaving like "wandering series". These results then were paving the way for modern day random walk theory. Unpredictability of future stock prices can be derived from the fact that if positive future performance is to be expected, it will cause a favorable current performance as the market participants will be exploiting the expected price increase. Hence, the stock price indicates market expectations as random steps around the trend (Bodie, Kane & Marcus, 2005).

2.1 Behavioral finance

According to Fama (1970), the optimal market prices reflect the information about firms' activities fully. This is based on Fama's suggestion that "*the primary role of the capital fact is allocation of ownership of the economy's capital stock"*. Fama's paper has been cited by academics countless times and it's undeniably an elementary study in today's finance, however the efficient market hypothesis (EMH) is challenged by the competing explanation based on investor psychology, where quite comprehensive overview of the studies is offered by Shefrin (2002). Behavioral finance is supported by commonly known discoveries of several persistent market anomalies, such as post-earnings announcement drift (e.g. Ball & Brown, 1968; Bernard & Thomas, 1990), calendar anomalies (e.g. Gibbons & Hess, 1981) and even sport result anomalies (Edmans, Garcia & Øyvind, 2007).

Volatility has been attributed to market inefficiency. Shiller's (1981) model inquires whether the price movements are disproportionately large in terms of information about future, dividends and real stock prices. According to Shiller the excessive variance could be explained with either very large movements on real interest rates or market irrationality. The author suggests that it's not implied that rational, optimizing investors could at all times profit from these "fads", meaning that mispricing is not necessarily corrected. Behavioral finance explains irrational market phenomena by investor sentiment, which is a combination of beliefs about asset returns and risk levels not based on facts (Baker & Wurgler, 2007). This leads to a situation where rational investors are not able to utilize all arbitrage possibilities and thus don't attempt to force prices to their fundamental, correct levels at all times. The authors suggest the same factors to cause mispricing from the fundamental values as did for instance Bernard and Thomas (1990); sentiment change on behalf of irrational investors and arbitrage limit on the part of rational investors. Arbitrage limits commonly refer to short sale constraints or to a situation, where utilizing the small mispricing is not profitable due to costly trading environment (e.g. transaction costs).

According to the underlying assumption of EMH an investor can't predict stock prices as the information is already discounted in the price. A mispriced asset would offer an arbitrage opportunity, but by EMH the abnormal profit opportunities will immediately be exploited by market participants. These would be ordinary returns (Bodie et al., 2005) and merely compensation for the risk. The explanation of reward for holding an asset has faced opposition; many of the earlier named anomalies have existed for decades and therefore weakened the risk-based explanation. Today's literature also acknowledges that market anomalies are caused by market participants, who, being human beings after all, naturally have their biases (e.g. Abarbanell & Bernard, 1992; Shefrin, 2002). Baker and Wurgler (2007) also note that the recent stock market history, Internet bubble and Nasdaq crashes further validate theories of investor psychology. Despite the sentimental fluctuation on broad market indices, Baker and Wurgler (2007) remind that aggregate risk aversion affects all stocks on some degree, but some individual stocks are more affected than others. The suggestion referring to sentiment beta seems justified, as investors valuations of firms differ. For instance, expectations of future cash flows of a growth company can be highly subjective in case of dispersed forecasts by analysts.

2.2 Three forms of market efficiency

The dialogue between the views of market efficiency hasn't ceased, and evidence has been uncovered both against and for market efficiency theory. Fama (1970) suggests three forms of efficiency, differed by weak form tests, semi-strong form tests and strong form tests.

2.2.1 Weak form tests

According to the weak form hypothesis the stock prices reflect all information that's possible to derive from past prices or volumes. Trading data is publicly available for all market participants, thus making technical analysis worthless. The hypothesis states that if historical data contained information that could be used to predict performance in the future, investors would utilize this immediately.

The informational inefficiency is also associated with emerging markets which for instance Bessembinder and Chan (1995) have found to be consistent with their results on testing technical analysis on the Asian stock market. From the six countries observed, technical rules indeed had the predictive power especially in Malaysia, Thailand and Taiwan, indicating inefficiency on these markets during the sample period. Hudson, Dempsey and Keasey (1995) however noted that even if their own findings on predictive ability of technical methods on UK market were positive, investors could not earn excess returns in a costly trading environment. Hence the conclusions of the latter supported the weak form hypothesis.

2.2.2 Semi-strong form tests

On a semi-strong market all publicly available information is at all market participants' hand at the same time. In addition to the historical data dictated by weak form hypothesis, the semi-strong form contains the firm's fundamentals, including but not limited to balance sheet, earnings and performance forecasts. Small but economically significant predictability has been found for instance by Ferson, Heuson and Su (2005) on US markets.

2.2.3 Strong form tests

The strong form is fulfilled if no market participants have monopolistic, insider information relevant for price formation. The statement is drastic, as examination of corporate insider information is difficult as such. Insider information is highly regulated in the market, but defining insider trading is far more difficult. Strong form hypothesis has been rejected for instance by Grossman and Stiglitz (1980) and Kara and Denning (1998).

3. THEORETICAL FOUNDATIONS AND UTILIZATIONS OF TECHNICAL ANALYSIS

As fundamental analysis recognizes the prospects and future performance forecasts of the firm, technical analysis recognizes the same information in stock price assessment. The principal difference between the disciplines is the price formation view, as technicians' pursue the supply and demand on the stock in addition to the expectations on the firm (Bodie et al, 2005). The theoretical foundation as a whole is thus based on changes in investor sentiment. The market participants' reaction to the information at hand is a gradual, trend developing process, which is believed to be captured from historical trading data, such as stock prices and volumes (Marshall, Young & Rose 2005). This statement is in an apparent contradiction with EMH, thus creating conflict among scholars. Both Alexander (1964) and Fama and Blume (1966) have concluded that the returns earned by technical filter rules are diminished by transaction costs. Consistent with EMH, the findings implicate that no abnormal returns can be achieved as the costs increase.

Many years of controversy surrounding EMH and the scholars' determination in explaining modern economy with a more dynamic model have led to introduction of adaptive market theory, AMH (Lo, 2004). Accounting for principles of supply and demand, Lo (1999) had suggested a framework of the three Ps of total investment management; prices, probabilities and preferences. According to the author this framework and the interactions between the three Ps would determine the equilibrium in which demand would equal supply across all markets. One of the key terms presented in AMH is survival, time-varying dynamics exist on the market, meaning that different methods of analytics perform in different markets in in different points of time. Support for the evolutionary nature of AMH has been found for instance by Neely, Weller and Ulrich (2009), who discovered that technical trading rules on foreign exchange markets were able to extract profit opportunities in the 1970s and 1980s but the opportunities disappeared by the early 1990s.

In their study on theories of financial anomalies, Brav and Heaton (2002) state: "*At a minimum, future work must focus on the interaction of rational and irrational investors. That work must start with the expectations formation of rational arbitrageurs (and their investors) in environments where irrationality might also exist.*" The authors note that market irrationality might also stem from external events, such as stock market crashes. This would suggest different levels of predictability under different market conditions.

In addition to applications on stock markets, technical methods are often employed as decision tools on commodity markets (e.g. Yen & Hsu, 2010) foreign exchange markets (e.g. Allen & Taylor, 1990; Gehrig & Menkhoff, 2006; Menkhoff & Taylor, 2007). Menkhoff and Taylor (2007) in fact conclude that in various surveys presented in eight academic studies, 90 % of the responded exchange professionals used technical analysis in some horizon and the weight given to technical analysis relative to fundamental analysis at various horizons varied between 30 % to a little over 50 %, which might partly explain the academic interest towards technical analysis on currency markets. Furthermore, the authors cast light on the reasons why technical analysis is continuously used on foreign exchange markets by presenting four explanations. First, if following the principles of EMH and considering foreign exchange markets at least weakly efficient, the use of technical analysis would be considered as evidence of irrational behavior (admitting that consistently irrational behavior by market professionals doesn't follow EMH either). Another explanation would be that the existence that market participants with significant influence on the market but no direct interest in generating profits could generate profit opportunities for technical analysts. Major central banks have been proposed to be such group. Thirdly, if it takes time for exchange rates to reflect economic fundamentals, technical analysis may detect the influences earlier. Finally, in addition to the fundamentals, financial prices may also reflect components influenced by other sources, such as noise traders (Trueman, 1988) and even self-fulfilling influences of technical method trading. An overview of some empirical studied on technical analysis is seen on table 1.

3.1 Momentum

The evidence of stock prices displaying short-term momentum over periods between six months exists (De Bondt & Thaler, 1985) and economically significant price reversals have been disclosed over short horizons between one week and one month (Jegadeesh, 1990). Significant results on momentum-based strategies have been recently disclosed by for instance Leivo and Pätäri (2011).

Jegadeesh and Titman (1993) have suggested that investors underreact to firm-specific information release. A similar psychological explanation was already established by Abarbanell and Bernard (1992) who attributed the effect to psychological forces causing

Table 1. Overview of previous academic literature. The table presents some studies on which empirical tests are performed to study predictive abilities of technical techniques. In the studies a variety of methods are used, of which not all are discussed in this study.

Study	Techniques tested	Market	Evidence of profitability of technical analysis	Conclusions and remarks
Allen & Karjalainen, 1999	Genetic algorithms	S&P 500	Negative	Systematic relation between trading rule signals and volatility found.
Bessembinder & Chan, 1998	MA, TRB	Dow Jones Industrial Average	Some positive	The forecast power might co-exist with random walk; suggesting break-even of 0,39 % for trading costs.
Bessembinder & Chan 1995	MA, TRB	Asia markets	Positive	Predictive ability observed especially in Malaysia, Thailand and Taiwan markets.
Brock, Lakonishok & LeBaron, 1992	MA, TRB	Dow Jones Industrial Average	Positive	Support found for predictive power of simple trading rules.
Fama & Blume, 1966	FR	U.S. stocks	Negative	Trading costs erode the profits, thus supporting random walk theory.
Garza-Gomez, Metghalchi & Chen, 2010	MACD, PSAR, RSI	Mexico's Stock Index	Positive	Support provided for the predictive power, Mexican market's efficiency thus questioned.
Hudson, Dempsey & Keasey, 1995	MA, TRB	Financial Times Industrial Ordinary Index	Negative	Predictive ability found, however no abnormal profit opportunities in costly trading environment.
Kho, 1996	MA	International Monetary Market of the Chicago Mercantile Exchange	Positive	Risk-adjusted profits are not abnormal.
Lo, Mamaysky & Wang, 2000	Computational algorithms and nonparametric kernel regression	U.S. stocks	Some positive	Nonlinear patterns extracted from noisy data and thus regularities in the time series of prices identified.
Marshall, Young and Rose, 2006	CA	Dow Jones Industrial Average	Negative	DJIA informationally efficient.
Neely, 2001	Genetic programming	S&P 500	Negative	Results consistent with market efficiency.
Sehgal & Garhyan, 2002	CC, DI, FI, LR, MACD, MOM, OBV, PO, QS, ROC, RSI, STO, WR	Bombay Stock Exchange Sensitive Index	Some positive	Confirming evidence on weak form efficiency on Indian capital market; however predictability detected under bull periods.
Sullivan, Timmermann & White, 1999	FR, MA, OBV, TRB	Dow Jones Industrial Average, S&P 500	Some positive	Discussed effects of data-snooping, suggested that markets have become more efficient recently.
Wong, Manzur & Chew, 2003	MA, RSI	Stock Exchange of Singapore	Some positive	Timing capabilities found, however transaction costs not controlled for.
Yen & Hsu, 2010	FR, MFI-RSI, MSV, OBV	Ten futures markets	Some positive	Sortino and reversed Sortino ratios indicating outperformance of technical rules.

Table 2. Explanations for the abbreviation used on table 1.

Indicator abbreviation	Indicator name	Indicator abbreviation	Indicator name
CA	Candlestick	MSV	Momentum Strategy in Volume
CC	Commodity Channel	OBV	On-balance volume
DI	Direction Indicator	PO	Price Oscillator
FI	Force Index	PSAR	Parabolic Stop and Reversal
FR	Filter rules	QS	Q-sticks
LR	Linear Regression	ROC	Rate of Change
MA	Moving Average	RSI	Relative Strength Index
MACD	Moving Average Convergence/Divergence	STO	Stochastic oscillator
MFI	Money Flow Index	TRB	Trading range breakout (support and resistance)
MOM	Momentum indicator	WR	Williams % R

humans placing too little weight on a change in a series. The phenomenon is known as the cognitive bias (Andreassen & Kraus, 1990).

Evidence of stronger momentum gains after bear markets has been discovered by Siganos and Steeley (2006) who attribute this to the bias of investors to underreact (overreact) to information following bear (bull) markets. Similar evidence had earlier been found by Griffin and Martin (2003), who reported on higher momentum profits during bear markets. Siganos et al conclude that this supports the theory according to which the momentum effect stems from underreaction to information (e.g. Hong & Stein, 1999).

Friesen, Weller and Dunham (2009) aim to provide an explanation for momentum by presenting a theoretical model for these autocorrelation patterns in asset returns by introducing confirmation bias (e.g. Hirshleifer, 2001) into the model. The approach is designed to identify investors' interpretation of information and relies on this information creating price patterns. The authors recognize return autocorrelations of different time horizons and suggest that the psychological bias based model evidently captures these fluctuations through technical analysis.

3.2 Trading volume

There are numerous studies documenting patterns and price-related correlations on trading volume. Volume translates to investor information, and is thus assumed to precede price. In academic literature it is also common to assume that volume is a result of investors taking long positions, since short selling costs often are high.

According to Karpoff's (1987) review of previous research, price data could be generated by conditional stochastic process, where a changing variable parameter could be explained by volume. Karpoff concludes that large volumes and large price changes are tied to information flows.

Models based on volume aim to extract information that's not possible to gather from price data only. In their study on the role of volume on commodity markets, Blume, Easley and O'Hara (1994) concluded volume to contain explanatory power on the quality of traders' information signals. The authors model volume as a factor affecting the behavior of the market and not only describing it. While the authors indeed find evidence of predictive power of technical analysis, it is important to note that the study discusses applications for thinly followed stocks, thus leaving more active and effective markets untouched.

According to Garfinkel and Sokobin (2005) in event studies it's possible to extract a component of volume that can't be explained by prior trading activities. The authors study post-earnings announcement drift (see e.g. Bernard & Thomas, 1990), interpreting volume as an indicator of opinion divergence among investors. When the opinions are more dispersed, post-event returns increase, suggesting that opinion divergence is an additional risk factor. Another explanation for high market-wide trading volume and high individual security turnover is offered by Statman, Thorley and Vorkin (2006), who propose investors to be overconfident about their own valuation and trading skills.

In their paper studying cross-autocorrelations in stock returns, Chordia and Swaminathan (2000) found trading volume to be a significant determinant. Exploring CRSP NYSE/AMEX stocks under 33 years, the authors said the results to suggest some level of market inefficiency. Consistent with Fama and Blume (1966), the reason for the profit opportunities not being arbitraged away could lie in transaction costs.

3.3 Volatility

Technical trading rule profits have been partly attributed for volatility and time-varying risk premia by for instance Kho (1996), who found time-varying conditional volatility to explain some of the profits. The author estimated the risk premium from a general model of conditional CAPM and concluded that the profits were not unusual compared to risk. Kho evaluated the profits with weekly data, noting that the results might not be consistent with tests performed on the profits at a higher frequency. Another discussion on the risk-adjustment was raised on Menkhoff's and Taylor's study (2007), where the authors suggest methods to measure risk when assessing profitability of technical methods. Sharpe ratio, being a popular information ratio, was mentioned as the first choice, however was admitted to have its own challenges. In a recent study of technical methods on commodity markets, Yen and Hsu (2010) apply Sortino ratio to weight "positive" volatility. Menkhoff and Taylor (2007) summarize the views of technical rule risk assessment and note that with the knowledge of today the, determination of (even appropriate) risk premia is questionable.

As for derivatives, the interest on leverage possibilities in technical analysis utilizations by scholars seems to be relatively low. Charlebois and Sap (2007) have suggested that moving-average trading rules generate excess returns and these returns increase when the information is assigned on the open interest differential on currency options[1]. The authors assumed this to reflect risk premia and extra fundamental information in options prices. The leverage advantage may imply that options are the instruments of choice for informed trader (Easley, O'Hara & Srinivas, 1998).

3.4 Technical analysis as a complement of fundamental valuation

Put in a simplified form, the traditional approach of scholars has been to view technical analysis as a substitute for fundamental factor inspection. In their study on equity valuation, Bettman, Sault and Schultz (2009) propose an integration of technical and fundamental methods. Measuring the book value of the firm's equity, the dividend earnings per share, the past share prices at two time points, the consensus forecast earnings per share and adding dummy variables dependant on past stock returns of two time points, the authors model share price momentum. According to the authors, the evidence of

[1] The net difference between the cumulative value in dollar terms of all put options that are still active on a given day less the cumulative value of all active call options (Menkhoff and Taylor, 2007).

superior explanatory power in comparison to isolated utilizations suggests a complementary nature of the two measures. Furthermore, the authors note that in addition to share price valuation the model could serve the purpose in other valuation exercises, referring to Taylor's and Allen's (1990) reports of the proportion of foreign exchange market dealers relying on both fundamental and technical analysis to be some 90 %. Conclusion similar to Bettman et als (2009) was done by de Zwart, Markwat, Swinkels and van Dijk (2009), who studied Sharpe ratios formed by technical analysts and fundamental analysts on emerging foreign exchange currency markets. Combining these types of information improved performance in terms of risk. Findings of improvements in risk-adjusted performance are in line with Gehrig's and Menkhoff's (2004) reports on the extensive use of combinations of fundamental and technical analysis on foreign exchange markets. The authors also suggested extensions in research of statistical techniques in combining fundamental and technical information.

3.5 Data snooping

Data snooping bias, also known as data mining bias, is often encountered as the phenomena most invalidating the robustness of results in scientific technical analysis studies. Data snooping occurs when a data set is used more than once for model selection, leading to selection of algorithms that model the sample in which they are generated but do not perform out-of-sample. In their comprehensive study of technical trading rules, Brock et al. (1992) addressed the data snooping issue and suggested a use of 15-20 years of data to avoid accidental parameter usage.

The actual method was introduced by Efron (1979) and is called bootstrap, literally referring to pulling oneself up by one's own shoe laces. A similar methodology was further employed by Sullivan et al. (1999) in their study of best performing technical investment rules. The authors reassessed the rules presented by Brock et al. (1992) and found the results to be robust for data snooping.

Today the concept of data snooping is also a subject of market dynamics, as according to AMH (Lo, 2004) the autocorrelations in the markets vary over time, making out-of-sample testing even more crucial. Evidence supporting th e AMH was found by Neely et al. (2009), who discovered that the profit opportunities generated by technical trading rule on 1970s and 1980s data could not be reproduced using data from the 1990s. A more recent conclusion in line with Lo (2004) and Neely et al. (2009) was made by Gialenco and Protopapadakis (2011), who studied 14 currencies in foreign exchange markets. The instability difficulties in the algorithms simulating out-of-sample returns casted serious doubt on the reliability and sustainability of technical rules used.

4. TECHNICAL INDICATORS

4.1 Momentum indicators

The methods used in technical analysis can be divided into two sub-groups. The applications in the first group are known as trend-following or “lagging” indicators. These tools, also known as momentum indicators, generally work best in a clearly defined trend (Menkhoff & Taylor, 2007). For instance, moving averages of different length are a very common momentum indicator. The use of moving or exponential averages aims to distinguish trends from noise by smoothing daily returns and identifying the fluctuations by observing intersections between short and long moving averages or between asset price and moving average. Evidence for significant profit opportunities have been found for instance by Wong, Manzur and Chew (2003). A simple moving average (MA) for *n* days is calculated

(1)
$$M_{t,n} = \frac{1}{n} \sum_{i=t-n+1}^{t} C_i$$
$$= (C_t + C_{t-1} + \ldots + C_{t-n+2} + C_{t-n+1})/n$$

where $M_{t,n}$ is the simple *n*-day moving average at period *t* and C_i is the closing price of period *i*.

In addition to price data, volume information is used in momentum indicators such as On-balance volume average, introduced by Granville in 1964 (Hillery, 1986), and Momentum strategy in volume (Chan, Jegadeesh & Lakonishok, 1996). Both indicators are mainly used to detect trend weakness and reversals. A study of combination of indicators has been performed by for instance Loh (2006), who performed tests on joint moving average indicator and a stochastic oscillator, which is a trend and momentum indicator. Investigating market index data from Australia, Japan, Singapore, the United Kingdom and the United States, the author reports that the favored method among practitioners is effective in capturing past price information. The author interprets beating the benchmark at 1 % significance level as evidence of predictive power, suggesting the time-varying nature of weak form market efficiency as a further research area.

4.2 Oscillators

Indicators designed to capture price reversals are commonly called oscillators. These devices generally oscillate between a given range and are used to detect “overbought” and “oversold” levels of asset prices. These indicators are also known as reversal indicators, as their purpose is the anticipation of trend changes. In this study the relative strength index is being under observation; however there are other methods with a similar purpose of seizing short-term price information content. For instance moving average convergence/divergence oscillator (MACD) and stochastic indicators have been subjects of empirical tests in academic literature (e.g. Garza-Gomez, Metghalchi & Chen, 2010 (MACD); Yen & Hsu, 2010 (stochastic indicator)).

4.3 Visual pattern analysis

A highly common approach by practitioners is visual observation of the price data which in it’s simplified form aims to identify “support” and “resistance” levels of stock price charts, and probably is the reason why academics call technicians “chartists” and the practice itself a “voodoo finance” (Lo et al, 2000). In this sense quantitative finance employed by academics differs quite drastically from technical methods. Lo et al (2000) suggest that the reason for employment of geometrical tools and pattern recognition rather than mathematical and statistical methods might lie in both conductivity for human cognition and in human recognition being superior to computers in visual pattern analysis. The authors however note that in the presence of today’s financial engineering the advantage is shifting towards computational analysis. This direction seems evident, considering that for the modern portfolio optimization it has always been an obvious choice to utilize the very edge of the available technology. From a theoretical perspective the visual pattern recognition, being virtually impossible to study empirically, hardly offers evidence for or against abnormal earning possibilities by technical analysis.

4.4 MFI-RSI hybrid

4.4.1 Relative strength index

Originally introduced by Welles Wilder (1978), relative strength index (hereafter RSI) is known as one of the most popular technical oscillators or counter-trend indicators (Wong et al, 2003). RSI is assumed to capture short-term trend reversals more accurately on a non-trending market, as it would indicate overbought and oversold conditions too quickly under a clear upward or downward trend (Srivastava, 2007).

RSI is the ratio of the positive price movement to the total movement over a given period of days. Let p_t = closing price of an asset on a day t. Then let $U_t \equiv p_t$ if $p_t > p_{t-1}$ and 0 otherwise and $D_t \equiv p_t$ if $p_t < p_{t-1}$ and 0 otherwise. An N-day *RSI* on day t is given by

(2) $$RSI_t(N) = 100 - 100/100/(1 + RS_t(N)),$$

where

$$RS_t(N) = \sum_{i=0}^{N-1} U_{t-i} / \sum_{i=0}^{N-1} D_{t-i}$$

4.4.2 Money flow index

Money flow index (hereafter MFI) was introduced by Birinyi, Jr (Yean & Hsu, 2010) and is also known as volume-weighted RSI. As MFI assumes values based on whether the daily returns have been positive or negative, it literally is designed to detect whether money is "flowing in or out" of the asset, that being, determining the direction of short-term price movements caused by investors' opinion divergence (e.g. Bernard & Thomas, 1990). The trading volume of day t is denoted by Vol_t and the closing price of day t is denoted by p_t, then $MF^{+}_{t} = p_t \times Vol_t$ if $p_t > p_{t-1}$ and 0 otherwise and $MF^{-}_{t} = p_t \times Vol_t$ if $p_t < p_{t-1}$ and 0 otherwise. We define positive money flow

(3) $$PMFt(N) \equiv \sum_{i=0}^{N-1} MF^{+}_{t-i}$$

and negative money flow

(4) $$NMFt(N) \equiv \sum_{i=0}^{N-1} MF^{-}_{t-i}$$

An N-day *MFI* on day t is given by

(5) $$MFI_t(N) = 100 - 100/100/(1 + MR_t(N)),$$

where $MR_t(N) = PMF_t(N) / NMF_t(N)$.

4.4.3 MFI and RSI trading methods

The use of more than one technical indicator is assumed to reduce the number of noisy trading signals. Yen & Hsu (2010) have suggested the hybrid of MFI and RSI and found the strategy to outperform the benchmark on seven commodity markets.

The trading signals indicated by MFI and RSI are dependant of both these values and the selected time period. As originally suggested by Wilder (1976), a 14-day period is a common length selection, however different lengths have been subjects of empirical testing by for instance Wong et al (2003), who found some evidence on predictive abilities on 14- and 20-day RSI strategies. The authors also summarize the properties of RSI parameters in terms of variation, concluding that a shorter (longer) time period is to be used on more (less) volatile markets. A longer time period translates to less frequent trading signals whereas a short period generates noise and false signals, thus affecting the stability of the strategy in terms of volatility.

As both MFI and RSI oscillate between 0 and 100, the trading signals are given by these values where several different methods have been introduced. Academics have recognized levels commonly used by practitioners to be 30 as a ‘buy’ signal (indicating an oversold market) and 70 as a ‘sell’ signal (indicating an overbought market), however Wong et al (2003) have also performed tests for lower bounds of 20, 30 and 40 and higher bounds of 60, 70 and 80. As longer time periods stabilize the signals of topping and bottoming markets, the values closer to each others are generally suitable for them.

Furthermore, Wong et al (2003) summarize the four main methods of utilizing RSI as a trading strategy:

Touch

The signal for entering long (short) position is generated when the *RSI* reaches the set lower (higher) bound, thus indicating oversold (overbought) market.

Peak

The signal for long (short) position is given when the *RSI* has crossed the lower (higher) bound and reverted in direction.

Retracement

The signal for long (short) position is given when the *RSI* has crossed the lower (higher) bound, reverted in direction and returned to the given lower (higher) bound.

50 Crossover

The signal for long (short) position is generated when the *RSI* rises above 50 (falls below 50).

4.4.4 MFI-RSI hybrid construction and trading rules

Utilizing the *50 Crossover* strategy, we define the trading rules of MFI-RSI hybrid according to Yen (2009) based on values of both *MFI* and *RSI.* Initially taking a long position, we alter the position simply when either *MFI* or *RSI* cross the given crossover level 50. The trading vehicle signals the positions as follow:

Long entry (short exit):
1. $MFI(N_t)$ and $RSI(N_t)$ cross the 50 level from below simultaneously.
2. $MFI(N_t)$ crosses the 50 level from below and $RSI(N_t)$ stays below 50.
3. $RSI(N_t)$ crosses the 50 level from below and $MFI(N_t)$ stays below 50.

Short entry (long exit):
1. $MFI(N_t)$ and $RSI(N_t)$ cross the 50 level from above simultaneously.
2. $MFI(N_t)$ crosses the 50 level from above and $RSI(N_t)$ stays above 50.
3. $RSI(N_t)$ crosses the 50 level from above and $MFI(N_t)$ stays above 50.

The trade is made on the closing price of the trading day, assuming that there's a possibility to alter the position immediately after the signal before the close. Thus, when a signal is given, the returns of that signal are calculated starting from the following trading day. Giving the said rules, the position is either long or short at any given time and no positions are assumed on risk-free assets.

The returns are controlled with transaction costs. Two typical costs are taken into account as concluded by Rantapuska (2004) on Finnish stock market. For brokers that are members of HEX the trading costs are 0.00244 % and the costs for active household investors are assumed to be 0.2 %[2]. As the MFI-RSI tests assume an environment where short selling is possible, every time the position is altered the transaction costs are deducted on both buying (selling) and short selling (buying) the asset.

[2] Rantapuska (2004) suggests an individual investor to have a cost per trade of EUR 8.25 + 0.2 %. In this study the trading universe is constructed assuming that the effect of fixed fee is insignificant when the investment is sufficiently large and the absolute costs are therefore not applied.

5. DATA AND METHODOLOGY

5.1 Market data and sample selection

The data utilized in this study consists of price and volume data of 450 stocks in Helsinki, Oslo and Stockholm stock exchanges during period 4.1.2005 – 29.3.2011. All data were collected from Datastream. Helsinki and Stockholm exchanges are part of NASDAQ OMX Nordic operating under NASDAQ OMX Group, Inc (NASDAQ OMX, 2011). Oslo stock exchange, Oslo Børs ASA, is fully owned by Oslo Børs VPS Holding ASA (Oslo Børs, 2011).

All in all Datastream includes 846 firms listed in Finnish, Norwegian and Swedish stock exchanges during the period between 2005 and 2011. In order to be included in the final sample a single firm however has to have an uninterrupted series of price and volume entries on 1611 trading days. In the final sample there are altogether 450 stocks, of which 112 Finnish, 107 Norwegian and 231 Swedish firms. The data does not include dividends, but as noted by Lakonishok and Smidt (1988), excluding dividends has not a significant effect on the results.

All data will be handled and tested on MS Excel. For the test four equally weighted indices will be constructed, as the three markets will be studied both as an aggregated index and each of them separately. The combined indexes are created by using mean daily returns of each firm, and then calculating the cumulative returns. Also the aggregated index is equally weighted between the three country indices, thus setting in fact more weight on the smaller markets Helsinki and Oslo. Equal weighting in a single market is likely to provide different results than observing an index generally used to follow the market. However the significance of this difference can be expected to diminish due to sample selection, which eliminates firms with IPOs and firms that have gone bankrupt during the observation period. Hence, a single extreme outlier is unlikely to distort the index.

For the aggregated index the observation period is divided into sub-periods. As the global financial crisis affected the Nordic stock market during the period of this study, it is reasonable to observe MFI-RSI abilities based on market trends. In order to do this, a simple 200-day moving average is applied, which allows dividing the whole period into bull and bear periods. A declining 200-day moving average of the aggregated index implies a bear market and an ascending moving average implies a bull market. Thus the period is divided into three sub-periods. The first period is bullish on 4.1.2005 – 8.11.2007 (1st Bull), the second period is bearish on 9.11.2007 – 3.7.2009 (Bear) and the third period is bullish on 2.9.2009 – 29.3.2011 (2nd Bull). Graph 1 illustrates the cumulative returns of equal weighted indices of Helsinki, Oslo and Stockholm stock markets on the sample period. The descriptive statistics of the final sample are presented in table 1.

Figure 1. Cumulative daily returns. The returns on an investment of 100 on Helsinki, Oslo and Stockholm sample stocks with equal weights during period 4.1.2005 – 29.3.2011.

5.1.1 Descriptive statistics

Table 3 contains summary statistics for the entire series. The returns are calculated by weighting daily returns equally and then constructing accumulated series for all indices. The first bull period for aggregated index appears strongest leptokurtic, whereas the corresponding value during the bear period is the smallest one. As one could intuitively expect, the standard deviation of the sample is at its highest under the financial crisis, and under this volatile period the only negative mean returns emerge as well.

Table 3. Descriptive statistics of the sample price data. The table indicates the summary statistics of daily returns of equal weighted indices in Helsinki, Oslo, Stockholm and aggregated index. The aggregated index constructed of the three markets has been divided into sub-periods

Sample	Mean	Standard Error	Standard Deviation	Kurtosis	Skewness	Number of observations
Helsinki	0.000499	0.000228	0.009167	5.444	0.1069	1611
Oslo	0.000510	0.000293	0.011756	7.359	-0.5680	1611
Stockholm	0.000716	0.000265	0.010653	8.312	-0.3710	1611
Aggregated index	0.000575	0.000243	0.009770	7.121	-0.4397	1611
Aggregated index 1^{st} Bull	0.000976	0.000271	0.007314	10.495	-1.3271	728
Aggregated index 1^{st} Bear	-0.000779	0.000675	0.014016	3.255	-0.0286	431
Aggregated index 2^{nd} Bull	0.001220	0.000379	0.008050	5.989	-0.0363	452

Similarly, volume statistics are summarized in table 4. Volume data isn’t to be observed as a continuous price time series, as the aggregated volume is to anticipate investor opinion divergence. The strategy under investigation considers only past 14-day volume information in price weighting.

Table 4. Descriptive statistics of the sample volume data. The table indicates the summary statistics of daily trading volumes of equal weighted indices in Helsinki, Oslo, Stockholm and aggregated index. The aggregated index constructed of the three markets has been divided into sub-periods

Sample	Mean daily volume (million shares)	Standard Deviation (millions)	Kurtosis	Skewness	Number of observations
Helsinki	92.460	37.576	22.549	2.724	1611
Oslo	168.305	74.009	16.027	2.548	1611
Stockholm	200.807	60.664	7.468	1.416	1611
Aggregated index	461.573	136.405	4.225	1.248	1611
Aggregated index 1st Bull	506.370	147.207	4.811	1.358	728
Aggregated index 1st Bear	470.368	119.420	1.017	0.469	431
Aggregated index 2nd Bull	379.550	87.569	2.890	1.010	452

The trading volumes in the observed Nordic markets have declined during the observation period. An average turnover in Finland, Norway and Sweden during the first bull period was over 500 million shares per trading day, whereas the average volume in the last period lies below 400 million shares. The daily trading volumes throughout the full sample period are graphed on figure 2. The two major peaks of the declining volume curve were experienced on 7.6.2005 and 3.5.2007.

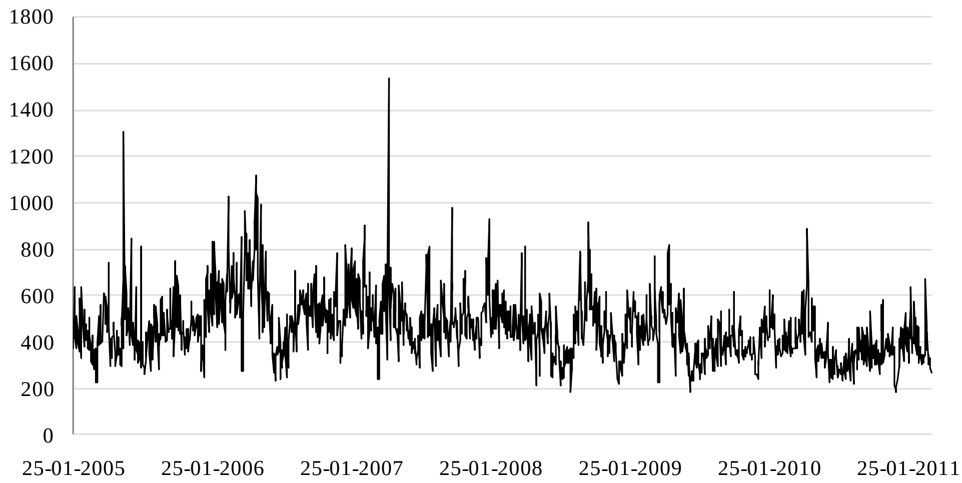

Figure 2. Aggregate volume under full sample period. The graph represents daily trading volume in Helsinki, Oslo and Stockholm in millions of shares.

5.2 Hypothesis

Prior research has identified predictive abilities on RSI and MFI strategies. However there is evidence that abnormal returns can't be earned using technical analysis. Assuming that Helsinki, Oslo and Stockholm stock exchanges are effective, the information content of historical volume and price data are reflected in the current asset prices and therefore does not offer abnormal profit opportunities. MFI-RSI hybrid relies on extracting profitable information from past volume and price data in order to indicate short-term trend changes by its money flow and relative strength index values. As the assumption is that Helsinki, Oslo and Stockholm stock exchanges effectively reflect all available information to an extent where profit opportunities exceeding market returns do not exist due to trading costs, the null hypothesis is formed

H_0: It is not possible to earn profits that exceed market return using MFI-RSI hybrid strategy in a costly trading environment.

Thus the alternative hypothesis is

H_1: It is possible to earn profits that exceed market return using MFI-RSI hybrid strategy in a costly trading environment.

5.3 Methods

5.3.1 Sharpe ratio

The risk adjustment cannot be done simply by comparing the standard deviations of the strategy portfolio to the benchmark index, as concluded by Menkhoff and Taylor (2007). In order to observe risk-adjusted returns, Sharpe ratios are calculated. Also known as reward-to-variability and information ratio, Sharpe measures excess return per unit of risk. Taking into account both systematic and idiosyncratic risk, the ratio is defined as

(6) $$S = \frac{\mu - r}{\sigma},$$

where μ = mean return of the observed investment strategy, r = mean return of the riskless asset and σ = standard deviation of the excess return μ - r. In this study 12 month Euribor rate is used as a measure of riskless asset. The Euribor rate is obtained from Datastream.

5.3.2 Sortino ratio

As Sharpe ratio can be criticized of its risk-simplifying properties, namely penalizing for both downside and upside volatility, another measure of risk-adjusted returns is introduced. Sortino ratio replaces Sharpe's standard deviation with the downside risk measure δ. Letting *x* denote the strategy returns, Sortino ratio is calculated

(7) $$So = \frac{\mu - r}{\delta},$$

where

$$\delta = \sqrt{\int_{-\infty}^{r} (r - x)^2 f(x) dx},$$

where *f(.)* is the probability density function of the strategy returns.

5.3.3 Kolmogorov-Smirnov test for distribution normality

Before choosing the test for statistical significance, the normality of the return distribution is to be examined. Applying Kolmogorov-Smirnov test, we use decision rule on the

1 % confidence level *Critical D-value* = 1.63 $/\sqrt{N}$, where N = the number of observations. The results of MFI-RSI strategy differences from buy-and-hold strategy are presented in table 5.

Table 5. The sample mean differences of the daily returns performed for test selection purposes. The tests performed on the aggregated index are done for the full observation period and under periods 1.2005 – 8.11.2007 (1st Bull), 9.11.2007 – 3.7.2009 (Bear) and 2.9.2009 – 29.3.2011 (2nd Bull).

Index	Transaction costs(%)	Number of observation pairs	Mean daily return	Standard deviation	D-value
HEL	0.00244	1611	0.000466	0.013507	0.35
HEL	0.2	1611	0.000026	0.013517	0.34
STO	0.00244	1611	0.000318	0.016007	0.37
STO	0.2	1611	-0.000090	0.016037	0.37
OSL	0.00244	1611	0.000445	0.017403	0.39
OSL	0.2	1611	0.000070	0.017369	0.38
Aggregated index	0.00244	1611	0.000434	0.014607	0.39
Aggregated index	0.2	1611	0.000091	0.014638	0.38
1st Bull	0.00244	728	-0.000001	0.009212	0.43
1st Bull	0.2	728	-0.000294	0.009180	0.42
Bear	0.00244	431	0.002065	0.023000	0.29
Bear	0.2	431	0.001689	0.023045	0.28
2nd Bull	0.00244	452	-0.000421	0.010794	0.38
2nd Bull	0.2	452	-0.000815	0.010895	0.37

D-ratios exceeding the decision limit at 1% level suggest that the mean return differences are not normally distributed in any of the samples and the basic t-test is not therefore suitable.

5.3.4 Mann-Whitney rank-sum test for statistical significance

For testing the MFI-RSI hybrid strategy against buy-and-hold strategy the basic Mann-Whitney test is introduced. Comparing MFI-RSI strategy against buy-and-hold strategy, the decision rule for rejecting H_0 is

(8) $$\frac{U-\mu_U}{\sigma_U} > z_{\alpha},$$

where

$$U = n_{BH}\, n_{C50} + \frac{n_{BH}\,(n_{BH}+1)}{2} - \sum_{i=n_{C50}+1}^{n_{BH}} R_i,$$

where N_{BH} = number of observations in buy-and-hold strategy sample, N_{C50} = number of observations in MFI-RSI strategy sample, R_i = rank of the sample size and

(9) $$\mu_U = E(U) = \frac{n_1 n_2}{2}$$

and

(10) $$\sigma_U^2 = \mathrm{Var}(U) = \frac{n_1 n_2 (n_1 + n_2 + 1)}{12}.$$

5.3.5 T-test for testing the long positions against short positions

For testing the MFI-RSI buy signal returns against sell signal returns the basic t-test is introduced (Brock et al, 1992; Chong & Ng, 2008). The *t*-statistic as a decision rule for rejecting buy signal as a more profitable rule on significance level α is

(11) $$\frac{\mu_L - \mu_S}{\sqrt{\dfrac{\sigma_L^2}{n_L} + \dfrac{\sigma_S^2}{n_S}}} < -z_{\alpha},$$

where μ_L = mean daily return of buy signals, μ_S = mean daily return of sell signals, σ_L^2 = variance of buy signal daily returns and σ_S^2 = variance of sell signal strategy daily returns.

5.3.6 Simple regression model for testing the risk ratio dependence on MFI-RSI trading bound values

For examination of Sharpe ratio sensitivity for all MFI-RSI crossover values between 0 and 100, a basic regression is employed. The regression model is

$$\mu_{MFI\text{-}RSI} = \alpha + \beta C_{MFI\text{-}RSI} + \varepsilon \,, \tag{12}$$

where $\mu_{MFI\text{-}RSI}$ = mean daily return of MFI-RSI strategy, α = the constant term, β = the coefficient term, $C_{MFI\text{-}RSI}$ = the crossover value of MFI-RSI strategy and ε = the error term. A higher constant term α would then indicate higher returns independent of the parameters set for trading as the coefficient term β defines how sensitive the returns are for MFI-RSI trading bound level.

6. RESULTS

This section presents the empirical findings of the paper. The results are organized in the tables and further discussed in the writing.

6.1 Strategy performance against the benchmark indices

Table 6. The results of Mann-Whitney tests on buy-and-hold strategy (BUY-HOLD) compared against MFI-RSI strategy (C50). The numbers marked with ** and * denote significance on 5% and 10% level respectively.

Sample	Transaction costs (%)	Investment strategy	Mean daily return	Z-statistic	p-value
HEL	0.00244	BUY-HOLD	0.000499	-0.78	0.434
		C50	0.000965		
HEL	0.2	BUY-HOLD	0.000499	0.74	0.460
		C50	0.000526		
STO	0.00244	BUY-HOLD	0.000716	0.50	0.620
		C50	0.001034		
STO	0.2	BUY-HOLD	0.000716	1.83	0.067
		C50	0.000627		
OSL	0.00244	BUY-HOLD	0.000510	0.53	0.598
		C50	0.000954		
OSL	0.2	BUY-HOLD	0.000510	1.63	0.103
		C50	0.000579		
Aggregated index	0.00244	BUY-HOLD	0.000575	-0.12	0.902
		C50	0.001009		
Aggregated index	0.2	BUY-HOLD	0.000575	1.00	0.317
		C50	0.000666		
1st Bull	0.00244	BUY-HOLD	0.000976	0.96	0.337
		C50	0.000975		
1st Bull	0.2	BUY-HOLD	0.000976	1.68	0.094
		C50	0.000682		
Bear	0.00244	BUY-HOLD	-0.000779	-2.08**	0.037
		C50	0.001286		
Bear	0.2	BUY-HOLD	-0.000779	-1.66*	0.097
		C50	0.000911		
2nd Bull	0.00244	BUY-HOLD	0.001220	1.12	0.261
		C50	0.000799		
2nd Bull	0.2	BUY-HOLD	0.001220	1.92	0.055
		C50	0.000406		

For the country indices during the full observation period the MFI-RSI in most cases yields profits higher than the market. However after Mann-Whitney test the results don’t appear to be significant on any of the country indices. Still, the only negative country index profits are found in Stockholm, where the higher transaction costs force the returns 0.009 % below the Swedish market average. The returns on Stockholm sample are negative at 10 % level. The mean daily returns are presented on table 6.

Market outperformance on significance level of 5 % is however found from the aggregated index during the 19 months of financial crisis between 9.11.2007 and 3.7.2009. The daily return exceeding the index is 0.206 % when controlled for the smaller financial institute trading cost of 0.00244 % per trade, and after controlling for the higher transaction costs the mean daily return of 0.169 % exceeding the index average is still significant on the 10 % level. Hence, the existence of profit opportunities under bearish stock market conditions suggests a change in investor sentiment and therefore inefficiency on some level. On the bull market MFI-RSI signals lead to frequent trading causes complete erosion of abnormal profits, and holding the artificially constructed index outperforms the MFI-RSI strategy in all tests. When controlled for the higher trading cost of 0.2 % per trade, the results emerge significantly negative on 10 % level. All accumulated returns are seen on appendix A and the graphs are presented jointly with MFI-RSI curve on appendix B.

6.2 Compensation for risk on bull and bear markets

As statistically significant evidence on MFI-RSI abnormal earning opportunities exists on 5 % under bearish market conditions, a reasonable question is whether this profit is a compensation for risk.

When controlled for the volatility, the MFI-RSI on country indices shows superior Sharpe and Sortino ratios under the full period on both high and low trading costs in all cases, except for Stockholm index when tested for higher transaction costs as indicated on Table 7. For aggregated index during the sub-periods the findings on risk-return ratios indicate that MFI-RSI underperforms under both bull periods and exceeds the market return and lowers the risk under the bear months, as is seen on Table 8. The buy-and-hold strategy under the bear market in the observed Nordic countries naturally led to negative returns and negative Sharpe and Sortino ratios, and MFI-RSI strategy therefore appears to offer predictive power for what seems to have been unstable market environment. The actual standard deviations on daily returns of buy-and-hold and MFI-RSI strategies under the bear period, varying between 1.39 and 1.41 %, do not disclose risk-relevant information, as both strategies

Table 7. The results of the tests performed on country indices under the full observation period with Sharpe and Sortino risk-return ratios. MFI-RSI 50 crossover strategy is indicated by C50 and the returns are controlled by two different transaction costs.

Sample	Investment strategy	Transaction costs	Number of observations	Mean daily return	Standard deviation	Sharpe ratio	Sortino ratio
HEL	BUY-HOLD	0.00244	1611	0.000499	0.009167	0.042289	0.001944
HEL	C50	0.00244	1611	0.000965	0.009129	0.093450	0.004643
HEL	BUY-HOLD	0.2	1611	0.000499	0.009167	0.042289	0.001944
HEL	C50	0.2	1611	0.000526	0.009196	0.045025	0.002051
STO	BUY-HOLD	0.00244	1611	0.000716	0.010653	0.056740	0.003094
STO	C50	0.00244	1611	0.001034	0.010627	0.086759	0.004874
STO	BUY-HOLD	0.2	1611	0.000716	0.010653	0.056740	0.003094
STO	C50	0.2	1611	0.000627	0.010702	0.048104	0.002498
OSL	BUY-HOLD	0.00244	1611	0.000510	0.011756	0.033838	0.001796
OSL	C50	0.00244	1611	0.000954	0.011728	0.071851	0.004225
OSL	BUY-HOLD	0.2	1611	0.000510	0.011756	0.033838	0.001796
OSL	C50	0.2	1611	0.000579	0.011737	0.039821	0.002123

Table 8. The results of the tests performed on aggregated index under the full observation period and sub-periods for Sharpe and Sortino ratios. The sub-periods consist of periods 25.1.2005 – 8.11.2007 (1st Bull), 9.11.2007 – 3.7.2009 (Bear) and 6.7.2009 – 29.3.2011 (2nd Bull).

Sample	Investment strategy	Transaction costs (%)	Number of observations	Mean daily return	Standard deviation	Sharpe ratio	Sortino ratio
Full period	BUY-HOLD	0.00244	1611	0.000575	0.009770	0.047420	0.002405
Full period	C50	0.00244	1611	0.001009	0.009735	0.092162	0.004959
Full period	BUY-HOLD	0.2	1611	0.000575	0.009770	0.047420	0.002405
Full period	C50	0.2	1611	0.000666	0.009815	0.056422	0.002865
1st Bull	BUY-HOLD	0.00244	728	0.000976	0.007314	0.116077	0.005467
1st Bull	C50	0.00244	728	0.000975	0.007314	0.115945	0.005317
1st Bull	BUY-HOLD	0.2	728	0.000976	0.007314	0.116077	0.005467
1st Bull	C50	0.2	728	0.000682	0.007352	0.075479	0.003317
Bear	BUY-HOLD	0.00244	431	-0.000779	0.014016	-0.066099	-0.004574
Bear	C50	0.00244	431	0.001286	0.013978	0.081463	0.005480
Bear	BUY-HOLD	0.2	431	-0.000779	0.014016	-0.066099	-0.004574
Bear	C50	0.2	431	0.000911	0.014071	0.054215	0.003492
2nd Bull	BUY-HOLD	0.00244	452	0.001220	0.008050	0.144994	0.006686
2nd Bull	C50	0.00244	452	0.000799	0.008103	0.092074	0.003879
2nd Bull	BUY-HOLD	0.2	452	0.001220	0.008050	0.144994	0.006686
2nd Bull	C50	0.2	452	0.000406	0.008241	0.042800	0.001505

assume positions on the same assets at all times. The differences in variance are caused by the costs of frequent trading, which in fact is why the volatility of MFI-RSI strategy returns is seemingly lower than holding the index under bear market. However the MFI-RSI positive returns during declining index translated to positive risk ratios indicate capabilities of timing the stock market. The results are contrary to findings of Kho (1996), who suggests that abnormal returns of technical analysis can be explained by an increase in risk. During the economic downturn it seems evident that MFI-RSI strategy in fact captures the price reversals, smoothing the excessive volatility. This risk-reducing property suggests that MFI-RSI applications are justified under somewhat exceptional conditions.

As observing the tool itself, it’s noteworthy that in the academic literature the theoretical foundations for altering time parameters are not strong. However the attribution for the Nordic equity market under financial crisis is found on the volatile market conditions; consistent with Wong et al (2003), a shorter time parameter increases the MFI-RSI sensitivity for short-term fluctuation. Utilizing the time span of two weeks appears to be a profitable investment method for the markets under examination under a declining 200-day moving average.

6.3 Trading frequency and the returns on long and short positions

The returns of long and short positions on country indices are summarized in Table 9. For the majority of the observation period (72.6 % on the aggregated index), a long position is assumed. The MFI-RSI strategy suggests most frequent trading on Helsinki stock index, where the position is altered 94 times, translating to an average investment period of 17 trading days. A high sensitivity for transaction costs is eminent, as the simulation of the environment of higher transaction costs leads to negative returns for short sales in Helsinki, Oslo and Stockholm stock exchanges. In fact, the only test where sell signals yield positive returns is the aggregated index during the bear period.

Of all trading days under the bear period the MFI-RSI strategy forecasted correctly 111 loss days and 127 gain days. A long position was assumed or maintained due to a false signal on 99 days and a respective short position on 94 days. On the aggregated index there were 221 bullish days and 210 bearish days during the bear period under observation. The bear days naturally yielded stronger losses than the respective bull days, also leading to a far more volatile market environment than those of the bull markets before and after the financial crisis.

Table 9. The profitability of MFI-RSI position signals. The marked 0.2 after the index name indicates transaction cost of 0.2 percent while the strategy name only indicates transaction cost of 0.00244 percent.

Sample	N position changes	Mean long	Mean short	Long days	Short days	Long on the market	Short on the market
HEL	94	0.001170	0.000574	1057	554	0.656	0.344
HEL 0.2	94	0.000848	-0.000089	1057	554	0.656	0.344
STO	86	0.001222	0.000598	1135	475	0.705	0.295
STO 0.2	86	0.000944	-0.000117	1135	475	0.705	0.295
OSL	77	0.001158	0.000391	1174	436	0.729	0.271
OSL 0.2	77	0.000906	-0.000307	1174	436	0.729	0.271
Aggregated index	75	0.001136	0.000663	1169	441	0.726	0.274
Aggregated index 0.2	75	0.000920	-0.000009	1169	441	0.726	0.274
1st Bull	27	0.001165	-0.000022	607	120	0.835	0.165
1st Bull 0.2	27	0.000996	-0.000911	607	120	0.835	0.165
Bear	23	0.000808	0.001814	226	205	0.524	0.476
Bear 0.2	23	0.000493	0.001371	226	205	0.524	0.476
2nd Bull	25	0.001303	-0.000662	336	116	0.743	0.257
2nd Bull	25	0.001068	-0.001514	336	116	0.743	0.257

For the aggregated index under the full sample period, an average period of investment was 21 days as seen on Table 10. In short, due to high frequency of trading, the profits appear as very sensitive for altering the transaction costs. Apart from the findings of profitable trading opportunities during a period under which the market experienced a great distress, the notions on profits eroded by transaction costs are very much in line with Fama & Blume (1966), stating that under efficient market no profitable information can be extracted of price and volume data in a costly trading environment. Table 10 presents the summary of the long and short position standard deviations and Sharpe ratios for the aggregated index.

Table 10. Aggregated index volatility and mean daily return for long and short positions. Transaction costs indicated by 0.00244 (%) and 0.2 (%). The numbers marked with ** and * denote significance on 5% and 10% level respectively for a two-tailed test. The figures inside the brackets are the *t*-statistics.

Period	Position	Mean daily return		Standard deviation	Sharpe ratio
Full sample 0.00244	Long	0.001136	(0.679)	0.007641	0.134021
	Short	0.000663		0.01384	0.039829
Full sample 0.2	Long	0.00092	(1.323)	0.007691	0.105031
	Short	-0.000009		0.01396	-0.008648
1st Bull 0.00244	Long	0.001165	(1.150)	0.006354	0.163385
	Short	-0.000022		0.010946	-0.013653
1st Bull 0.2	Long	0.000996*	(1.836)	0.006354	0.136752
	Short	-0.000911		0.011022	-0.094215
Bear 0.00244	Long	0.000808	(-0.732)	0.011042	0.059771
	Short	0.001814		0.016639	0.100157
Bear 0.2	Long	0.000493	(-0.634)	0.011081	0.031159
	Short	0.001371		0.016777	0.072907
2nd Bull 0.00244	Long	0.001303*	(1.857)	0.006967	0.179491
	Short	-0.000662		0.010639	-0.067219
2nd Bull 0.2	Long	0.001068**	(2.424)	0.007110	0.142809
	Short	-0.001514		0.010680	-0.146690

Buy signals appear to outperform sell signals on the full period, however during the bear period sell signals are more profitable and outperform the buy signals also on Sharpe measurement. Overall MFI-RSI doesn't seem to generate usable signals for short positions during a bullish period, and when controlled for the higher trading cost level of 0.2 %, all sell signals generate negative profits. It is noteworthy that the standard deviations under short positions exceed the ones under long positions at all times, thus referring to a very volatile strategy. The high risk suggests a failure in capturing any profitable information on a climbing stock market. To illustrate the volatility difference between short and long signals, the 10-day return distributions of the returns exceeding aggregate benchmark index returns are graphed in figure 3. The figure of distribution when going short indicates a volatile period, whereas long position returns appear low but stable. For the first day on a new position, the transaction cost of 0.2 % is included.

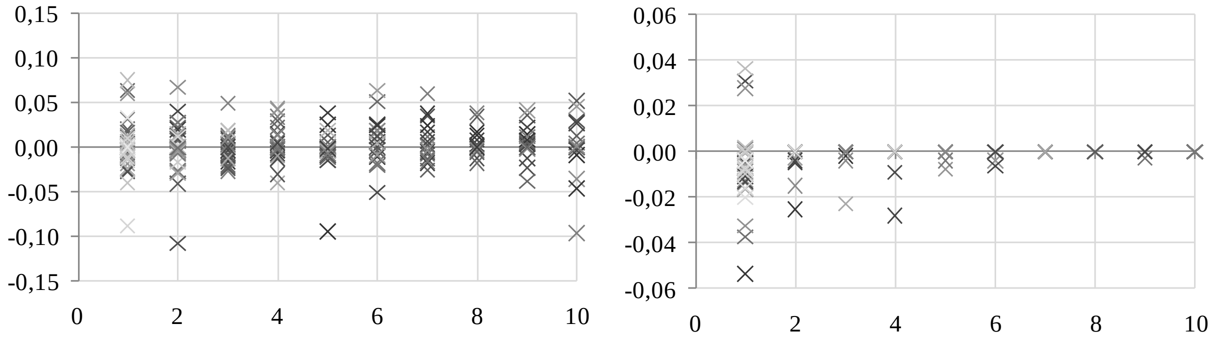

Figure 3. The daily return distributions of first 10 days of aggregate index difference between buy-and-hold strategy and MFI-RSI strategy. The returns are reported on y-axis in percentages for both positions, short (left) and long (right), with x-axis representing function of time as the first 10 days. The returns are controlled for transaction costs of 0.2%.

6.4 Additional insight for the sensitivity of Sharpe ratio for MFI-RSI parameter adjustment

According to some scholars, the value of technical analysis in addition to generating returns exceeding the benchmark is adding value to the investment process (e.g. Lo et al.,2000; Bettmann et al., 2009). As risk-reducing properties have been identified on MFI-RSI strategy, an attention should be paid on a simple optimization for Sharpe ratio or similar risk-to-reward ratio in terms of parameter selection.

In order to avoid risk of data mining, this thesis has only tested the results that have been obtained using a single value of 50 on MFI-RSI trading signal bound. In this section a brief overview of risk ratio sensitivity for parameter altering is presented. The additional sensitivity control is performed on the aggregate index for the full sample period controlling for trading cost of 0.2 %. All crossover values between 0 and 100 are tested using interval of 0.1. The regression results are reported on table 11.

The regression is as previously stated

(12) $$\mu_{MFI\text{-}RSI} = \alpha + \beta C_{MFI\text{-}RSI} + \varepsilon ,$$

where $\mu_{MFI\text{-}RSI}$ = mean daily return of MFI-RSI strategy, α = the constant term, β = the coefficient term, $C_{MFI\text{-}RSI}$ = the crossover value of MFI-RSI strategy and ε = the error term. A higher constant term α is to indicate higher returns independent of the parameters set for trading and the coefficient term β is expected to describe how sensitive the returns are for MFI-RSI trading value.

Table 11. The simple regression results for mean daily return dependence of crossover values. None of the values are statistically significant. The values inside the brackets are *t*-statistics.

	α	β
	0.085016	-0.001372
p-value	0.000	0.000
Standard error	0.001721	0.000030
	(49.410)	(-46.054)
Squared R	0.680	

Significant t-stats are reported, suggesting that the simple regression model supports assumption of daily return dependence of the trading signal value used. For minimum value of 0 the MFI-RSI strategy earns the returns of holding the benchmark index, and using the maximum value of 100 corresponds shorting the index for the full sample period. For all values of interval of 0.1 between 0 and 100 the highest mean daily return is earned using crossover bound of 47.5 (0.085 %), translating to a slightly higher weighting for long positions. The most unprofitable value in terms of mean daily returns is 92.2 (-0.058 %), as the short signals are dominative when the crossover value is higher.

As for adjusting for risk, applying Sharpe ratios allows controlling for volatility. The highest and lowest Sharpe ratios for the aggregate index are achieved using the same parameters as the highest and lowest daily return averages, 47.5 and 92.2 respectively. Sharpe ratio varies between 0.075 and -0.071. The sensitivity of Sharpe ratio for adjusting the MFI-RSI signal bound is graphically presented on figure 4. Significant dependence is found between adjusting the crossover signal bound and the risk-to-reward ratio, and even a simple visual observations gives an indication of how adjusting the weighting for long and short signals effect the riskiness. Intuitively concluded, an optimal value in terms of risk and reward is found between 30 and 60. This value is possibly placing more weight on the long position, which is a natural assumption on a period under which the benchmark index yielded cumulative returns of 138 % and that only experienced one bearish period in terms of 200-day moving average of daily returns.

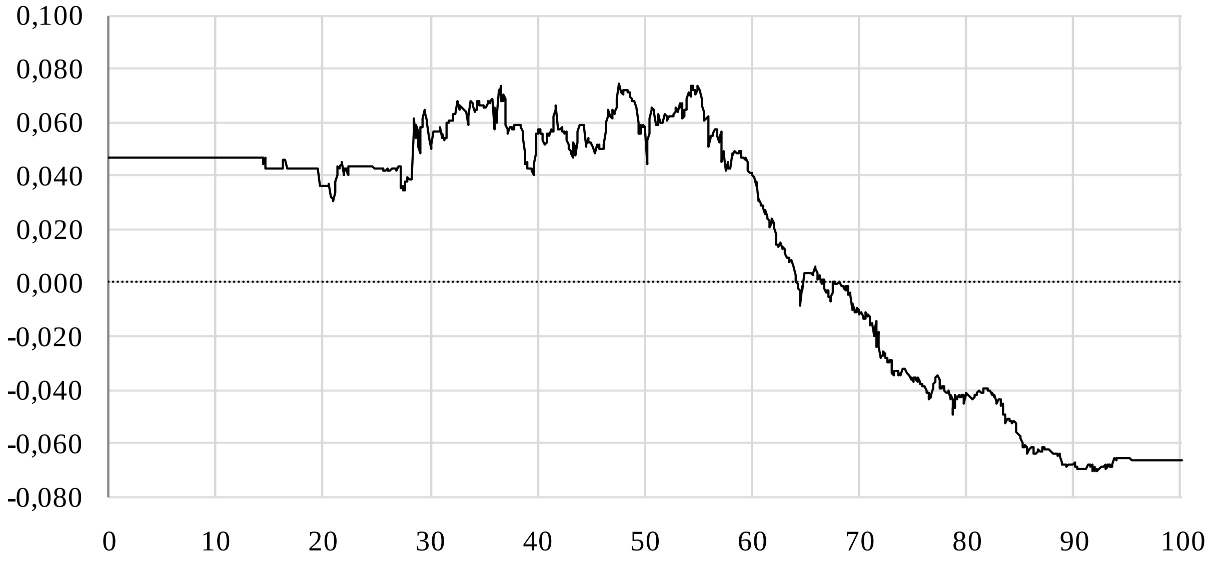

Figure 4. The sensitivity curve of Sharpe ratio for MFI-RSI Crossover strategy's trading bound adjustment between 0 and 100 with intervals of 0.1. The graph represents mean daily returns of MFI-RSI strategy utilized for aggregate index on full sample period controlled with transaction cost of 0.2 % per trade.

7. SUMMARY AND CONCLUSIONS

The purpose of this thesis is to investigate whether abnormal returns can be yielded using MFI-RSI hybrid strategy. In order to further elaborate the predictive abilities of the strategy, the observation period was divided into sub-periods for examination of the capabilities under different market conditions.

The results show no evidence of the abnormal profit opportunities during bull markets when utilizing only MFI-RSI strategy. The strategy in most occasions is superior to holding the market index, but statistical significance for beating the buy-and-hold strategy is only found on 10 % level. During the bear market however the MFI-RSI strategy appears to beat the market and when controlled for the lower transaction costs applied for financial institutes, a significance of 5 % is discovered.

Even though the sensitivity for the transaction costs in most tests suggests market efficiency, the high level of predictability under the financial crisis raises an important question: As a hybrid of two technical oscillators in its very simplest form captures abnormal profit opportunities, does the market irrationality peak as the stock market falls? Shefrin (2002) suggests that the primary emotions determining investor's risk-taking behavior are greed, hope and fear – fear being intuitively the dominant emotion during a financial crisis. The uncertainty under the distress months 2007-2009 led to excessive volatility, forcing the prices to fluctuate further away from the fundamental values, thus possibly creating a trading environment suitable for technical analysis. Volatility has been attributed to market inefficiency by for instance Shiller (1981). The risk ratios calculated for MFI-RSI strategy returns suggest that the method in fact has a smoothing effect on volatility and it thus enables reducing risk on short-term investments. Yet the strategy doesn't capture profitable components in bull market, suggesting that the market would reflect the past price and volume information, thus functioning in a rational manner in accordance with weak form efficiency tests. Furthermore, it should be observed that the bear period on which the strategy outperformed the benchmark indices is relatively short, raising a question on the validity of the results. According to Brock et al. (1992), a period of at least 15 years should be used to completely avoid the data snooping biases. The final conclusion drawn on MFI-RSI strategy performance results under the maximum period of 123 months in this study therefore can not be interpreted as supporting the alternative hypothesis claiming the strategy to contain predictive power. The uncovered predictive properties surely support the assumptions of adding value to the investment process, but in terms of extracting valuable technical components the hypothesis of efficiency in the Nordic markets stands.

In technical tool studies different bootstrap methods and sets of parameters have traditionally been used to estimate the predictive properties of each tool (e.g. Sullivan et al., 1999). On the thesis at hand the interest lies mainly in a single tool with default settings, and its performance under different market conditions. An additional sensitivity test was performed for Sharpe ratio sensitivity for parameter adjustment in order to detect the maximum and minimum risk-reward ratios between the oscillator value range. It is however noteworthy that due to a relatively short observation period used in the study, one can, using in fact nothing but intuition, create bootstrap methods that seemingly capture asset price reversals[3]. The possibilities of reproducing this kind of tests are very low, and out-of-sample tests show that the modeling of patterns could be done for random numbers in an equal manner (Jensen & Benington, 1970; Sullivan et al., 1999). Still, as significance at 5 % level was found for MFI-RSI strategy outperforming the benchmark index on bear market when controlled for the lower transaction costs of 0.00244 %, a relevant subject of parameter manipulation is the adjustment of the bound marking overbought and oversold levels. For an oscillator assuming values between 0-100 the tested value of 50 is not sensitive for market condition in any way. If allowed for adjustment of buy and sell signal threshold depending on the direction of 200-day moving average of the index, it can be possible to simply weight the sensitivity for long and short signals. In this study the buy signals beat sell signals significantly (10 %) on both bull periods, further suggesting the timing adjustment. Indeed, the short signals timed the aggregate index correctly only during the bear period, when the Nordic market fell as a result of the financial crisis. When the weighting for the short position was increased, the Sharpe ratio fell drastically below zero. The negative risk-return ratio is naturally a result of shorting the index on bullish period. Still, even a visual observation of Sharpe ratio curve in terms of MFI-RSI values gives an intuitive suggestion of an optimal crossover signal value to lie between 30 and 60. This translates to risk-reducing properties for the investment process that are achieved through an active trading and that do outperform holding the benchmark index.

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[3] Apart from this study, I have constructed a technical indicator vehicle on MS Excel using eleven signals based on five different technical indicators. Using approximately 18 months of price and volume data at a time, the parameters of each indicator can be adjusted to simulate best performing rules for individual stocks. Again, with a rather little effort, buy-and-hold strategy is beaten in the simulation but no evidence exists on whether the rules in reality outperform the benchmark out-of-sample or not. The vehicle is available on request.

The examination of distribution of the MFI-RSI strategy returns is a research area that could be extended as well. Practitioners' approaches include a variety of ways to empirically mine for risk-reducing strategies in short horizon trades, such as setting stop-loss limits or investigating different lengths of investments periods, and a range of methods to exploit speculative investment forms in terms of derivative trading for leverage gain. If a sufficiently long observation period is used, the results of predictive power of MFI-RSI strategy could be extended. Given that this amount of data were sufficiently large and the strategy's 'oversold' and 'overbought' limits aiming to reflect the price and volume fluctuation information content were further deconstructed, perhaps components even more valuable to the investment process could be extracted. This would mean a more rational technical approach to studying the informational content of volatility and trading volume, and the tests could be made on for instance timing of the trade. When the MFI-RSI strategy gives a trading signal, an indication is theoretically given on whether the market is sentimentally preparing for a short horizon increase or decrease in value. On a short 14-day time span, the indication of a change in the sentiment is expected to be utilized immediately. However, the shorter the period in use, the more sensitive the oscillator is and more often a false signal occurs. For longer periods MFI and RSI provide more reliable signals, but analyzing technical details in longer horizon arguably does not respond well to changes in fundamentals and macroeconomic factors.

In this study some evidence has been found for technical analysis profitability under a market downturn, supporting the use of technical methods as decision assistance. As a further research I would, as an even more robust subject of investigation than the earlier said parameter manipulation, suggest the use of fundamental ratios and parameters as a supporting vehicle to the MFI-RSI strategy or another technical indicator. The condition of the broad market has effect on the usability of technical methods, however certain events are derived from investor irrationality and can not be explained by change in fundamentals. Therefore the technical predictabilities in terms of investor sentiment and opinion divergence are equally favorable subjects for future research. On a broad market index level a weighted index should be used to ensure an effortless replication of the results.

Further integration of technical and fundamental analysis has been suggested by e.g. Bettman et al. (2008), who studied momentum strategy alongside book value and dividend history. On a firm level, a large number of financial ratios could be used to estimate the suitability of MFI-RSI application as an investment decision support tool or a position timing indicator. As the Nordic markets in this study were selected geographically and include quite thinly traded stocks, a firm's capitalization's effect on the technical rule profitability on the said markets is an especially interesting subject of future research.

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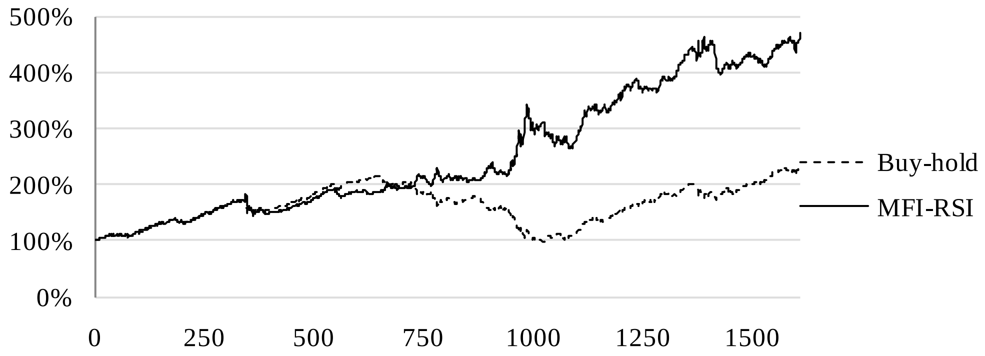
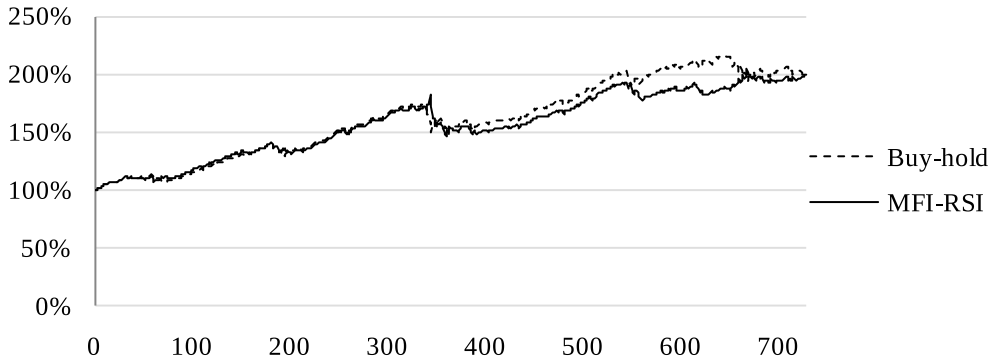
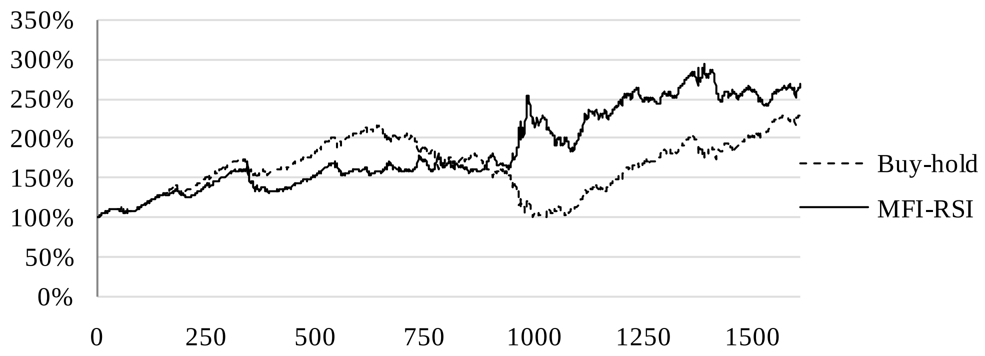
APPENDIX A. Graphed cumulative daily returns of the performed tests on the constructed equally weighted indices



Aggregated index under full sample period, transaction costs 0.00244%.



Aggregated index under full sample period, transaction costs 0.2%.



Aggregated index on the first bull period, transaction costs 0.00244 %.

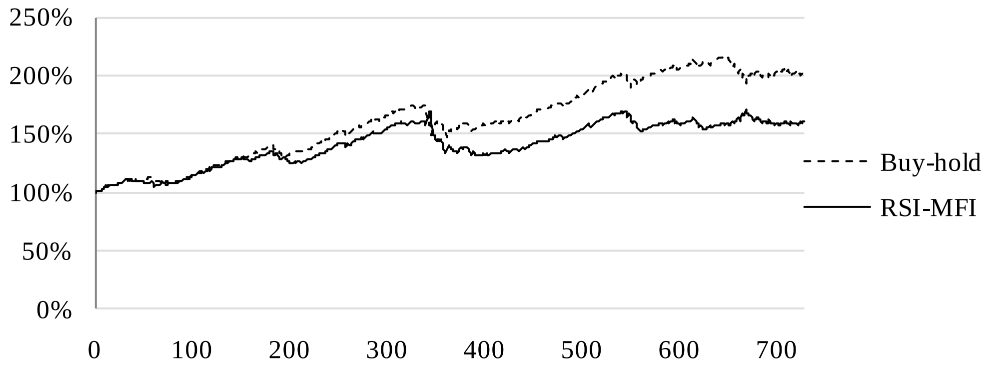
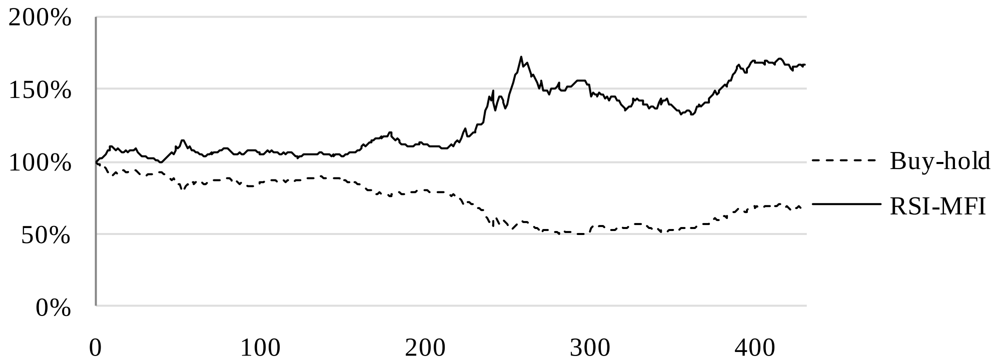
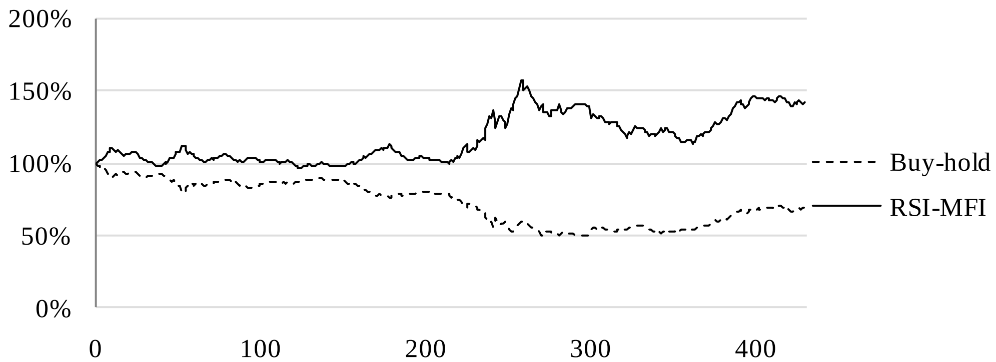


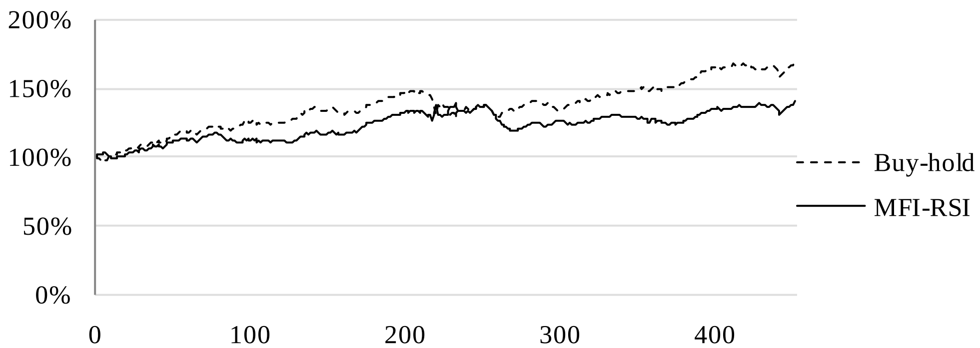
Chart 3. Aggregated index on the first bull period, transaction costs 0.2 %.



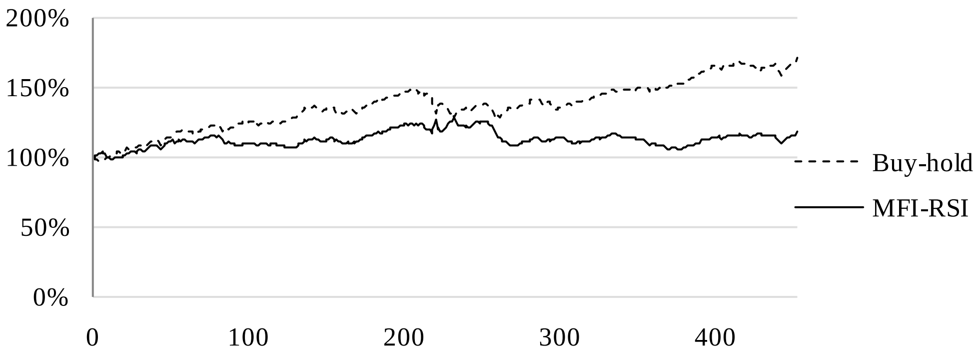
Aggregated index on the bear period, transaction costs 0.00244 %.



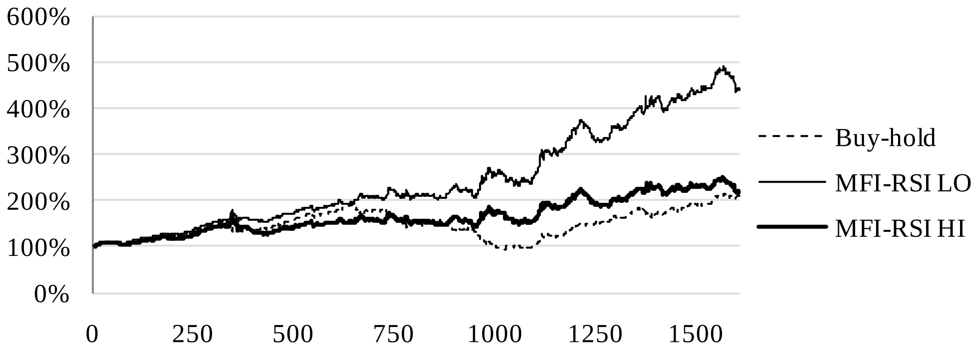
Aggregated index on the bear period, transaction costs 0.2 %.



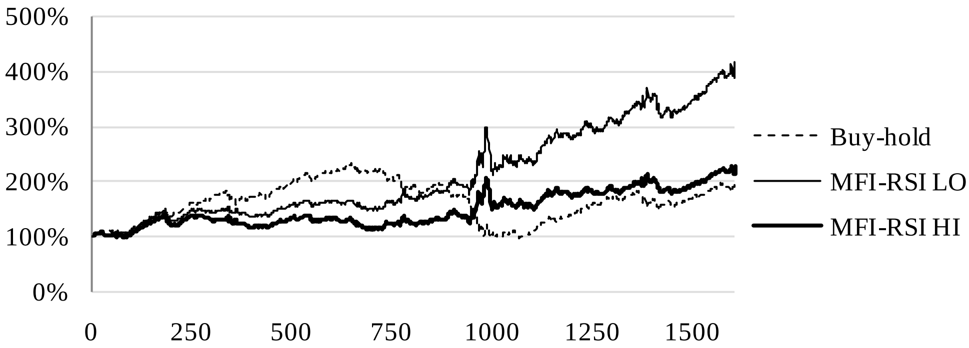
Aggregated index on second bull period, transaction costs 0.00244 %.



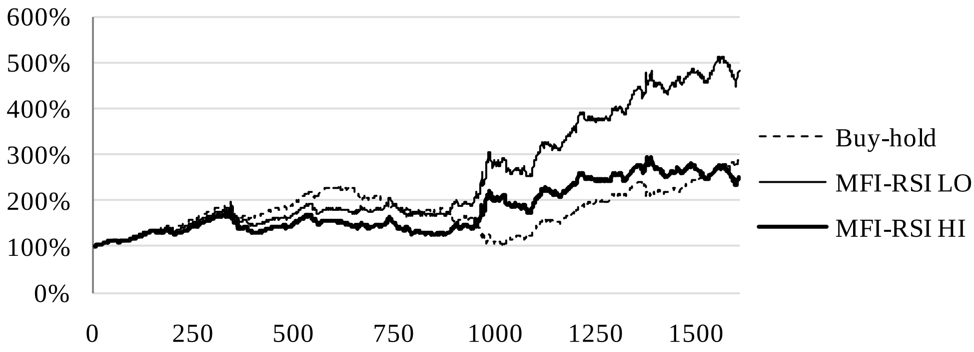
Aggregated index on second bull period, transaction costs 0.2 %.



Helsinki stock index during the full sample period. On the graph LO stands for transaction costs of 0.00244 % and HI stands for costs of 0.2 %.

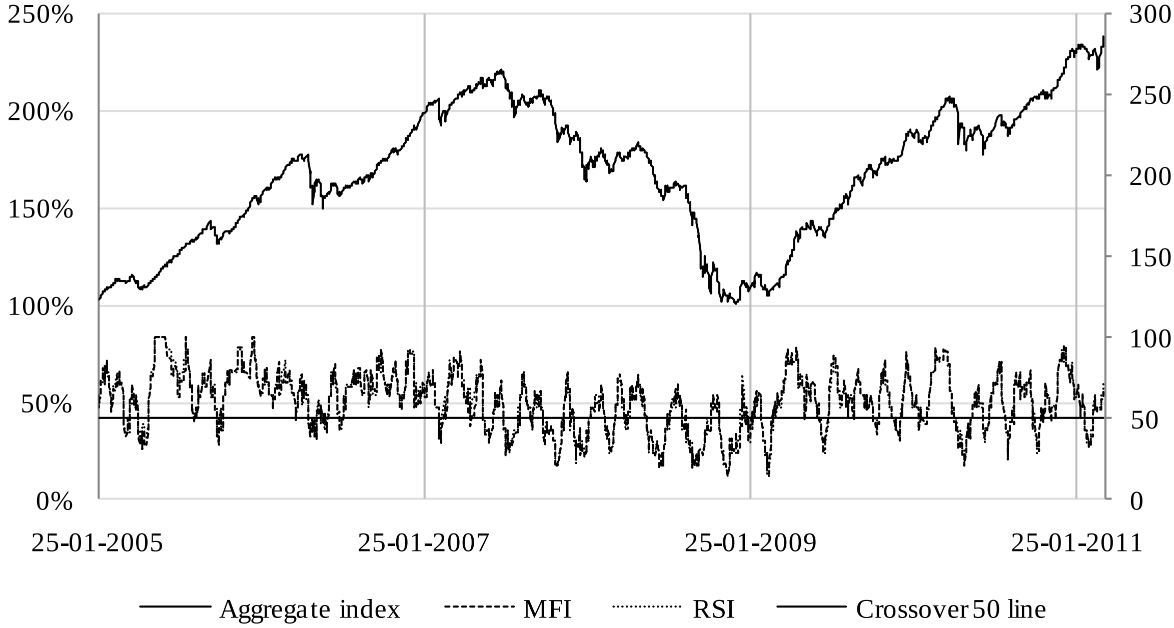


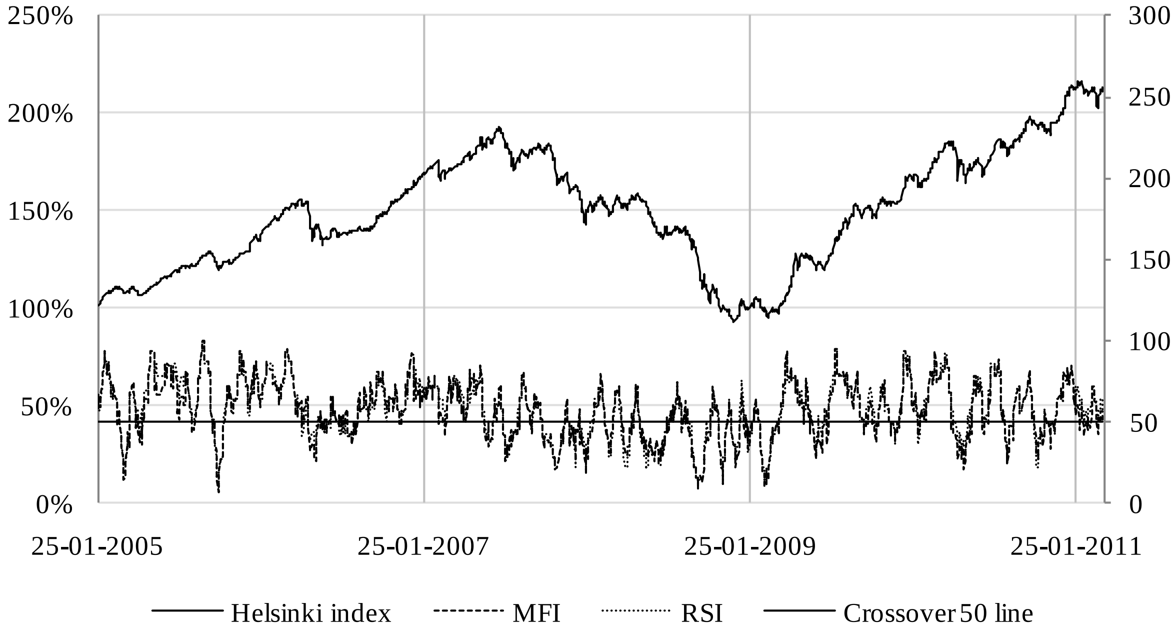
Oslo stock index during the full sample period. On the graph LO stands for transaction costs of 0.00244 % and HI stands for costs of 0.2 %.

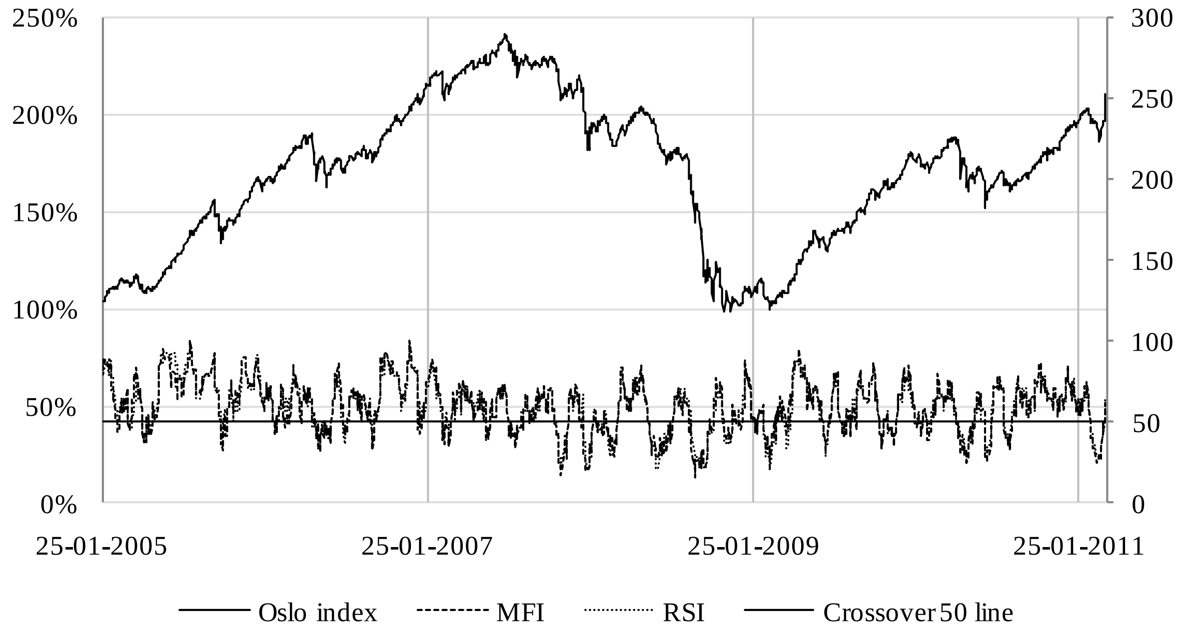


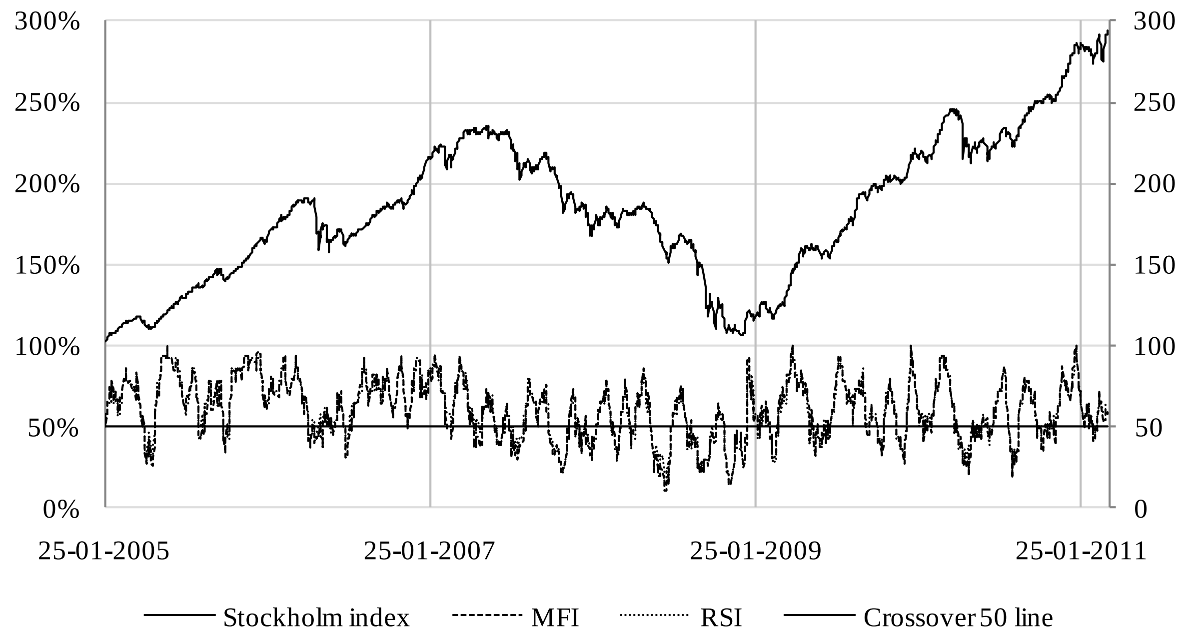
Stockholm stock index during the full sample period. On the graph LO stands for transaction costs of 0.00244 % and HI stands for costs of 0.2 %

APPENDIX B. The indices graphed jointly with the respective MFI and RSI oscillator curves






250%
200%
150%
100%
50%
0%
300
250
200
150
100
50
0
25-01-2005
25-01-2007
25-01-2009
25-01-2011
Oslo index
MFI
RSI
Crossover 50 line


300%
250%
200%
150%
100%
50%
0%
300
250
200
150
100
50
0
25-01-2005
25-01-2007
25-01-2009
25-01-2011
Stockholm index
MFI
RSI
Crossover 50 line

APPENDIX C. Stocks included in the study

HELSINKI

Alandsbanken ABP
Aldata Solution OYJ
Amanda Capital OYJ
Amer Sports OYJ
Aspo OYJ
Aspocomp Group OYJ
Atria OYJ
Basware OYJ
Biohit OYJ
Biotie Therapies OYJ
Capman OYJ
Cencorp OYJ
Citycon OYJ
Componenta OYJ
Comptel OYJ
Cramo OYJ
Digia PLC
Dovre Group OYJ
Efore OYJ
Elecster OYJ
Elektrobit OYJ
Elisa OYJ
Etteplan OYJ
Exel Composites OYJ
F-Secure OYJ
Finnair OYJ
Finnlines OYJ
Fiskars OYJ
Fortum OYJ
Geosentric OYJ
Glaston OYJ
Hkscan OYJ
Honkarakenne OYJ
Huhtamaki OYJ
Ilkka Yhtyma OYJ
Incap OYJ
Innofactor PLC
Interavanti OYJ
Ixonos OYJ
Kemira OYJ
Keskisuomalainen OYJ
Kesko OYJ
Kesla OYJ
Kone OYJ
Konecranes OYJ
Lannen Tehtaat OYJ
Lassila & Tikanoja PLC
Lemminkainen OYJ
M-Real OYJ
Marimekko OYJ
Martela OYJ
Metso OYJ
Neo Industrial OYJ
Nokia Corporation
Nokian Renkaat OYJ
Nordic Aluminium OYJ
Norvestia OYJ
Nurminen Logistics OYJ
Okmetic OYJ
Olvi OYJ
Oral Hammaslaakarit OYJ
Orion Corp.
Outokumpu OYJ
Panostaja OYJ
PKC Group OYJ
Pohjois-Karjalan Kirjapaino OYJ
Pohjola Pankki A
Ponsse OYJ
Poyry OYJ
QPR Software PLC
Raisio PLC
Ramirent OYJ
Rapala VMC Corp.
Rautaruukki OYJ
Raute OYJ
Revenio Group OYJ
Ruukki Group OYJ
Sampo OYJ
Sanoma Corporation
Scanfil OYJ
Solteq OYJ
Soprano OYJ
Sponda OYJ
SSK Suomen Saastajien Kiinteistot OYJ
Stockmann OYJ
Stonesoft OYJ
Stora Enso OYJ
Suominen Yhtyma OYJ
Takoma OYJ
Talentum OYJ
Technopolis OYJ
Tecnotree OYJ
Tectia OYJ
Tekla OYJ

Teleste OYJ
Tieto OYJ
Tiimari PLC
Trainers House OYJ
Tulikivi OYJ
Turkistuottajat OYJ
Turvatiimi OYJ
UPM-Kymmene OYJ
Uponor OYJ
Vacon OYJ
Vaisala OYJ
Viking Line ABP
Wartsila OYJ
Wulff-Group PLC
YIT OYJ
Yleiselektroniikka OYJ
Nordea Bank AB
Teliasonera AB

STOCKHOLM

3L System AB
A-Com AB
Acando AB
Acap Invest AB
Accelerator Nordic AB
Active Biotech AB
Addnode AB
Addtech AB
Addvise LAB Solutions AB
AF AB
Alfa Laval AB
Alliance Oil Company Limited
Altero AB
Anoto Group AB
Aqua Terrena International AB
Aros Quality Group AB
Artimplant AB
Aspiro AB
Assa Abloy AB
Atlas Copco AB
Atrium Ljungberg AB
Avanza Bank Holding AB
Avensia Innovation AB
Axfood AB
Axis AB
Axlon Group AB
B & B Tools AB
Beijer Alma AB
Beijer Electronics AB
Bergs Timber AB
Betsson AB
Bilia AB
Billerud AB
Biogaia AB
Bioinvent International AB
Biophausia AB
Biotage AB
Bjorn Borg AB
Boliden AB
Bong Ljungdahl AB
Bredband2 I Skandinavien AB
Bringwell International AB
Brinova Fastigheter AB
BTS Group AB
Bure Equity AB
Cardo AB
Castellum AB
Catella 'A'
Cellpoint Connect AB
Cision AB
Clas Ohlson AB
Clean Tech East Holding AB
Concordia Maritime AB
Connecta AB
Conpharm AB
Consilium AB
Corem Property Group AB
Creative Antibiotics Sweden AB
CTT Systems AB
Cybercom Group Europe AB
Diamyd Medical AB
Digital Vision AB
Doro AB
Duroc AB
Elanders AB
Electrolux AB
Elekta AB
Elektronikgruppen Bk AB
Elos AB
Emitor Holding AB
Enea AB
Eniro AB
Entraction Holding AB
Ericsson Telephone AB
Expanda AB
Fabege AB
Factum Electronics Holding AB
Fagerhult AB
Fast Partner AB

Fastighets Balder AB
Feelgood Svenska AB
Fenix Outdoor AB
Fingerprint Cards AB
Firefly AB
G & L Beijer AB
Getinge AB
Getupdated Internet Marketing AB
Geveko AB
Gunnebo AB
H & M Hennes & Mauritz AB
Haldex AB
Heba AB
Hedson Technologies International AB
Hexagon AB
Hifab Group AB
HIQ International AB
Hoganas AB
Holmen AB
HQ AB
Hufvudstaden AB
IBS AB
IDL Biotech AB
Impact Coatings AB
Industrial & Financial Systems AB
Industrivarden AB
Intellecta AB
Intoi AB
Intrum Justitia AB
Investment AB Kinnevik B
Investor AB
Invisio Communications AB
Itab Shop Concept AB
Jeeves Information Systems AB
JLT Mobile Computers AB
JM AB
Kabe Husvagnar AB
Karo Bio AB
Kindwalls AB
Klick Data AB
Klovern AB
Know It AB
Kungsleden AB
Labs2Group AB
Lagercrantz AB
Lappland Goldminers AB
Latour Investment AB
Lundbergforetagen AB
Lundin Petroleum AB
Malmbergs Elektriska AB
Meda AB
Medcap AB
Medivir AB
Mekonomen AB
Metro International SA
Micronic Mydata AB
Midsona AB
Midway Holdings AB
Mobyson AB
Modern Times Group MTG AB
Morphic Technologies AB
Multiq International AB
NCC AB
Net Insight AB
Netonnet AB
Netrevelation AB
New Wave Group AB
Nibe Industrier AB
Nobia AB
Nolato AB
Nordea Bank AB
Nordic Service Partners Holdings AB
Nordnet AB
Note AB
Novestra AB
Novotek AB
OEM International AB
Opcon AB
Orasolv AB
ORC Software AB
Oresund Investment AB
Oriflame Cosmetics SA
Ortivus AB
PA Resources AB
Partnertech AB
PEAB AB
Phonera AB
Poolia AB
Precio Systemutveckling
Precise Biometrics AB
Prevas AB
Pricer AB
Proact It Group AB
Probi AB
Proffice AB
Profilgruppen AB
Ratos AB
Raysearch Laboratories AB

Luxonen SA
Rederi AB Transatlantic
Rejlerkoncernen AB
RNB Retail And Brands AB
Rorvik Timber AB
Rottneros AB
Saab AB
Sagax AB
SAK I AB
Sandvik AB
SAS AB
SCA AB
Scania AB
SE Banken
Seco Tools AB
Sectra AB
Securitas AB
Semcon AB
Sensys Traffic AB
Sigma AB
Sintercast AB
Skanska AB
SKF AB
Skistar AB
Smarteq AB
Softronic AB
Srab Shipping AB
SSAB AB
Starbreeze AB
Studsvik AB
Svedbergs AB
Svenska Handelsbanken AB
Svolder AB
Sweco AB
Swedbank AB
Swedish Match AB
Switchcore AB
Taurus Energy AB
Tele2 AB
Teliasonera AB
Tethys Oil AB
Traction AB
Transcom Worldwide SA
Trelleborg AB
Unibet Group PLC
Uniflex AB
VBG Group AB
Venue Retail Group AB
Vitec Software Group AB
Vitrolife AB
Volvo AB
Readsoft AB
Wallenstam AB
Xano Industri AB

OSLO

ABG Sundal Collier Holding ASA
Acta Holding ASA
AF Gruppen ASA
Aker ASA
Aker Biomarine ASA
Aker Solutions ASA
Aktiv Kapital ASA
Apptix ASA
Arendals Fossekompani
Atea ASA
Aurskog Sparebank ASA
Bionor Pharma ASA
Birdstep Technology ASA
Blom ASA
Bonheur ASA
Borgestad ASA
Byggma ASA
Camillo Eitzen & Co
Contextvision AB
Data Respons ASA
Diagenic ASA
DNB Nor ASA
DNO International ASA
DOF ASA
Domstein ASA
EDB Ergogroup ASA
Eitzen Maritime Services ASA
Ekornes ASA
Eltek ASA
Farstad Shipping ASA
Fred Olsen Energy ASA
Frontline Limited
Ganger Rolf ASA
GC Rieber Shipping ASA
Golar LNG Limited
Golden Ocean Group Limited
Goodtech ASA
Green Reefers ASA
Hafslund ASA
Helgeland Sparebank ASA
Hexagon Composites ASA
HOL Sparebank ASA
Holand OG Setskog Sparebank
Hurtigruten ASA
IGE Resources AB

Ignis ASA
IM Skaugen ASA
Indre Sogn Sparebank
Inmeta Crayon ASA
Itera ASA
Jinhui Shipping & Transportation Limited
Kitron ASA
Komplett ASA
Kongsberg Gruppen ASA
Kverneland ASA
Leroy Seafood Group ASA
Marine Harvest ASA
Medi-Stim ASA
NES Prestegjelds Sparebank
Nordic Semiconductor ASA
Norse Energy Corp. ASA
Norsk Hydro ASA
Norske Skogindustrier ASA
Norwegian Air Shuttle ASA
Norwegian Car Carriers ASA
Odfjell ASA
Olav Thon Eiendomsselskap
Opera Software ASA
Origio A/S
Orkla ASA
Petroleum Geo Services ASA
Petrolia ASA
Photocure ASA
Prosafe SE
PSI Group ASA
Q-Free ASA
Rieber & SON ASA
Rocksource ASA
Sandnes Sparebank ASA
Scana Industrier ASA
Schibsted ASA
Sevan Marine ASA
Sinoceanic Shipping ASA
Skiens Aktiemolle ASA
Solstad Offshore ASA
Sparebank 1 Buskerud Vestfold ASA
Sparebank 1 Nord-Norge ASA
Sparebank 1 SMN
Sparebank 1 SR Bank ASA
Sparebanken More ASA
Sparebanken Ost ASA
Sparebanken Pluss ASA
Sparebanken Vest ASA
Statoil ASA
Stolt-Nielsen Limited
Storebrand ASA
Subsea 7 SA
SWAN REEFER ASA
Teco Maritime ASA
Telenor ASA
TGS-Nopec Geophysical Company ASA
Tomra Systems ASA
Totens Sparebank ASA
TTS Group ASA
Veidekke ASA
Wilhelmsens Wilhelmsen Holdings ASA
Yara International ASA