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Can simple technical trading rules be successful in the Norwegian stock market?

An analysis of profitability and predictive power of technical trading.

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Abstract

In this analysis, two simple technical trading rules, moving average and trading-range breakout, are tested by utilizing OBX and OSESX from Oslo Stock Exchange in 1997-2013. To assess if the rules are successful, the performance is tested with a traditional t-test and a residual bootstrap by Brock, Lakonishok and LeBaron (1992). To correct for possible data snooping bias, White's (2000) Reality Check is applied. The t-test signals that the trading rules are profitable on OSESX, and that buy signals consistently generate higher returns than sell signals. Further, the returns following buy signals are less volatile than returns following sell signals. The returns following sell signals are negative, which is not consistent with existing equilibrium models. The profits are not eliminated by transaction costs, but the performance is not robust across subperiods. The results are significant after correcting for data snooping. The residual bootstrap shows that returns from the trading rules are not consistent with a random walk, but suggests time-varying expected returns as an explanation. The volatility following buy and sell signals is not as easily explained by time-varying volatility. This indicates that the profitability is not due to predictive power of the rules, but that the rules may be able to detect periods with lower volatility. Overall, the results provide low support for technical analysis in the Norwegian stock market.

Abstrakt

I denne analysen er to enkle, tekniske handleregler, moving average og trading-range breakout, testet ved bruk av data fra OBX og OSESX fra Oslo Børs i 1997-2013. For å avgjøre om reglene er suksessfulle, er resultatene testet med en tradisjonell t-test og en residual bootstrap av Brock, Lakonishok og LeBaron (1992). For å korrigere for eventuelle data snooping bias, er White's (2000) Reality Check benyttet. T-testen signaliserer at reglene kun genererer profitt på OSESX, og at kjøpssignaler konsekvent genererer høyere avkastning enn salgssignaler. Avkastningen som følger kjøpssignaler er også mindre volatil enn avkastningen som følger salgssignaler. Salgsavkastningen er negativ, hvilket er uforenelig med eksisterende likevektsmodeller. Avkastningen elimineres ikke som følge av transaksjonskostnader, men resultatene er ikke robuste over delperioder. Resultatene er signifikant etter å ha korrigert for data snooping. Resultatene fra residual bootstrap viser at avkastningen fra handlereglene ikke er forenelig med en random walk, men foreslår tidsvarierende forventet avkastning som en forklaring. Volatiliteten som følger kjøps- og salgssignaler er ikke like enkelt å forklare med tidsvarierende volatilitet. Dette indikerer at profitt på OSESX ikke skyldes at reglene har prediktiv kraft, men at reglene likevel kan oppdage perioder med lavere volatilitet. Generelt sett gir resultatene lav støtte for teknisk analyse i det norske aksjemarkedet.

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1 Introduction

The usefulness of technical analysis is controversial in academic and applied finance. Technical analysis seeks to identify market trends through the use of past price and volume information. The purpose is to utilize predefined rules to time market positions, and outperform a passive strategy. While numerous investors rely on computer-based technical trading systems, academics are generally skeptical to its value. However, two pioneering papers by Brock, Lakonishok and LeBaron (1992) and Sullivan, Timmermann and White (1999) propose that technical analysis is valuable. The first paper implements a popular method to evaluate technical analysis, and is frequently referred to as the BLL bootstrap. The method attempts to examine if technical trading rules can be credited with predictive power, or if other aspects can explain the performance. This method does not properly account for data snooping biases, which might arise when exhaustively searching for well-performing rules within a data set. The latter paper introduces a comprehensive test called the Reality Check[1] to account for such biases. Following these papers, several studies have provided support for technical trading, though not many examine the Norwegian market. The purpose of this paper is to assess the value of technical trading in the Norwegian stock market by applying methods from Brock et al. (1992) and Sullivan et al. (1999).

The theoretical foundation for technical trading is relatively scarce, and the well-established efficient market hypothesis (EMH) states that technical analysis has no value. Fama (1970) claims that market participants behave rationally, and that market prices therefore include all relevant information at any given time. This implies that past prices are impossible to exploit to predict future price movements. The EMH is challenged by behavioral finance theory, which explores irrational market behavior. By undermining the assumptions of efficient markets, the foundation for technical analysis is strengthened.

When evaluating technical analysis, it is important to consider both profitability and predictive power of the trading rules. Profitability implies that the rules outperform a passive strategy,

[1] First described in a working paper by White (2000).

and are robust to market conditions, while predictive power implies that the rules correctly identify and exploit predefined patterns. To examine if technical analysis is successful, it is common to initially test the trading rules in markets ex-post. However, it is important to consider that market conditions may affect the results. For example, if a trading rule only seems successful during certain trends, such as bull and bear markets, the trading rule might not be robust. This emphasizes the importance of examining how the rules perform during periods with different market conditions. Also, relevant market frictions, such as transaction costs, must be considered before suggesting that the rules are profitable. Another possible error of testing market efficiency is the risk of an outcome being a result of chance. Stock prices are heavily examined, and it is almost inevitable that a rule eventually discovers a market pattern. It is therefore important to consider that profitability can merely be a result of luck. It is also important to consider that outperformance from the rules does not necessarily imply that the rules have predictive power. If a market has characteristics that can easily be discovered without the use of a technical trading rule, it is possible that these characteristics can explain outperformance from the rule.

These aspects form the basis of this analysis, and they are examined in order to answer the following research question: Can simple technical trading rules be successful in the Norwegian stock market? The analysis applies stock indices to represent two sides of the Norwegian market, high liquidity and small-capitalization, to examine the relationship between the value of technical analysis and these market features. If technical trading rules are successful, it means that the rules are profitable, and that this is due to the predictive power of the rules. The profitability of the rules is examined in a long sample and during periods with specific trends. Also, the break-even transaction costs are considered. To examine if the rules have predictive power, the Reality Check is applied to correct for data snooping bias, and the BLL bootstrap will evaluate if possible patterns in the market are more guiding than the rules.

This paper is structured in the following order: In chapter 2, the appropriate theory on technical analysis is assessed. Also, four hypotheses are formed to help answer the research question. In chapter 3, the relevant literature on technical trading is reviewed. The applied methods for testing the four hypotheses are described in chapter 4, and the test results are displayed in chapter 5. The findings and limitations of this study are discussed in chapter 6.

2 Technical analysis: Preliminaries

Stock market analysis can be divided into two broad categories: fundamental and technical analysis. Fundamental analysis uses company information, such as earnings and profit margins, to make investment decisions, while technical analysis applies only indicators generated by market activity, such as price and volume. The latter category is the focus of this paper.

The objective of technical analysis is to use a set of rules to identify trends, and signal when investors should enter and exit the market in order to achieve profits. Indications of an upward trend commonly trigger buy signals, while indications of a downward trend trigger sell signals. Such a market tendency, where it is expected that trends continue in the future, is known as a momentum effect. The opposing effect is known as contrarian, where the trends are caused by price changes that are temporary and therefore expected to reverse. To exploit contrarian effects, buy signals translate into sell signals, and sell signals translate into buy signals.

Technical analysis is based on the following three assumptions: 1) prices discount everything, 2) prices move in trends, and 3) history repeats itself. The first assumption implies that prices reflect everything that could affect the price. This indicates that fundamental factors are not necessary to consider, as they are already reflected in the price. The second assumption implies that once a trend is established, future price movement is likely to be in the same direction. The basic idea of trends originates from Dow theory[2], which states that the market has three trends: a primary, secondary and minor. The primary trend can last for several years, while the secondary trend can continue for weeks to months. The minor trend is usually only a few days. Most technical trading rules are based on the second assumption. The third assumption relies on market psychology, and the expectation that investors react consistent to similar market conditions over time. Traditionally, economic theory is based on rational behavior, which implies that investors quickly adjust to new information. However, such theories are limited in understanding why and how individual market participants trade. The theories of behavioral finance explore irrational behavior to explain why and how markets can be inefficient.

[2] Formed from a series of Wall Street Journal Editorials authored by Charles Dow in 1900-1902.

Technical analysis is greatly criticized for a number of reasons, and firstly, for only considering technical indicators. Historical price information can only provide information of the past, and it is therefore considered inadequate to apply this information to assess the future. Second, if several investors utilize the same market signals, it will create a price pressure and therefore render technical analysis self-fulfilling. However, if too many investors follow the same signals, the strategy will be self-destructive, as not enough investors are willing to take the opposite position. Third, technical trading has low support in well-known theories, and it violates fundamental concepts such as market efficiency. Lastly, technical traders are dependent on other participants performing fundamental analysis in order for prices to incorporate fundamental factors. However, technical analysis is considered attractive because the information is available to most investors.

In this chapter, behavioral finance is assessed as a theoretical foundation for technical analysis. Thereafter follows a section with some common technical indicators and rules. Lastly, some theories related to profitability and predictive power of technical trading are reviewed. This forms the basis for the four hypotheses that will help answer the research question.

2.1 Behavioral finance: Theoretical foundation

The theory of behavioral finance challenges market efficiency by introducing irrational investors that create market anomalies. According to behavioral finance, these market anomalies arise as a result of an under- or overreaction by the investors. Underreaction indicates that prices are slowly adjusting to new information, which creates a momentum effect. Overreaction causes prices to move above true value and then later reverse. This implies a momentum effect in the short run, and a contrarian effect in the long run. The theory of behavioral finance consists of many aspects, but only a few will be introduced in this analysis. First is an overview of important studies on behavioral finance, followed by some common explanations to irrational behavior. Thereafter follows an overview of some studies recognizing market anomalies. Last, some criticisms of behavioral finance are addressed.

In the field of behavioral finance, Tversky and Kahneman (1974), Kahneman and Tversky (1979) and Thaler (1980) are important contributions. Tversky and Kahneman (1974) describe how heuristics can lead to systematic and predictable biases in investors' behavior. Heuristics refers to experience-based techniques for solving problems, and the biases occur when investors attempt to subjectively assess a scenario based on limited information. The heuristics discussed are representativeness, availability, and adjustment and anchoring. The representative heuristic is used to judge a scenario by comparing it to representative information already possessed. The bias is that investors confuse similarities in a scenario with probability of reoccurrence. The availability heuristic is a mental shortcut that relies on the immediate information that comes to mind. The bias is that investors heavily weigh their decisions on more recent information. The adjustment and anchoring heuristic refers to a scenario where investors stay within a range of what they already know when giving estimates on what they do not know. The bias is that the estimates will be skewed towards the relevant information that they already possess. Tversky and Kahneman (1974) argue that the heuristic biases also apply to experienced investors, and emphasize that a better understanding of heuristics can improve judgment and decisions under uncertainty. Kahneman and Tversky (1979) utilize cognitive psychology to explain economic decision-making, and propose the prospect theory. Cognitive psychology is the study of mental processes such as memory, perception, and problem solving. Cognitive biases are patterns of deviation in judgment that occur in certain situations. The prospect theory challenges the conventional expected utility theory (von Neumann and Morgenstern, 1944), as it accounts for observed attitudes towards risk. The prospect theory advocates that gains and losses are valued differently, and that decisions are based on perceived gains rather than perceived losses. This implies that given two equal options, where one is expressed in terms of gains and the other in losses, the option expressed in terms of gains are preferred. This is because investors find the drawback from losing larger than the benefit from gaining, even if the result is the same. Thaler (1980) argues that many investors act inconsistent with economic theory, and that economic theory will make systematic errors in predicting behavior. Thaler forms a hypothesis on human behavior called the endowment effect, which states that people describe more value to objects if they own them. The endowment effect is inconsistent with economic theory, which assumes that consumers' willingness to pay for a good and willingness to accept to be deprived of a good is equal.

In this study, behavioral finance is applied to explain two issues that cause market anomalies: 1) the problems investors have with processing information, and 2) the biases arising from investors' behavior in the market. The information process problems arise because investors do not always process information correctly. There are three typical biases that create problems in investors' information process: forecasting errors, lack of representativeness, and conservatism. Forecasting errors occur when investors give too much weight to recent information, make extreme forecasts, and act accordingly. The subsequent price pressure will create short-term trends in the market. When investors recognize the mispricing, the prices reverse and correct the mispricing. The bias of representativeness occurs when investors base a decision on information that is misrepresentative for the market. For example, investors may rely too much on past performance of a stock. This will initiate price pressure and create a trend. When investors recognize the mispricing, the prices will reverse and correct the mispricing. The bias of conservatism implies that investors are slow at responding to new information. When the investors recognize the mispricing, the prices will adjust and create a trend. The other set of biases arise because investors make inconsistent or suboptimal decisions. These are known as behavioral biases. There are four typical biases that affect investors trading behavior:

overconfidence, regret-avoidance, limited attention, and trend chasing. The bias of overconfidence indicates that investors incorrectly believe that acquired information and investment ability is perfectly precise. This will cause investors to make irrational and bold decisions, which might not be of best interest. The second bias arises when investors try to manage the emotions of investing. Trading with reduced regret indicates for example that investors will hold on to a stock until it performs well. In other words, investors are willing to bare risk to avoid a loss, but not to gain a win, and therefore hold on to losers too long and winners too briefly. The third bias results from investors having a limited attention span, and not being able to process all possible alternatives. The investors solve the problem by only considering the alternatives that captures their attention. The final bias is trend chasing, where investors bias their behavior towards the current market trend.

Irrational behavior can cause under- and overreaction to new information, and result in partial price adjustment, in which trades occur at prices that do not reflect all available information. The partial price adjustment results in price trends, such as momentum and contrarian effects. Several studies provide support for momentum and contrarian effect in stock markets. Jegadeesh and Titman (1993) identify a momentum effect in the US stock market through buying previously well-performing stocks and selling previously poor-performing stocks. Jegadeesh and Titman (2001) confirms that the momentum effect also persists in an out-of-sample test. In addition, Jegadeesh and Titman (2001) find some indications of a long-term contrarian effect in the US stock market. De Bondt and Thaler (1985) investigate the presence of contrarian effects in the US stock market through buying past losers and selling past winners. The results are in accordance with overreaction and contrarian effects in the US stock market. Also, De Bondt and Thaler (1987) find evidence that support the behavioral hypothesis of overreaction. More recently, Zhang (2006) argues that stocks with low analyst coverage exhibit stronger statistical evidence of mispricing.

As behavioral finance attempts to explain market anomalies, it is criticized for giving little guidance on how to exploit the anomalies. The theories are conflicting, as some indicate overreaction and others underreaction, and it is not always clear which theory can be attributed the anomalies. Other challenges for behavioral finance is that irrational behavior on average will be unprofitable, and that such investors eventually will exit the market. However, De Long, Shleifer, Summers and Waldman (1991) argue that irrational investors can bear high risk due to overconfident behavior, which may result in profits in the long run. Kyle and Wang (1997) also argue that irrational investors can achieve higher profits than rational investors. Behavioral finance is also criticized because anomalies accredited to irrational behavior will disappear once rational investors exploit the arbitrage opportunities. Arbitrage is the opportunity to earn risk free profits, and such opportunities are due to mispricing. Thus, for market anomalies to persist there must be some limitations to arbitrage. Shleifer and Vishny

(1997) note that arbitrage may not fully correct the mispricing, especially under extreme circumstances. The arguments for limited arbitrage are that investors generally avoid the most volatile opportunities, and that arbitrage may be restricted because it is costly. Daniel, Hirshleifer and Subrahmanyam (2001) suggest that risk aversion, transaction costs and irrational behavior limits arbitrage. If a mispricing is identified, there are no guarantees for when it will be corrected. This is known as fundamental risk, and it may force investors to be reluctant to exploit the mispricing opportunities. Also, the identification of mispricing may be spurious, which has no economic meaning. Specifically, the bias is either a result of nonsynchronous trading or bid-ask bounce. Non-synchronous trading means that the sample consists of stale prices. Such prices are recorded at the end of the day to represent the outcome of transactions that occur at different times, and do not fully reflect all available information. This implies that the prices will depend on previous prices until information is obtained. Such dependency is not exploitable, as it is due to flaws in the data that do not exist in the market. Bid-ask bounce means that the sample consists of prices that only change within the bid-ask spread, creating a perception of volatility. Such price changes are not exploitable, as it is due to flaws in the data that do not exist in the market. Results from technical analysis that do not account for such spuriousness may wrongfully credit technical analysis as successful.

2.2 Review of technical trading rules

Technical trading rule classes can either be simple or complex. Simple rules rely on one or few indicators to generate signals, while complex rules combine the use of many indicators. The indicators can be either leading or lagging. Leading indicators indicate the probability of trend or reversal in advance, while lagging indicators signal trends or reversal after price changes are initiated. In this section, the following eight simple rule classes are reviewed: moving average, on-balance volume, moving average convergence-divergence, trading-range breakout, channel breakout, relative strength index, filter rule and candlestick. The following three complex rules classes are reviewed: learning rules, vote rules and fractional position rules. The rules are applied to generate signals for market positions. A buy signal implies entering a long position, and a sell signal implies either entering a short position or exiting the market. The rules is this review aim to exploit momentum effects.

The moving average rule (MA) is a lagging indicator based on moving averages of the price. If the price breaks through the moving average, it signals a shift in trend. If the price is above the moving average, it signals an upward trend, and if the price is below the moving average, it signals a downward trend. To study short-term trends, a moving average of 20 days is often used, while 100-200 days is applied to analyze long-term trends. The moving average rules can be applied with both fixed (FMA) and variable (VMA) days of holding. With variable days of holding, the position is held until a signal for the opposite position is generated. Using only one moving average may cause false signals to occur frequently. A false signal is when the price fluctuates around the moving average, causing unnecessary changes of position. To filter out such signals, the use of a short moving average and a long moving average can be applied. Another approach is to impose a percentage band, forcing a difference between the moving average and price for the signal to be valid. A second filter is to enforce a time delay between signal and trade. This requires the signal to be valid for a specified number of days.

The on-balance volume rule (OBV) is a lagging indicator. The rule is based on keeping a running total of volume, and adding the daily volume when price increases, and subtracting when price decreases. An increase in OBV confirms an upward trend, while a decrease in OBV indicates a downward trend. An upward trend is a buy signal, and the downward trend is a sell signal. If the change in OBV and price is opposite, it suggests that the investors are exiting their positions and expect a shift in trend.

The moving average convergence-divergence rule (MACD) is a lagging indicator that applies two moving averages of the price. The MACD is the difference between a short and long exponential moving average, which will fluctuate around zero. A positive value of MACD implies that short moving average is above long moving average, and a negative value of MACD implies that short moving average is below long moving average. An increasing positive value of MACD indicates upward trend, while a decreasing negative value of MACD indicates downward trend. Also, a moving average with a horizon between short and long moving average is estimated, which is referred to as a signal line. If MACD exceeds the signal line, it indicates an upward trend, and if MACD falls below the signal line, it indicates a downward trend. The signals from MACD occur frequently, and it should therefore be combined with other indicators to filter out false signals.

The trading-range breakout rule (TRB) is a lagging indicator based on support and resistance levels. The support and resistance levels are based on historical price bottoms and peaks respectively, and is used to indicate changes in trends. The support and resistance levels are based on pressure to buy and sell according to price movement. If the price approaches the support or resistance level, the investors expect the price to reverse according to previous experience. If the price approaches the resistance level, the investors expect the price to decrease, as it did at the last high, causing less price pressure. If the price falls towards the support level, the investors expect the price to increase, as it did at the last low, causing increased price pressure. However, if the price breaks through the resistance level, the investors will anticipate a new high, triggering a buy signal. Opposite, if the price falls through the support level, the investors will anticipate a new low, triggering a sell signal.

The channel breakout rule is a lagging indicator, and similar to a trading-range breakout rule. A channel occurs when the highest price is within a certain percentage of the lowest price, not including current price. A buy signal is generated if the current price exceeds the channel, and a sell signal is generated if the current price falls below the channel.

The relative strength index (RSI) is a leading indicator that displays the strength of the price development, taking a value between 0 and 100. Relative strength is the average of price increases divided by average of price decreases. It is common to compute the averages based on a 14-day horizon. An increasing RSI indicates strength of the price movement, while a decreasing RSI indicates weakness of the price movement. However, too high or low values of RSI signal that the current trend is misleading. A high value of RSI indicates that it is overbought, and low value of RSI indicates is oversold. If the RSI crosses the overbought or oversold boundary, it indicates a shift in trend. If RSI exceeds the overbought boundary, the pressure to sell is expected to cause a downward trend. If RSI falls below the oversold boundary, the pressure to buy is expected to cause an upward trend. Commonly used boundaries are 70 for overbought and 30 for oversold.

The filter rule is a lagging indicator, and applies a percentage movement in price to generate buy and sell signals. A buy signal is generated if the price moves up by a certain percentage, and a sell signal is generated if the price falls by a certain percentage. The rule has variable length of holding, as the position is held until a new signal occurs.

Candlestick is a lagging indicator, which uses opening, closing, high, and low price listings to analyze the market. The candlestick is a chart with a body and a shadow. The body displays the opening and closing price, while the shadow displays high and low price. The body is white if opening price is below closing price, indicating an upward trend, and black if opening price is above closing price, indicating a downward trend. The body can either be long or short depending on the price pressure. A long body indicates high pressure and short body indicates low pressure. The bodies can also have an upper and lower shadow, which represents the highest and lowest price respectively. A long upper shadow and short lower shadow indicate pressure to buy at opening and pressure to sell at closing. A short upper shadow and long lower shadow indicate pressure to sell at opening and pressure to buy at closing. A body with no shadow is a stronger signal, as the price is at its peak or bottom at closing price. The bodies and shadows can be used in multiple ways to determine signals.

Learning rules signal changes of position by following the best-performing rule within a class. Learning rules have three dimensions: memory span, review span and performance measure. The memory span specifies the horizon for evaluation of the rules, while the review span indicates how often performance is evaluated and the best-performing rule is reviewed.

Vote rules are based on counting signals within a rule class. Each rule generates a vote to long or short position, depending on the signal. The position with most votes is the position that is initiated. To avoid that one rule class dominates the voting results, only separate rule classes are considered. The vote rules have the following dimensions: memory span and review span. These dimensions are explained for the learning rules.

Fractional position rules apply an evaluation index to determine the fractional position between a short and long position. The evaluation index is between -1 and 1, where negative values indicate short position and positive values indicate long position. The value of the index indicates the fraction that is held in the position. An example of an evaluation index is based on the vote rule, where the fraction of votes with the winning position indicates the size of the position.

2.3 Hypotheses on the successfulness of technical trading

The motivation for this section is to form four hypotheses on the successfulness of technical trading. The first two hypotheses address the profitability of technical trading. First, the efficient market hypothesis is reviewed, as it opposes the existence of profitable trading rules. This is the basis for the first hypothesis. Second, it is important to consider that market conditions can affect profitability of trading rules. This is the basis for the second hypothesis. The last two hypotheses address the predictive power of technical trading. First, the issue of data snooping is considered, as the performance of the trading rules can be a result of chance. This is the basis for the third hypothesis. Second, it is important to examine whether the performance of the trading rules are generated from the predefined patterns in the rules or other market characteristics. This is the basis for the fourth hypothesis. In the following, these four hypotheses are elaborated.

The existence of profitable trading rules is not compatible with the efficient market hypothesis (Fama, 1970). The idea of EMH is that prices follow a “random walk”, indicating that all price changes represent a random difference from the previous price. EMH claims that when information arises, the news spreads quickly and is incorporated into prices without delay. Thus, market prices are unpredictable, indicating that trading rules are unprofitable. Fama (1970) describes three forms of market efficiency: weak, semi-strong and strong. Weak form efficiency indicates that market information is fully incorporated into current prices. Semi-strong form efficiency assumes that all publicly known information is discounted in current prices. The strong form efficiency states that all information, public and private, is accounted for in current prices. The weak form efficiency is the focus of this paper. In such a market, prices are unpredictable, and should be an unbiased assessment of the true value of the investment at any given time. Hypothesis 1 is based on market efficiency, and is as following: “The trading rules will, on average, not outperform the market.”

Market conditions, such as specific events, market trends and frictions, are important aspects to consider when assessing the profitability of technical analysis. In case of events causing extreme fluctuations in the market, the results from the trading rules may be heavily impacted. Technical analysis where profits are mainly driven by extreme events is not considered favorable. For the trading rules to be considered robust, the rules must be able to perform in different market trends. Technical trading often requires frequent transactions, which may reduce the profitability of the rules. If transaction costs are not taken into account, the results from the trading rules may be misleading, and unprofitable rules may appear profitable. Hypothesis 2 is based on market conditions, and is as following: "If the trading rules outperform the market, it is not robust to market conditions."

Data snooping bias occurs when the same set of data is used more than once to examine a set of rules. If the same data are applied to test the predictive power of a large number of technical trading rules, some of the outcomes will eventually be positive. However, the positive outcomes do not necessarily indicate predictive power of the given rules, as it can be a result of chance. Survivorship bias is a form of unintentional data snooping, where the applied set of trading rules only consists of rules that have been historically successful. Hypothesis 3 is based on the issue of data snooping, and is as following: "If the trading rules outperform the market, it is a result of chance."

Fama (1991) emphasizes that market efficiency cannot truly be rejected, due to the joint hypothesis problem. The primary hypothesis is that the market is efficient, and the joint hypothesis is that the efficient market is defined correctly. Fama states that market efficiency cannot be rejected without rejecting the description of the market. This implies that if a trading rule outperforms the market, it does not necessarily imply market inefficiency; it can merely be that some characteristics are not included in the market description, and that these characteristics drive the profits. This means that the predictive power of the trading rules should be evaluated in accordance with appropriate market characteristics that can cause performance to vary over time. If time-varying expected return can explain the performance, the trading rule should not be credited with predictive power. Hypothesis 4 is based on the joint hypothesis problem, and is as following: "If the trading rules outperform the market, it is explained by time-varying expected return."

In the following chapter, previous studies on technical analysis are reviewed. The chapter includes studies that introduce relevant methods for this analysis, recent studies that apply these methods, and also a number of student papers.

3 Literature review of technical analysis

In this section, studies on technical trading are reviewed. The first section consists of two publications that use original methods to evaluate technical analysis. The second section features papers published after 2000, and primarily includes studies that examine technical analysis using the methods described in the first section. In the last part, student papers on technical analysis in the Norwegian stock market are reviewed.

3.1 Introducing relevant methods

The methods that are applied in the following two studies form the basis of this analysis, and are frequently referred to later in the paper. The reviews list data, trading rules, methods, and results. The methods are explained, as they are applied in this analysis.

Brock, Lakonishok and LeBaron (1992) introduce a method for evaluating technical trading, later known as the BLL bootstrap. For the analysis, daily data from Dow Jones Industrial Average index (DIJA) in 1897-1986 is applied to test a total of 26 rules from the rule classes moving average and trading-range breakout. The moving average is tested with variable and fixed length of holding, while the trading-range breakout only has fixed holding of 10 days. Brock et al. apply the t-test, and use buy-hold as benchmark to test average excess return from following buy and sell signals. In addition, the spread between buy and sell return is tested. A significantly positive buy-sell spread signals that the rules detect buy and sell periods with positive and negative return respectively. To examine the predictive power of the rules, the BLL bootstrap is introduced. Brock et al. compare the performance from the trading rules in the original market to performance in simulated markets. To simulate markets, the method utilizes a parametric bootstrap inspired by Efron (1979). The parameters are obtained by using processes that contain characteristics from the original time series, and the purpose is to examine if these characteristics can help explain the trading rule performance. Brock et al. apply an autoregressive (AR) process to account for dependency in the time series, and generalized autoregressive conditional heteroscedasticity (GARCH) processes to model time-varying volatility. Also, a random walk is used to examine if the processes with time-variation are necessary to explain the performance of the trading rules. The processes applied to simulate markets are labeled null models. Brock et al. bootstrap 500 time series to generate simulated p-values, which denote the fraction of bootstraps where the rule performs just as well as in the original series. Performance is measured as excess return and volatility in periods following buy and sell signals, and the buy-sell spread. Brock et al. find that 500 bootstrapped series is sufficient, as extending the number of bootstraps to 2000 results in minimal change in the p-values. The simulated p-values are applied to test the null hypothesis of no predictive power of the trading rule. If the simulated p-value is below significance level, performance from the rule in the original market is significantly higher than in the simulated market. Thus, the performance is not likely generated from the null models, indicating predictive power of the rule. Brock et al. acknowledge that data snooping might affect the results, and deal with it by 1) reporting results from all trading rules, 2) using a long time series, and 3) testing robustness across four non-overlapping subperiods. The results from the t-test reveal significant excess return and buy-sell spread in both full sample and subperiods. As support to these findings, Brock et al. find that none of the null models can explain return or volatility in buy and sell periods. The rules consistently generate higher return following buy signals and lower return following sell signals in the original time series. Also, the results suggest that return from the rules are not easily explained by changing risk levels, as returns are less volatile in periods following buy signals than sell signals. It is therefore concluded that technical analysis helps predict stock prices. Brock et al. mention a possible sensitivity issue to the applied length of the moving averages. However, LeBaron (1998) suggests that the results are not sensitive to the chosen length of the rules. Brock et al. assume that non-synchronous trading is of little concern, as the stocks in DJIA are actively traded. The issue of transaction costs is not handled, but noted as something that must be carefully considered before implementing trading rules.

Sullivan, Timmermann and White (1999) use daily data from DJIA in 1897-1996, and apply the Reality Check (White, 2000) to test the results of Brock et al. for data snooping bias. In addition to the universe of Brock et al., a full universe of nearly 8000 rules is tested. The full universe consists of filter rules, moving averages, trading-range breakout rules, channel breakouts and on-balance volume averages. Sullivan et al. apply a full sample from 1897-1986 and four non-overlapping subperiods. Also, an out-of-sample period, 1987-1996, is used to enhance the robustness check. The issue of non-synchronous trading is handled by implementing a one-day delay between signal and trade, and transaction costs are considered by using futures data. Sullivan et al. mention that a common way to handle data snooping is to focus on the performance of a small subset of trading rules. However, this may not work in practice, as historically successful rules are most likely promoted. Thus, data snooping can occur due to survivorship bias. Sullivan et al. also emphasize that if a large universe of rules is considered, some rules are bound by luck to outperform a benchmark even if the rules do not possess predictive power. The Reality Check (RC) addresses whether a performance is due to predictive power, or a result of chance, by considering dependency across the rules. In the RC, a time series is constructed for the rules, where each observation is performance at a point in time. Sullivan et al. consider both excess return and Sharpe ratio as measures of performance, and the benchmark is buy-hold or risk free interest rate. After the time series is constructed, a stationary bootstrap by Politis and Romano (1994) is applied. The bootstrap ensures stationarity of the time series. Sullivan et al. apply 500 bootstrapped time series to construct simulated p-values. The simulated p-values are the fraction of best rule performance in each bootstrapped series that exceeds best rule performance in the original series. The p-values are applied to test the null hypothesis of the best-performance being due to data snooping, indicating that the best rule does not have predictive power. The study shows that the results from Brock et al. are robust to data snooping, both in full sample and subperiods. However, this does not hold for the out-of-sample period, as Sullivan et al. find low support of predictive power of the rules during this period. The findings also apply to the full universe of rules. Sullivan et al. suggest that the results can indicate that the best-performing rule has predictive power, but that markets have become more efficient over time, eliminating the profitability of trading rules.

3.2 Studies after 2000

The following studies evaluate the performance of technical trading rules, and are published after 2000. The reviews list data, trading rules, methods, and results.

Kwon and Kish (2002) test simple technical trading rules on daily data from New York Stock Exchange (NYSE) value-weighted index in 1962-1996. The study applies simple moving average rules combined with volume and price change indicators. A percentage band is applied as a filter, and a total of 24 rules are examined. Kwon and Kish apply both a t-test and the BLL bootstrap to test significance of excess buy and sell return and buy-sell spread, using a buy-hold as benchmark. Kwon and Kish account for data snooping by testing a variety of moving average rules, but do not consider transaction costs. The t-test signals significant excess return for the moving average rule, and that the significance is greater when the volume and price change indicators are added. The results also reveal that return is more volatile in sell periods than buy periods for all rules. In addition to the full sample, the rules are tested in three non-overlapping subsamples. The results from the subsamples are varying, and suggest that profits from the rules may depend on market conditions. For the BLL bootstrap, Kwon and Kish apply random walk and GARCH-M as null models. The GARCH-M model includes an in-mean term, which allows return to directly depend on conditional heteroscedasticity. Also, some additional variables are included in the model, such as January effect, dividend yields and bond premiums. The results imply that a random walk cannot explain return or volatility from the trading rules. The GARCH-M models can replicate the return to some extent, but fail to replicate the volatility. The volatility in periods following buy and sell signals is lower in the original series than in the bootstrapped series. The results indicate some predictive power for the rules, as the rules are able to detect periods with lower volatility. However, the results are weaker in the more recent part of the sample.

Hsu and Kuan (2005) use daily data from four US indices in 1989-2002 to test the profitability of simple and complex trading rules. 2002 serves as an out-of-sample period. The DIJA and Standard & Poor's (S&P) 500 represent mature markets, while the NASDAQ Composite and Russell 2000 represent young markets. Russell 2000 is a small-cap index, while the other indices are large-cap. The universe of trading rules in this study contains almost 40 000 rules, where 18 000 are simple rules, 18 000 are contrarian versions of the simple rules, and the remaining are complex rules. Among the simple rule classes are filter rules, moving averages, trading-range breakout, channel breakout and on balance volume averages. The complex rule classes are learning strategies, vote strategies and fractional position strategies. To test the results, the RC and Superior Predictive Ability (SPA) test (Hansen, 2005) are applied. The latter is a standardized version of the RC, which improves sensitivity to testing poor-performing trading rules. The possible bias from non-synchronous trading is not considered. The results show significant profitability for some rule classes, including moving averages and filter rules, when applied to the young markets. The complex rules are more profitable, and generate best results when applied with the moving averages and filter rules. The rules are not profitable when applied to the mature markets. Hsu and Kuan utilize a transaction cost of 0.05% per trade, and compare the profitable rules with a buy-hold position. The best rules do not consistently outperform, but the results indicate that several rules are favorable to buy-hold. Both the RC and SPA test suggest that the results are not due to data snooping.

Marshall and Cahan (2005) test market efficiency in the New Zealand stock market by applying moving averages and trading-range breakout rules to the NZSE 40 capital index[3] in 1970-2002. Marshall and Cahan conduct the study on New Zealand Stock Exchange because of characteristics that suggested that the market could be less than efficient. The following characteristics are listed: small and isolated market, unique rules regarding insider trading, lack of analyst's coverage, and rapid and significant deregulations. The study applies daily data, and three non-overlapping 11-year periods. A total of 12 rules are tested, where the trading-range breakout rules has fixed holding, and moving average rules have both fixed and variable length of holding. The fixed length of holding is 10 days. To test the results, the t-test and BLL bootstrap is applied. For the BLL bootstrap, the following null models are applied: AR, GARCH-M and E-GARCH. The E-GARCH model allows volatility to be affected differently by direction of the price change, and captures that negative returns usually are followed by

[3] Replaced Barclays index in 1992, and replaced by NZX 50 index in 2003.

larger volatility. The issue of data snooping is handled by applying rule classes that "are extremely unlikely to have been developed using data from New Zealand" (Marshall and Cahan, 2005:386). To address the issue of non-synchronous trading, it is assumed that stocks can be traded at closing price the day after a trading signal. The rules generate significant return in the first subperiod, but not in the most recent subperiod. In addition, the variable length moving average and trading-range breakout rules provide stronger results than the fixed length moving average rules. The results from the BLL bootstrap show that the null models cannot explain anything in the first periods, but can explain the results in the last period. This suggests that the predictive power has diminished, and that the market has become more efficient. The estimated break-even transaction costs confirm that technical trading has become less profitable in the last subperiod.

Chong and Ng (2008) use daily data from the Financial Times 30 index (FT30) from 1935-1994 to examine the profitability of moving average convergence-divergence rules and relative strength rules in UK stock market. A fixed holding period of 10 days is applied. Chong and Ng handle possible data snooping biases by dividing up the sample into subperiods. Profitability is examined by testing returns from buy and sell signals and the buy-sell spread with a t-test. The results indicate that the trading rules outperform buy-hold, both in the full sample and all subperiods. Transaction costs and non-synchronous trading are not considered.

Marshall, Cahan and Cahan (2008) test profitability of five rule classes on 5-minute intraday US data from Standard & Poor's Depositary Receipts (SPDR) in 2002-2003. The SPDR is an exchange-traded fund (ETF), designed to track S&P 500. The full sample is split in two yearlong subperiods, where 2002 represents a bear market and 2003 is a bull market. In total, almost 8000 rules are tested from the following rule classes: filter, moving averages, trading-range breakout, channel breakouts and on-balance volume averages. The study applies the BLL bootstrap to test significance of returns, and Reality Check to correct for data snooping bias. For the BLL bootstrap, a GARCH-M process with a variable representing overnight return is applied as null model. The some rules occasionally generate significant return, but do not pass the Reality Check for data snooping. Marshall et al. conclude that the trading rules are not valuable in either bull or bear markets when applied to intraday data.

Metghalchi, Chang and Marcucci (2008) examine the profitability of moving average rules on the Swedish stock market. The analysis applies daily data from the OMX Stockholm 30 index (OMXS30) in 1986-2004. To filter out false signals, a percentage band is applied. The benchmark is buy-hold or out of the market. Profitability is examined by testing excess returns in buy and sell periods, and the buy-sell spread with a t-test. The results display that only rules that apply more than one moving average to generate signals, give significant results. These rules are also robust to a transaction cost of 0.5 % per trade. The rules are tested with the RC, and the results indicate that performance is not biased from data snooping. Non-synchronous trading is not taken into account. Overall, Metghalchi et al. conclude that some of the rules are profitable and have predictive power.

Schulmeister (2009) applies a total of 2580 rules to both daily and intraday data in the S&P 500 spot and futures market in 1960-2007. In the analysis, moving averages and relative strength index are used. The results are tested with a t-test, and data snooping biases are handled by using a long sample and several subperiods. The results reveal declining profitability in both spot and futures market when applying daily data. Overall, the rules perform worse in 2001-2007 compared to 1980-2000, and Schulmeister emphasizes that profitability also could be shifting from daily data to higher-frequency data. When the rules are tested on 30-minute-data, there are no clear signs of declining profitability. Schulmeister explains the shift in profitability from daily to intraday data as a result of increased efficiency and rise in speed of transactions in financial markets. Also, it is claimed that market efficiency has increased due to increasing use of market analysis and arbitrage mechanisms, and rise in speed of transactions imply that technical analysis is more applicable to high frequency data.

Marshall, Qian and Young (2009) apply moving average and trading-range breakout rule classes to daily data from US stocks listed on NASDAQ and NYSE in 1990-2004. The focus is to examine the possible relationship between return and size, liquidity and industry, and the stocks are therefore selected based on these criteria. The study uses BLL bootstrap to test the results. For the BLL bootstrap, the following null models are applied: random walk, AR, GARCH-M and E-GARCH. Marshall et al. account for non-synchronous trading by implementing a day between signals and trade, but find that this has little impact on the results. The results indicate low support for technical trading, and do not support a relationship between profitability of technical analysis and firm's industry. However, the rules may be more profitable in small, illiquid stocks, suggesting that the value of technical analysis is related to both size and volume. The rules also seem more profitable when applied to identify long-term trends. In addition, the profitable rules are robust to transaction costs. The study does not account for data snooping, as the findings mainly do not support technical trading.

Hsu, Hsu and Kuan (2010) apply almost 16 500 rules to indices of growth and developing markets to examine if market efficiency has improved after introducing ETFs. The rules are moving averages and filter rules. The study applies three and six indices from growth and emerging markets respectively, and ETFs that track the indices. The indices for growth markets are S&P 600 SmallCap, Russell 2000 and NASDAQ Composite. The indices for emerging markets are the following MSCI indices: Emerging Markets, Brazil, South Korea, Malaysia, Mexico and Taiwan. The indices are recorded between 1988 and 1999, while the ETFs are from 1996 to 2005. Hsu et al. apply a SPA test to evaluate the predictive power of the rules. Performance is measured as both mean return and Sharpe ratio. The results from the growth market indices provide strong support for predictive power pre ETFs. However, none of the rules generate significant return on growth market ETFs. The empirical findings in the pre ETF period for emerging markets are consistent with those for the growth market. Also, a few rules generate significant results for some emerging market ETFs. The results also support profitability of trading rules after accounting for transaction costs. The SPA test suggests that the rules have predictive power in both the growth and emerging market indices before introducing ETFs. However, it is noted that it does not necessarily imply inefficiency, as the profitability might be due to tail risk or market friction. The predictive power of the rules declines after introducing ETFs, suggesting that the markets have become more efficient.

Metghalchi, Marcucci and Chang (2012) examine simple moving average rules in 16 European stock markets, including Norway, in 1990-2006. The analysis applies daily data from main indices, uses mean return and Sharpe ratio as performance measure, and tests the results with a t-test. The profitability is examined by testing if average buy and sell return is different from buy-hold, and if buy-sell spread is positive. The moving average rules perform well in all countries, and the results also hold after accounting for transaction costs. The study applies the RC to test for data snooping bias, and the results suggest that the best-performing rule has predictive power for all but three countries. In addition, the trading rules perform better in small and medium capitalized markets. The bias from non-synchronous trading is not discussed.

To briefly summarize, a majority of these studies provide some support for technical trading. However, the profitability seems to be declining over time. Also, some studies find that technical analysis has more value in smaller and less liquid stocks.

3.3 Student papers

The following studies on technical analysis in the Norwegian stock market are master theses, and the reviews list data, methods, and results.

Juel, Thorsen and Færder (2005) examine if it is possible to achieve significant return by applying trading-range breakout rules to daily data from OBX Total Return Index. The full sample is 1987-2004, which is divided in two subperiods. In the study, excess return from buy and sell signals are tested with a t-test and buy-hold is applied as benchmark. The results indicate that only sell signals generate significant excess return. Also, volatility is higher during sell periods. The rules that generate high significant return are also applied to the futures market in order to consider transaction costs, and the results are similar. The advantage of using the BLL bootstrap is mentioned, but as a normal distribution is assumed, only a t-test is applied. The study indicates some support for technical trading rules, mainly driven by sell returns.

Bjørnmyr and Bolstad (2007) examine market efficiency at Oslo Stock Exchange by applying a self-developed trading rule to five yearly periods in 2003-2007. After filtering out stocks that do not fit the criteria of sufficient number of trades per year, the data consists of 45-86 stocks, depending on the year. A transaction cost of 0.03 % per trade is assumed. The study uses candlestick patterns and relative strength as indicators to trigger buy and sell signals, and a target and stop-loss function to secure the returns. Short sales are excluded from the analysis, and thus, sell signals indicate exiting the market. Bjørnmyr and Bolstad use 2002 to identify the trading rule with highest return, and test it in 2003-2007. The candlestick formation is also combined with a relative strength indicator. The combination that provides the highest return forms a new rule, which is further tested. To evaluate profitability, excess return from the rule is tested, where the benchmark is buy-hold. The rule detects periods with lower volatility compared to buy-hold for all subperiods, but only generates excess return in 2006 and 2007. Bjørnmyr and Bolstad state that the return series is not normally distributed, and therefore conduct the non-parametric, unpaired Mann-Whitney-Wilcoxon test for significance. The test offers greater efficiency than a t-test on non-normal distributions, and it is nearly as efficient as the t-test on normal distributions. The results display that excess return from the rule is not significant. The identification year, 2002, is considered a bear market, and the rest of the sample is bull. Bjørnmyr and Bolstad suggest that the rule may be more profitable in a bear market.

Nerva (2009) applies several technical indicators to stocks from Oslo Stock Exchange in 2004-2009. Penny stocks and illiquid stocks are filtered out of the sample. The rule utilizes a combination of moving averages, price changes and relative strength indicators, and also a stop-loss function. For the rule to provide signals, all indicators must unanimously confirm a trend. Short sales are not permitted, and therefore sell signals imply exiting the market. Nerva applies a non-parametric test, to assess whether the rule generates significant return over buy-hold. After accounting for transaction costs, the rule outperforms buy-hold for all years except 2005. Also, volatility is lower for the rule compared to buy-hold. Nerva displays that the exposure in the market is reduced when the market is downward trending, and increased when the market is upward trending. Overall, Nerva provide support for the applied trading rules.

Tollefsen (2010) examines market efficiency at Oslo Stock Exchange in 1998-2010 by testing if two rules are able to outperform buy-hold. After filtering out illiquid stocks and penny stock, the data consists of 21-33 stocks, depending on the subperiod. Also, the stocks had to be listed at OSE for the entire sample. The first rule combines the use of trading-range breakout and moving averages to generate signals, while the second rule applies relative strength, price changes and moving averages as indicators. The rules are optimized with data from one year, and tested in an out-of-sample period. The issue of data snooping is handled by using a long sample, well-established rules, subperiods, and an out-of-sample period. Tollefsen notes that it is preferred to use the BLL bootstrap, but it is not applied. To account for transaction costs, the study applies 0.20 % per trade. The profitability is examined by testing average return over buy-hold with a t-test. The results indicate that the first rule is best performing and most robust. This rule also generates a relative high average of winning trades. Tollefsen points out that different market characteristics in optimization and testing period can affect profitability of the trading rules. The results provide some support for profitability of technical trading, mainly based on the results from the first rule. For the second rule, there are no indications of the signals having any value.

Simonsen (2012) tests four simple trading rules on intra-daily data from stocks on Oslo Stock Exchange in 2003-2010. Penny-stocks and illiquid stocks are filtered out. The rules are based on momentum indicators, and a total of four rules are tested. The rules are founded on the assumption that strong price increases during a day will result in a higher opening price the subsequent day. The strategy is to invest at the end of the day, and exit the position at the subsequent opening price. The rules implement 10 % increase during the day or during the last opening hour as an indicator for strong price increase, which generates a buy signal. The same indicators are used to identify strong price decrease, which generates a sell signal. The profitability is examined by testing average return over buy-hold with a t-test. The only rule that provides positive results is the rule that applies 10 % increase during the day as an indicator. However, the returns are relatively small, and the results therefore provide no support for profitability of the rules.

The studies generally provide some support for technical analysis in the Norwegian stock market. However, an issue is that few properly account for data snooping bias and non-synchronous trading. Also, most of the studies do not consider that the profits may not be accredited predictive power of the trading rule.

The following chapter consists of a presentation of trading rules applied in this analysis, and the methods that test profitability and predictive power.

4 Methods for analyzing technical trading

This chapter presents the trading rules and methods applied to evaluate the profitability and predictive power of technical analysis. Testing hypothesis 1 and 2 evaluates the profitability, and testing hypothesis 3 and 4 evaluates the predictive power.

4.1 Technical trading rules

Technical trading is based on using a set of rules that trigger signals that are founded in price movement. The signals suggest which position should be taken to exploit future market behavior. The following rule classes are applied in this analysis: moving average and trading-range breakout, as these rules are common and easy to implement. The rules exhibit buy, sell or neutral signals. In this analysis, a buy signal suggests taking a long position, sell signal suggests taking a short position, and a neutral signal suggests exiting the market. Being out of the market implies earning risk-free interest rate. The rules have variable or fixed holding, and the positions are closed out at the end of the year. For the trading rules with fixed holding, signals that occur while holding a position are ignored. Also, if the rules signal more than two consecutive periods of holding in the same position, the subsequent holding becomes variable. In this analysis, the fixed holding period is 10 days, as this allows for short-term trading. This imposes a maximum of 20 fixed holding days in same position. After 20 days, the position adjusts according to next signal regardless. This is imposed for convenience in the process of setting up the trading rule systems. To filter out false signals arising from small fluctuations in price, two filters are imposed; a percentage band and a time delay. In this analysis, the percentage band is referred to as filter F1, and the time delay as filter F2. A percentage band ensures that a change of a certain percentage must occur before a signal is generated. A time delay demands that a signal must be valid for at least a specified number of days before action is taken. In this analysis, a band of 0.10 % or a time delay of 2 days is applied. Only one filter is imposed at a given time. To address the issue of non-synchronous trading, a delay of one day is implemented between signal and trade. The bid-ask bounce is not addressed as the effect is assumed to be small.

The return and standard deviation from following buy and sell signals are used to measure the performance of the trading rules. If a signal occurs on day 0, the position is taken on day 1 and exited on day 2. The one-day delay between signal and entering a position is to account for non-synchronous trading. Daily return (r_t) is defined as the natural logarithm of price relatives,

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right). \tag{1}$$

The mean return and variance conditional on buy (sell) signals is defined as,

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

$$\hat{\sigma}_{b(s)}^2 = \frac{1}{N_{b(s)}}\sum_{t=1}^{N}\left(r_t - \bar{r}_{b(s)}\right)^2 * I_{t-2}^{b(s)}\,, \tag{3}$$

where $N_{b(s)}$ is total days in period following buy (sell) signal, and $I_{t-2}^{b(s)}$ is an indicator variable taking the value 1 if a buy (sell) signal is observed at time $t-2$, and 0 otherwise.

4.1.1 Moving Average

The moving average rule uses current price and a moving average to trigger signals. A buy signal occurs when the price crosses the moving average from below, and a sell signal occurs when the price crosses the moving average from above. The motivation for the rule is that if current price is above trend, it signals the start of an upward trend, and if current price is below trend, it signals the start of a downward trend. The moving average rule can either have a variable or fixed holding period. For the variable length moving average rule (VMA), the position is held until the signal changes, while the fixed length moving average (FMA) has a holding period of 10 days. The moving average is 25 or 50 days to identify short-term trends, and 100 or 200 days to identify long-term trends, which gives four versions of the MA rule. Imposing a percentage band ensures that there must be a difference between the price and moving average before triggering a signal. Applying a time delay requires that the price must always be above (below) the moving average between signal and action for a buy (sell) signal to be valid. In total, 24 MA rules are tested, 12 VMA and 12 FMA, where eight rules have no filter, eight rules have filter F1, and eight rules have filter F2.

4.1.2 Trading-Range Breakout

The trading-range breakout rule relies on support and resistance level for prices, where the support level is a local minimum, and resistance level is a local maximum. A buy signal occurs if the price exceeds the resistance level, and a sell signal occurs if the price falls below the support level. The motivation for the rule is that if the current price breaks the resistance or support level, the subsequent prices will move further in the same direction. The TRB has a fixed holding period of 10 days. The horizon measuring local extreme prices is 25 and 50 days to identify short-term trends, and 100 and 200 days to identify long-term trends. This gives four versions of the TRB rule. Imposing a percentage band ensures that the price must cross the support or resistance level by at least a percentage before triggering a signal. Applying a time delay requires that the price must always be above (below) local maximum (minimum) between signal and action for a buy (sell) signal to be valid. In total, 12 TRB rules are tested, where four rules have no filter, four rules have filter F1, and four rules have filter F2.

4.2 Testing the performance of the trading rules

The profitability of the trading rules is examined by testing hypothesis 1 and 2, and applied methods are described in the following sections. The first method tests significance of the performance, and the second method tests if the trading rules are robust.

4.2.1 Testing significance of the performance

To examine if the trading rules outperform the market, two null hypotheses are formed. The first null hypothesis is that buy (sell) return is not significantly different from buy-hold return. The buy-hold is a long position, and represents the passive strategy. This implies that excess buy (sell) return is equal to zero,

$$H_0\colon \bar{r}_{b(s)} - \bar{r} = 0, \qquad H_A\colon \bar{r}_{b(s)} - \bar{r} \neq 0, \tag{4}$$

The second null hypothesis is that buy return is not significantly different from sell return, so that mean buy-sell spread is equal to zero,

$$H_0\colon \bar{r}_b - \bar{r}_s = 0, \qquad H_A\colon \bar{r}_b - \bar{r}_s \neq 0, \tag{5}$$

The buy signals result in a 100 % long position, the sell signals result in a 100 % short position, and consequently, the buy-sell spread is a 200 % position. The purpose of the buy-sell spread is to test if the rules generate valuable signals. A significantly positive spread indicates that buy and sell signals on average detect periods with positive and negative return respectively. The null hypotheses are tested with a t-test. The test statistic for excess buy (sell) return is,

$$t = \frac{\bar{r}_{b(s)} - \bar{r}}{\sqrt{\sigma^2_{b(s)}/N_{b(s)} + \sigma^2/N}}, \tag{6}$$

and the test statistic for buy-sell spread is,

$$t = \frac{\bar{r}_b - \bar{r}_s}{\sqrt{\sigma^2_b/N_b + \sigma^2_s/N_s}}. \tag{7}$$

The null hypotheses are rejected if absolute value of the test statistics exceeds critical $t_{\alpha/2,N}$, where α is significance level. This method is applied to test hypothesis 1.

4.2.2 Testing robustness of the performance

To examine if the performance of the trading rules is driven by specific events in the market, the rules are tested in subperiods. The subperiods are also chosen to capture trends, such as bullish and bearish markets. If the trading rules perform well across periods with different market conditions, the performance of the rules is considered robust. The results are tested for significance with a t-test. To examine how transaction costs will affect trading rule profitability, the break-even costs are estimated. This is defined as the percentage cost that eliminates the excess return,

$$\text{break-even} = \frac{\frac{1}{2} * (\bar{r}_b - \bar{r}_s) - \bar{r}}{2 * (NS_b + NS_s)/Y}, \tag{8}$$

where the buy-sell spread is annualized, and reduced to a 100 % position to illustrate an equal investment following buy and sell signals. Y is total number of years in the sample, and NS is number of changes in position. The latter is doubled, as each change requires the investor to exit the initial position and enter the new position. Several online brokers[4] provide services that apply 0.05-0.15 % per trade, and a middle ground of 0.10 % is therefore applied in this analysis. The use of minimum fees is ignored, and it is assumed that investors do not trade too small. Accounting for transaction costs and market events will give indications to which extent the trading rules are robust and realistically profitable, and therefore test hypothesis 2.

4.3 The Reality Check bootstrap methodology

To evaluate if performance from the rules is a result of predictive power, and not just chance, White (2000) introduces the Reality Check (RC). This method is applied to test hypothesis 3, and is described in the following. The performance of the trading rules is measured as excess return relative to buy-hold,

$$\begin{gathered} f_{k,t} = r_t S_{k,t-2} - r_t S \\ k = 1, \dots, K, \end{gathered} \tag{9}$$

where $f_{k,t}$ is excess return for trading rule k, and S_k is a signal for trading rule k, which takes the value of 1 if buy signal, -1 if sell signal, or 0 if neutral. S is a signal for buy-hold, which

[4] DnB Markets, Netfonds, Nordea, Nordnet, Skandiabanken, and Storebrand (April 2014).

always takes the value of 1, and K is the number of trading rules. The null hypothesis is that the trading rules have no predictive power, which means that the best performing trading rule does not beat buy-hold,

$$H_0\text{: } \max \{E(f_k)\} \leq 0 \tag{10}$$

Rejecting the null hypothesis implies that the best-performing trading rule is superior to buy-hold. White (2000) demonstrates that this null hypothesis can be evaluated by using a stationary bootstrap (Politis and Romano, 1994) to the values of $f_{k,t}$. The bootstrap resamples blocks of variable length, which ensures that the bootstrap samples are stationary. The bootstrap is conducted using the following steps,

1. Select a random observation from the original series.
2. With probability q, the next observation is random, and with probability $(1-q)$, the next observation is the subsequent.
3. Repeat step 2 until N observations are bootstrapped in a series.
4. Repeat step 2 and 3 until B series are bootstrapped.

The mean block length in the bootstrapped series should represent the dependency in the original series, and is determined by $1/q$. A high q indicates low dependency, while a low q indicates high dependency. The stationary bootstrap applies a wrap-up resampling technique, where the first observation is treated as the subsequent after the last observation. To keep the computation manageable, the number of bootstraps is 500. This is also the number applied in Sullivan et al. (1999). The test statistics is as following,

$$\bar{V}_k = \max\left\{N^{1/2}\left(\bar{f}_k - E(f_k)\right)\right\}, \tag{11}$$

$$\bar{V}^*_{k,i} = \max\left\{N^{1/2}\left(\bar{f}^*_{k,i} - \bar{f}_k\right)\right\}, \quad i = 1, \ldots, B, \tag{12}$$

where $E[f_k]$ is 0, as this is the strictest form of the null hypothesis. This gives $\bar{V}_k$ as the best-performing trading rule in the original series, and $\bar{V}^*_{k,i}$ as the best-performing trading rule in bootstrap i. The fraction of bootstrapped performances that beat the original performances is denoted as the simulated p-value.

The RC can only account for data snooping biases within the included rules, and therefore, adding rules to a universe is likely to change the outcome of the test (Sullivan et al., 1999). If additional trading rules do not outperform the previously best-performing rule, the p-value will increase and reveal data snooping. If additional trading rules outperform the previously best-performing rule, the p-value will decrease, which signals no data snooping. Increasing the number of rules that outperform, increases the probability that the best rule contains genuine information of predictive power. Inclusion of only well-performing rules can bias the p-value towards no data snooping. However, the data snooping effect can still dominate if the improvements from the additional rules are small. The RC is also sensitive to inclusion of many poor trading rules, and the p-value can bias towards data snooping (Hansen, 2005). The applied universe is small and consists of well-established rules. As the RC is sensitive to including only under- or outperforming rules exclusively, it is important to consider the following: 1) increasing a universe of well-established rules may imply that additional rules will underperform, as the existing rules are likely to have survived due to outperformance, and 2) even if the existing rules are well-established, they may not perform well in this particular market. The latter is the motivation behind performing RC on this universe, as the test still can correct for data snooping bias in small universes.

4.4 The BLL bootstrap methodology

It is common to test the trading rule performance for significance using a t-test, as in hypothesis 1. However, as a t-test requires a normal distribution and financial time series often exhibit fat tails, the test is imprecise. Therefore, the results are also analyzed using the BLL bootstrap. This examines whether performance of the rules is a result of market inefficiency or time-varying expected return. This method is applied to test hypothesis 4, and will indicate if the trading rules have predictive power. The method uses null models in a parametric bootstrap to simulate return series, and test the trading rules in the exponentiated price series. The bootstrap is conducted using the following steps,

1. Estimate parameters of appropriate null model.
2. Obtain residuals, and redraw with replacement to form a scrambled series.
3. Keep the first observation from original return series.
4. Define the subsequent observation using the estimated parameters and scrambled residuals.
5. Repeat step 4 until N observations are bootstrapped in a series.
6. Repeat step 3, 4 and 5 until B return series are bootstrapped.

In order to apply the trading rules, the B bootstrapped return series are exponentiated back to prices using the first original price observation. If the rules perform well in the bootstrapped series, time-varying equilibrium return from the model can explain the performance. Accordingly, the null hypothesis is that excess return in original series does not exceed excess return in bootstrap series,

$$\begin{gathered} H_0\colon \bar{r}_{k,0} \leq \bar{r}_{k,i}, \\ k = 1,\dots, K, \\ i = 1,\dots, B, \end{gathered} \tag{13}$$

where $\bar{r}_{k,0}$ is return in original series from trading rule k, $\bar{r}_{k,i}$ is return in bootstrapped series i, K is number of trading rules, and B is number of bootstrapped series. Brock et al. (1992) use 500 bootstraps, and confirm that extending the replications beyond 500 does not add much reliability to the estimated p-values. In this analysis, B is therefore set to 500.

The fraction of bootstraps in which the trading rule generates equal or better return than in original series is denoted as the simulated p-value. The p-value tests if the original return differs significantly from the simulated return, with significance level of α. A p-value less than α, indicates that the return from the original series is significantly higher than in the bootstrapped series. A p-value greater than $1-\alpha$, indicates that the return from the original series is significantly lower than in the bootstrapped series. If return from original series is not significantly different from the bootstrapped series, the model characteristics can explain the return. In addition, the standard deviation in periods following buy and sell signals is tested. Results for excess return are labeled Buy and Sell, and the spread is labeled Buy-Sell, while the results for standard deviations are labeled σ(Buy) and σ(Sell). To provide support for the rules, the following results are necessary:

Buy	P-value $< \alpha$	Excess return is significantly higher in original series.
Sell	P-value $> 1 - \alpha$	Excess return is significantly lower in original series.
Buy-Sell	P-value $< \alpha$	Spread is significantly higher in original series.
σ(Buy)	P-value $> 1 - \alpha$	Standard deviation is significantly lower in original series.
σ(Sell)	P-value $> 1 - \alpha$	Standard deviation is significantly lower in original series.

The Box-Jenkins method (1976) for identifying, estimating and diagnosing the null models are described in the following sections.

4.4.1 Identifying market characteristics

It is common to describe dependency in stock return as an autoregressive (AR) process. This indicates that current return depends on previous return, that is, it has a memory. Another way to model serial dependence is as a moving average (MA) process. This allows return to depend directly on previous shocks in the market, whereas the AR process relates indirectly to shock through previous returns. Such shocks can for example be an important technological event or a natural disaster, as both can affect the stock market. The AR and MA process are distinctive, as the AR process never forgets a shock, while the MA process is only affected immediately. By examining the autocorrelation and partial autocorrelation in return, possible moving average (MA) and autoregressive (AR) terms can be identified. The autocorrelation function (ACF) is the correlation between periods t and $t-p$ of a time series, where t is time and p is number of lags. ACF can therefore help identify MA terms. The partial autocorrelation function (PACF) is the correlation between periods t and $t-p$ of a time series that is not explained by correlation effects in lower lags. PACF can therefore help identify AR terms.

A second feature of stock prices is time-varying volatility. Time-varying volatility is the tendency that large price changes often are followed by additional large changes, and small price changes often are followed by additional small changes. This results in clustering of price changes, and therefore volatility clustering. As the risk-return tradeoff indicates that returns should match risk, it is common for a return process to depend on conditional volatility. Conditional implies that volatility is allowed to vary over time and depend on all information up to that point, which accounts for the dynamic properties of return. It is common to describe such dependency with a generalized autoregressive conditional heteroscedasticity (GARCH) process. This process allows the conditional volatility to depend directly on previous volatility and shocks in the market. Squared returns are often used as a proxy for volatility, because it measures deviation from an assumed zero mean. By examining the autocorrelation in squared return, possible autoregressive conditional variance (ARCH) effects can be identified. If the return exhibits significant autocorrelation in squared returns, GARCH-models are appropriate. The joint significance of autocorrelation is tested with Ljung-Box test. The null hypothesis of no autocorrelation is tested using the following Q-statistic,

$$Q = N(N+2)\sum_{j=1}^{h}\frac{\rho_j^2}{N-j}, \tag{14}$$

where N is sample size, ρ_j is autocorrelation in lag j, and h is number of tested lags. The null hypothesis is rejected if the Q-statistic exceeds critical $\chi^2_{1-\alpha,h}$.

A third aspect of stock prices is calendar effects, and the notion that certain days, months or seasons are subject to price changes above average. Financial literature has not fully recognized this phenomenon, as the effects have no foundation in theory, and that the discovery of calendar effects could be a result of data snooping. However, it is common to credit some extreme changes in stock return to certain seasons. Two common calendar effects are weekend and January effect. The weekend effect refers to that stock returns on Mondays are on average lower than returns on Fridays. An explanation for this effect is the notion that bad new tends to be delayed until the weekend, which results in decreased prices on Monday relative to Friday. The January effect refers to that stock returns in January are on average higher than returns in any other month. This effect is often explained by a new-year optimism, which results in increased prices in January. Additionally, the market often experiences a drop in prices in December, as investors seek to claim capital losses at the end of the year. To check for calendar effects, return conditional on each weekday and month is examined. If a weekday or month outperforms, it suggests a potential calendar effect.

As this analysis applies a long financial time series, it is likely that market characteristics have changed during the sample period, causing structural breaks. A structural break means that model parameters will differ significantly in certain periods. This may complicate the process of identifying one model to fit the whole sample, and it can result in unreliable and unstable parameters. To test for structural breaks, a likelihood ratio test is applied. The null hypothesis is no structural break, and the likelihood ratio is,

$$\mathrm{LR} = 2(\mathrm{L_{UR}} - \mathrm{L_R}), \tag{15}$$

where $\mathrm{L_{UR}}$ and $\mathrm{L_R}$ is log-likelihood for the unrestricted and restricted model. The restricted model is identified from examining PACF, ACF and ARCH-effects. The unrestricted model also includes dummies for subperiods. The null hypothesis is rejected if the LR-statistic exceeds critical $\chi^2_{1-\alpha,\mathrm{v}}$, where v is number of extra variables in the unrestricted model. Rejecting the null hypothesis implies that it is appropriate to account for structural breaks, and to include dummies for subperiods to improve the model parameters.

4.4.2 Estimating market models

Three common processes for modeling financial time series are random walk, autoregressive moving average (ARMA), and generalized autoregressive conditional heteroscedasticity (GARCH) processes. The random walk process is as following,

$$\mathrm{P_t} = \mathrm{a_0} + \mathrm{P_{t-1}} + \mathrm{e_t}, \tag{16}$$

where $\mathrm{P_t}$ is closing price, $\mathrm{a_0}$ is unconditional mean, and $\mathrm{e_t}$ is the error term. The ARMA(m,n) process with the autoregressive and moving average component in the disturbance is as following,

$$\mathrm{r_t} = \alpha_0 + \mu_\mathrm{t}, \tag{17}$$

$$\mu_\mathrm{t} = \sum_{\mathrm{i}=1}^{\mathrm{m}} \rho_\mathrm{i}\, \mu_{\mathrm{t-i}} + \sum_{\mathrm{j}=1}^{\mathrm{n}} \theta_\mathrm{j}\varepsilon_{\mathrm{t-j}} + \varepsilon_\mathrm{t}, \tag{18}$$

where α_0 is unconditional mean, $\mathrm{r_t}$ is the structural equation, μ_t is the disturbance equation, m is number of lags in the autoregressive process, n is number of lags in the moving average process, and ε_t is white noise disturbance. To ensure stationarity in mean, ρ_i and θ_j must be less than 1. If necessary, this is tested with a t-test. Combining the structural and disturbance equation, gives the following process,

$$\mathrm{r_t} = \alpha_0 + \sum_{\mathrm{i}=1}^{\mathrm{m}} \rho_\mathrm{i}\, (\mathrm{r_{t-i}} - \alpha_0) + \sum_{\mathrm{j}=1}^{\mathrm{n}} \theta_\mathrm{j}\varepsilon_{\mathrm{t-j}} + \varepsilon_\mathrm{t}, \tag{19}$$

The GARCH(p,q) process is as following,

$$r_t = \alpha_0 + \varepsilon_t, \tag{20}$$

$$h_t = \varphi + \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \delta_j h_{t-j}\,, \tag{21}$$

$$\varepsilon_t = v_t \sqrt{h_t}, \tag{22}$$

where h_t is conditional variance, v_t is white noise disturbance and ε_t is the conditional disturbance. To ensure stationarity in variance, the sum of $\gamma_i$and δ_j must be less than 1. If necessary, this is tested with a Wald-test. The null hypothesis is that the sum equals 1, which is rejected if the test statistic exceeds $\chi^2_{1-\alpha,u}$, where u is number of restrictions tested. The test statistic is considered advanced, and is therefore not displayed in this paper.

The ARMA and GARCH process form the basis for the null models, and are estimated using Maximum Likelihood. In addition, the rules are tested in a random walk to determine whether it is necessary to include time-varying processes to explain the performance of the trading rules. The parameters are tested for significance with a t-test, and the joint significance is tested with a likelihood ratio test. The test statistic for the likelihood ratio is described in equation (15), where the restricted model only has a constant term and the unrestricted model includes all parameters. The null hypothesis of no joint significance is rejected if the LR-statistic exceeds critical $\chi^2_{1-\alpha,v}$, where v is number of extra variables in the unrestricted model.

4.4.3 Model diagnostics

In order for the model to be correctly specified, the residuals must be white noise. The residuals are tested for autocorrelation and heteroscedasticity using the Ljung-Box test. If the residuals or squared residuals exhibit significant autocorrelation, the model is not properly specified. The BLL bootstrap is therefore robust to autocorrelation and heteroscedasticity. In the next chapter, the results from testing the four hypotheses on profitability and predictive power are displayed and discussed.

5 Results from analyzing technical trading

This chapter presents descriptive statistics for the applied indices, the results from testing profitability of the trading rules with hypothesis 1 and 2, and the results from testing predictive power of the trading rules with hypothesis 3 and 4. For all hypothesis testing, the significance level is set to 5 %.

5.1 Data sample from the Norwegian stock market

The sample consists of daily closing prices of the OBX Total Return Index (OBX) and Oslo Børs Small Cap Index (OSESX) from Oslo Stock Exchange (OSE). The data are obtained from Netfonds. The sample period is 1997-2013, a total of 4269 observations. The first trading day using the rules is 1/1/98, and observations prior to this date are only used as computation for the trading rules. The Government Bond Index with fixed duration of three months (ST1X) is applied as risk-free return.

The OBX consists of the 25 most liquid stocks on OSE, and is constructed as a representative reflection of OSE. Liquidity is measured as last six months turnover rating. The index is adjusted for dividends to properly display the actual change in value, and is reviewed semi-annually. The index is capped, so that the market value of the largest constituent does not exceed 30 % of total market value of the index. Also, the market value of the other constituents cannot exceed 15 % of total market value of the index. The index is tradable, with futures and options available at OSE. The OSESX consists of the 10 % lowest capitalized stocks on OSE. The index is adjusted for dividends, and is reviewed semi-annually. There are no futures or options available at OSE, but the index can be made tradable by constructing a portfolio.

In addition to the full sample, the data is divided into the following four subsamples: 1/1/98-31/12/02, 1/1/03-31/12/06, 1/1/07-31/12/08, and 1/1/09-31/12/13. The first subsample (98-02) represents a somewhat flat market. The second subsample (03-06) is characterized as a bullish market, while the Financial Crisis represents the third and bearish subsample (07-08). The last subsample (09-13) denotes the recovery period for the 2008 crash. Figure 1 displays the price development for OBX and OSESX in 1997-2013, where the price is set to 100 on 1/1/97 for both indices.

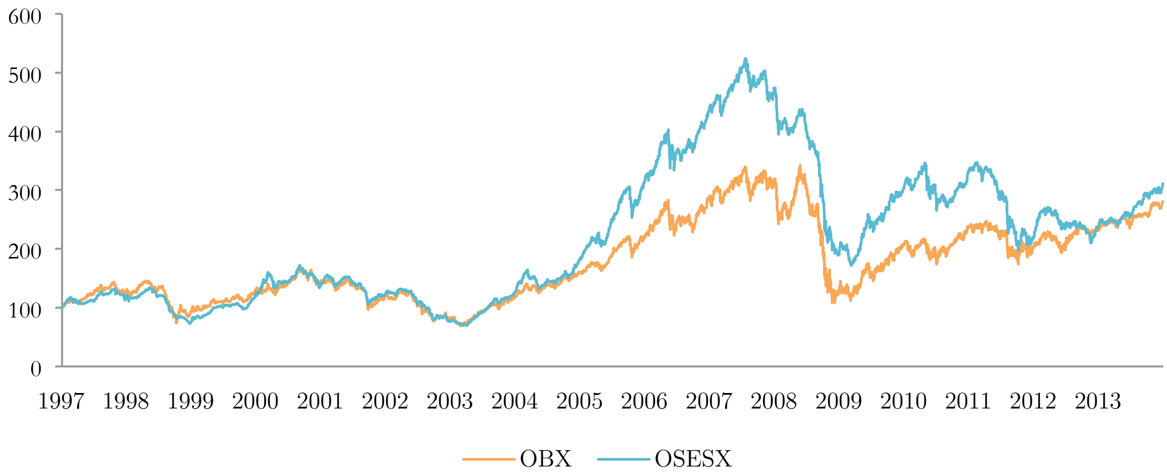

Figure 1. Price development in OBX and OSESX. Data sample is 1997-2013. Daily closing prices are indexed to 100 on 1/1/97.

The two indices follow a similar trend, but as the OSESX experience a much stronger upside in the second subsample, it also bears an equally greater fall during the financial crisis. However, the extreme fluctuations are not unexpected as the index consists of low capitalized stocks, which are considered more volatile compared to OBX constituents. Table 1 contains descriptive statistics for OBX and OSESX returns for the full sample and four subsamples. The statistics are the returns from buy-hold, and to be comparable with the trading rule results, 1997 is excluded. The OBX and OSESX returns are presented respectively in Panel I and II.

Table 1. Descriptive statistics for return in OBX and OSESX

Panel I: OBX					
	Full sample	1998-2002	2003-2006	2007-2008	2009-2013
N	4015	1251	1007	502	1255
Mean	0.00032	-0.00003	0.00132 **	-0.00115	0.00069
Standard deviation	0.01633	0.01496	0.01196	0.02585	0.01572
Skewness	-0.528	-0.379	-0.399	-0.543	-0.222
Kurtosis	8.846	5.425	6.577	7.304	5.091
JB-Stat	5909.0	337.7	563.6	412.2	238.9
Annualized mean	0.08102	-0.00660	0.33231	-0.28909	0.17403
Annualized std. dev.	0.25930	0.23753	0.18985	0.41029	0.24953
Panel II: OSESX					
	Full sample	1998-2002	2003-2006	2007-2008	2009-2013
N	4015	1251	1007	502	1255
Mean	0.00030	-0.00031	0.00179 **	-0.00158**	0.00045
Standard deviation	0.01085	0.00989	0.01033	0.01256	0.01126
Skewness	-0.906	-0.615	-1.267	-1.255	-0.636
Kurtosis	8.521	8.500	10.044	8.256	7.370
JB-Stat	5652.0	1657.0	2351.0	709.7	1084.0
Annualized mean	0.07487	-0.07686	0.45206	-0.39695	0.11229
Annualized std. dev.	0.17218	0.15697	0.16404	0.19933	0.17880

*Note: Descriptive statistics for daily return for full sample and four non-overlapping subperiods. Data sample is 1998-2013. Significance at 5 % is noted as * and 1 % is noted as **. Critical value for Jarque-Bera at 5 % is 5.99.*

The returns are leptokurtic and show signs of negative skewness for the entire sample and all subsamples. Subperiod 2 is the only period with significantly positive return for both indices. The third subperiod has significant negative return for OSESX. The Jarque-Bera statistics reject a normal distribution of returns for both indices. Volatility is highest in subperiod 3, which contains the Financial Crisis of 07-08. To examine if the indices have volatility clustering, the squared returns are presented in figure 2 and 3. Volatility clustering indicates that the risk changes over time, and thus changes in expected returns may be explained by changes in risk levels.

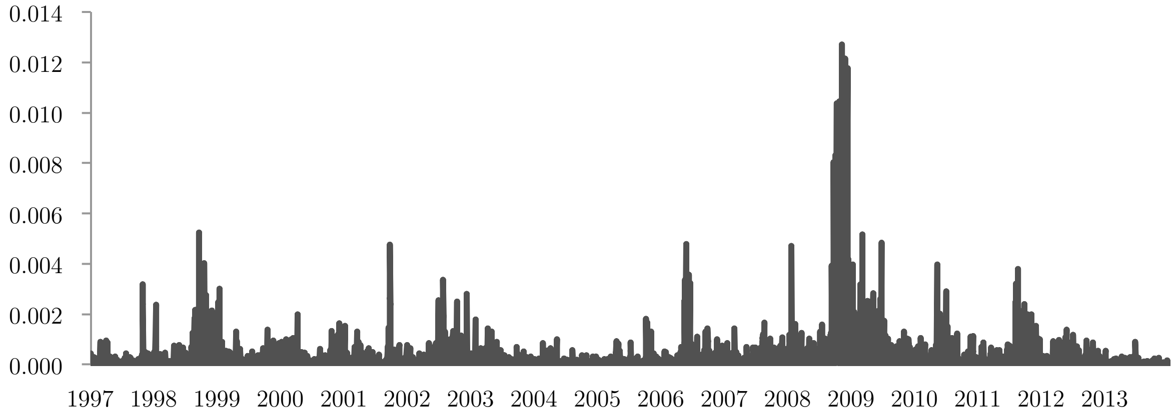

Figure 2. Squared daily returns in OBX. Data sample is 1997-2013.

Figure 2 displays that large price changes are clustered together, which implies that volatility in OBX is not constant over time. The clustering is especially evident in 2008-2009.

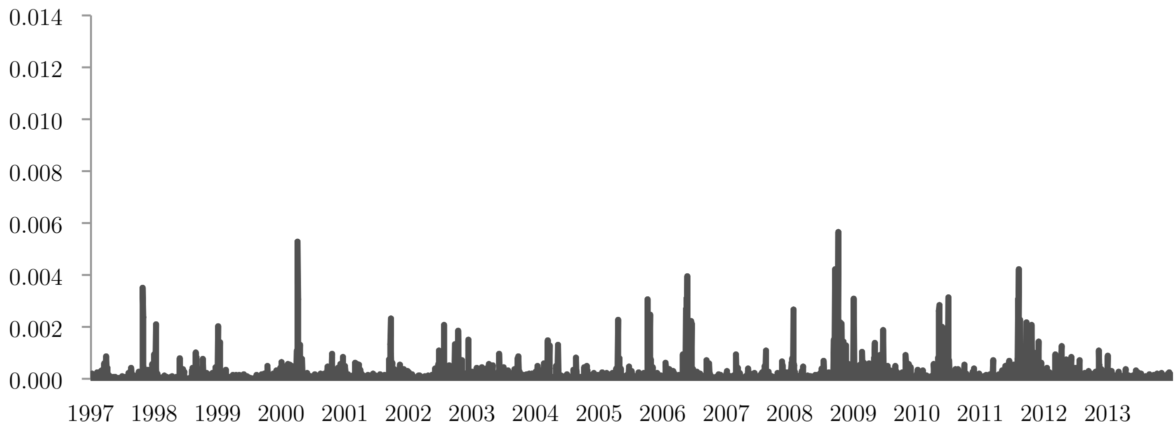

Figure 3. Squared daily returns in OSESX. Data sample is 1997-2013.

Figure 3 displays some indications of volatility clustering, which implies that volatility in OSESX is not constant over time. However, the clustering is not as apparent as for OBX, and none of the subperiods have distinctly more clustering than other periods.

5.2 Testing the performance of the trading rules

The profitability of the trading rules is examined by testing hypothesis 1 and 2. Hypothesis 1 is examined by testing the significance of the performance of the rules with a t-test. Hypothesis 2 is examined by dividing the sample into four subperiods, and testing the significance of the performance. This indicates if the trading rules are robust for different market trends. Also, the break-even transactions costs are presented in order to illustrate the extent of trading rule profitability.

5.2.1 Trading rule performance

The trading rules are tested on OBX and OSESX, and the performance is measured as excess buy and sell return, and buy-sell spread. The standard deviations from following buy and sell signals are also displayed. The hit rates for the trading rule signals are displayed to give indications on the value of the signals. The hit rate for buy signals is the fraction of returns from following buy signals that are positive. The hit rate for sell signals is the fraction of returns from following sell signals that are negative. To demonstrate the exposure in long and short positions, the number of buy and sell days are displayed.

The following notation applies to all tables in this section: Rule denotes the trading rule (horizon, filter), where horizon is number of days used to compute indicators in the trading rules. No filter is denoted as 0, the percentage band as filter F1, and the time delay as filter F2. N(Buy) and N(Sell) are the total number of days following buy and sell signals for the full sample. Imposing a filter does not necessarily reduce the number of buy or sell signals, because the signals that initially are ignored may become valid. Buy and Sell is the average daily excess return, and Buy-Sell is the spread. The standard deviations following buy signals are labeled (Buy). The standard deviation following sell signals are labeled (Sell). Buy>0 is the hit rate for buy signals, and Sell<0 is the hit rate for sell signals. A hit rate above 0.500 implies that the signals detect periods with favorable return more often than not. The numbers in parentheses are t-ratios. For convenience, only the results from rules with no filter are displayed in the following tables, and any deviations in results from applying trading rules with percentage band or time delay as filter are mentioned. The results for the trading rules are compared to buy-hold position, and the results for this strategy are displayed in table 1. Panel I displays individual rules, and Panel II displays averages for all variations of the rule. Complete tables of all trading rules are found in appendix 1-6.

The variable-length moving average (VMA) trading rule is tested on both OBX and OSESX, and the results are displayed in the following. Table 2 displays the results from the VMA trading rule when tested on OBX.

Table 2. Test results for variable-length moving average (VMA) on OBX

Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
Panel I: Individual Rules									
(25, 0)	2475	1510	0.00032	-0.00069	0.0129	0.0207	0.538	0.474	0.00101
			(0.89)	(-1.16)					(1.71)
(50, 0)	2548	1437	0.00032	-0.00074	0.0124	0.0216	0.536	0.472	0.00106
			(0.91)	(-1.18)					(1.71)
(100, 0)	2651	1334	0.00032	-0.00081	0.0121	0.0224	0.540	0.481	0.00113
			(0.91)	(-1.22)					(1.72)
(200, 0)	2744	1241	0.00025	-0.00075	0.0122	0.0229	0.543	0.489	0.00101
			(0.73)	(-1.08)					(1.46)
Panel II: Rule Average									
Average	2606	1378	0.00032	-0.00067	0.0117	0.0193	0.540	0.477	0.00098
Annualized			0.07943	-0.16774	0.1856	0.3066			0.24717

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). Rules without filters are displayed. N(buy) and N(sell) are the number of days in buy and sell periods. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

The number of buy days exceeds sell days for all VMA rules, indicating higher exposure in the long position. Buy return is always positive and sell return is always negative. Also, sell return is higher than buy return in absolute value, indicating that return from short position is higher than long position. However, the excess return is not significant for any of the rules. The standard deviation following buy signals is lower than for buy-hold, and following sell signals it is generally higher. The hit rates for buy and sell signals are close to 0.500, indicating that VMA does not produce useful signals. The buy-sell spread is always positive, but only the rules with filter F2 generate significant spread, implying that the filter improves the performance of VMA. Table 3 displays the results from the VMA trading rule when tested on OSESX.

Table 3. Test results for variable-length moving average (VMA) on OSESX

Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
Panel I: Individual Rules									
(25, 0)	2347	1638	0.00104	-0.00169	0.0086	0.0131	0.607	0.510	0.00273
			(4.22)	(-4.62)					(7.40)
(50, 0)	2312	1673	0.00100	-0.00158	0.0087	0.0129	0.612	0.515	0.00257
			(4.00)	(-4.38)					(7.06)
(100, 0)	2385	1600	0.00086	-0.00149	0.0094	0.0124	0.614	0.523	0.00235
			(3.33)	(-4.22)					(6.45)
(200, 0)	2478	1507	0.00065	-0.00129	0.0097	0.0122	0.603	0.516	0.00195
			(2.52)	(-3.61)					(5.26)
Panel II: Rule Average									
Average	2381	1603	0.00089	-0.00145	0.0085	0.0113	0.609	0.515	0.00233
Annualized			0.22331	-0.36461	0.1354	0.1795			0.58793

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). Rules without filters are displayed. N(buy) and N(sell) are the number of days in buy and sell periods. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

The number of buy days exceeds sell days for all VMA rules, indicating higher exposure in the long position. Buy return is always positive, and sell return is always negative. Also, sell return is higher than buy return in absolute value, indicating that return from short position is higher than long position. The excess return is significant for all rules. The standard deviation following buy signals is lower than for buy-hold, and following sell signals it is generally higher. The hit rate for buy signals is above 0.6, while the hit rate for sell signals is close to 0.500. This indicates that VMA produce more useful buy than sell signals. Buy-sell spread is always significantly positive. Utilizing filter F2 increases the spread significance, implying that this filter improves the performance of VMA.

The results from VMA on OSESX and OBX show that buy signals detect periods with positive return and lower volatility, and sell signals detect periods with negative return and higher volatility. In addition, the number of days in long position exceeds number of days in short position, which indicates less exposure in short positions. The rule averages display that VMA performs better in OSESX, as return from buy signals are higher, return from sell signals are lower, the buy-sell spread is higher, and the volatility in buy and sell periods is lower. Also, the hit rates are higher in OSESX.

The fixed-length moving average (FMA) trading rule is tested on both OBX and OSESX, and the results are displayed in the following. Table 4 displays the results from testing FMA on OBX.

Table 4. Test results for fixed-length moving average (FMA) on OBX

Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
Panel I: Individual Rules									
(25, 0)	585	875	0.00066	-0.00059	0.0154	0.0159	0.562	0.475	0.00126
			(0.96)	(-1.00)					(1.51)
(50, 0)	420	538	0.00028	-0.00056	0.0151	0.0170	0.564	0.489	0.00084
			(0.35)	(-0.72)					(0.80)
(100, 0)	303	370	-0.00042	-0.00022	0.0153	0.0172	0.558	0.449	-0.00020
			(-0.46)	(-0.23)					(-0.16)
(200, 0)	190	213	0.00036	-0.00088	0.0132	0.0191	0.537	0.446	0.00123
			(0.36)	(-0.66)					(0.76)
Panel II: Rule Average									
Average	409	452	0.00012	-0.00064	0.0146	0.0175	0.550	0.468	0.00076
Annualized			0.03099	-0.16106	0.2314	0.2774			0.19204

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). Rules without filters are displayed. N(buy) and N(sell) are the number of days in buy and sell periods. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

The number of buy days is less than sell days for most FMA rules, indicating higher exposure in the short position. Buy return is positive and sell return is negative for most rules, but none are significant. The standard deviation following buy signals is lower than for buy-hold, and following sell signals it is generally higher. The hit rate for buy signals is above 0.500, indicating that the buy signals can be useful. The hit rate for sell signals is below 0.500, indicating that the sell signals are not useful. Buy-sell spread is positive for most rules, but none are significant. Table 5 displays the results from testing FMA on OSESX.

Table 5. Test results for fixed-length moving average (FMA) on OSESX

Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
Panel I: Individual Rules									
(25, 0)	566	654	-0.00037	-0.00071	0.0104	0.0121	0.542	0.465	0.00034
			(-0.78)	(-1.42)					(0.53)
(50, 0)	341	378	0.00082	-0.00057	0.0099	0.0135	0.592	0.426	0.00139
			(1.47)	(-0.80)					(1.59)
(100, 0)	190	241	0.00130	-0.00015	0.0075	0.0129	0.589	0.452	0.00145
			(2.28)	(-0.18)					(1.46)
(200, 0)	110	150	0.00240	-0.00053	0.0066	0.0121	0.673	0.473	0.00294
			(3.69)	(-0.53)					(2.50)
Panel II: Rule Average									
Average	310	336	0.00092	-0.00054	0.0087	0.0124	0.601	0.459	0.00146
Annualized			0.23251	-0.13636	0.1376	0.1970			0.36888

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). Rules without filters are displayed. N(buy) and N(sell) are the number of days in buy and sell periods. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

The number of buy days is similar to sell days for most FMA rules, indicating equal exposure in both positions. Buy return is positive for most rules, but few are significant. Sell return is negative for most rules, but none are significant. The standard deviation following buy signals is lower than for buy-hold, and following sell signals it is generally higher. The hit rate for buy signals is above 0.500, and increases for rules that identify long-term trends. The hit rate for sell signals is below 0.500. This indicates that FMA only can produce useful buy signals. Buy-sell spread is positive for all rules, but few are significant.

The results from FMA on OSESX and OBX show that buy signals primarily detect periods with positive return and lower volatility, and sell signals detect periods with negative return and higher volatility. In addition, the number of days in the long position is generally equal or less than in the short position, indicating less exposure in the long position. The rule averages display that FMA performs better in OSESX, as buy return is higher, the buy-sell spread is higher, and the volatility in buy and sell periods is lower. Also, the hit rate for buy signals is higher in OSESX.

The trading-range breakout (TRB) trading rule is tested on both OBX and OSESX, and the results are displayed in the following. Table 6 displays the results for testing TRB on OBX.

Table 6. Test results for trading-range breakout (TRB) on OBX

Panel I: Individual Rules									
Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
(25, 0)	1594	825	0.00021	-0.00077	0.0132	0.0220	0.542	0.482	0.00098
			(0.51)	(-0.95)					(1.18)
(50, 0)	1302	534	0.00021	-0.00184	0.0122	0.0262	0.538	0.483	0.00206
			(0.50)	(-1.59)					(1.74)
(100, 0)	1114	297	0.00013	-0.00361	0.0119	0.0313	0.538	0.498	0.00374
			(0.30)	(-1.96)					(2.02)
(200, 0)	929	190	-0.00011	-0.00298	0.0112	0.0341	0.524	0.516	0.00288
			(-0.23)	(-1.20)					(1.15)
Panel II: Rule Average									
Average	991	370	0.00024	-0.00193	0.0123	0.0302	0.541	0.490	0.00217
Annualized			0.06017	-0.48645	0.1947	0.4791			0.54663

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). Rules without filters are displayed. N(buy) and N(sell) are the number of days in buy and sell periods. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

The number of buy days exceeds sell days for all TRB rules, indicating higher exposure in the long position. Buy return is primarily positive and sell return is always negative. Also, sell return is higher than buy return in absolute value, indicating that return from a short position is higher than a long position. However, the return is not significant for any of the rules. The standard deviation following buy signals is lower than for buy-hold, and following sell signals it is generally higher. The hit rate for buy signals is somewhat above 0.500, implying that the buy signals may be useful. The hit rate for sell signals is close to 0.500, indicating that the sell signals are not as useful. Buy-sell spread is always positive, but few rules generate significant spread. Table 7 displays the results from testing TRB on OSESX.

Table 7. Test results for trading-range breakout (TRB) on OSESX

Panel I: Individual Rules									
Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
(25, 0)	1654	936	0.00119	-0.00181	0.0089	0.0138	0.629	0.530	0.00301
			(4.29)	(-3.75)					(5.99)
(50, 0)	1384	692	0.00104	-0.00246	0.0091	0.0143	0.623	0.549	0.00350
			(3.49)	(-4.31)					(5.86)
(100, 0)	1144	478	0.00128	-0.00312	0.0093	0.0148	0.637	0.577	0.00441
			(3.97)	(-4.47)					(6.02)
(200, 0)	880	339	0.00107	-0.00382	0.0095	0.0159	0.630	0.602	0.00489
			(2.94)	(-4.35)					(5.31)
Panel II: Rule Average									
Average	1104	520	0.00137	-0.00287	0.0092	0.0149	0.636	0.563	0.00424
Annualized			0.34462	-0.72328	0.1455	0.2364			1.06790

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). Rules without filters are displayed. N(buy) and N(sell) are the number of days in buy and sell periods. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

The number of buy days exceeds sell days for all TRB rules, indicating higher exposure in the long position. Buy return is always positive, and sell return is always negative. The excess return is significant for all rules. Also, sell return is higher than buy return in absolute value, indicating that return from short position is higher than long position. The standard deviation following buy signals is lower than for buy-hold, and following sell signals it is higher. The hit rates for buy and sell signals are above 0.500. This implies that the rules produce useful signals. Buy-sell spread is always significantly positive.

The results from TRB on OSESX and OBX show that buy signals primarily detect periods with positive return and lower volatility, and sell signals detect periods with negative return and higher volatility. In addition, the number of days in long position exceeds number of days in short position. The rule averages display that TRB performs better in OSESX, as buy return is higher, sell return is lower, the buy-sell spread is higher, and the volatility in buy and sell periods is lower. The hit rates are also better in OSESX.

For all rules, buy signals detect periods with lower volatility and higher return, and in addition, sell signals detect periods with negative return. These results are inconsistent with existing equilibrium models, as return should reflect risk level. The results show that only VMA with time delay generate significant results in OBX, indicating that the trading rules are generally not profitable when applied to OBX. Panel II in table 2-7 illustrates that the rules achieve higher average return and lower volatility in OSESX than in OBX. The hit rates indicate that the signals are more useful when the rules are applied to OSESX. VMA and TRB perform best on OSESX, and all rules generate highly significant return. For FMA, the results are weaker. The results from OSESX are intriguing, as they are primarily significant and indicate that the trading rules generate useful signals. This suggests that including small-cap stocks improves the results from the trading rules. For an extended analysis of the trading rules, only OSESX is applied.

To further examine the profitability of the trading rules on OSESX, the cumulative returns from following a trading rule in the full test period are explored. As rules that identify short-term trends generate more signals than rules that identify long-term trends, it is interesting to examine if this affects the investment growth. The trading-range breakout rules perform well on OSESX, and achieve relatively high hit rates for both buy and sell signals. This indicates that the rule class may be successful, and thus, the value of pursuing this strategy is further explored. Figure 4 and 5 displays the trading-range breakout rule with 25- and 200-day horizon respectively. The long position is returns from following buy signals, the short position is returns from following sell signals, and the long + short is the strategy with equal investment in short and long position.

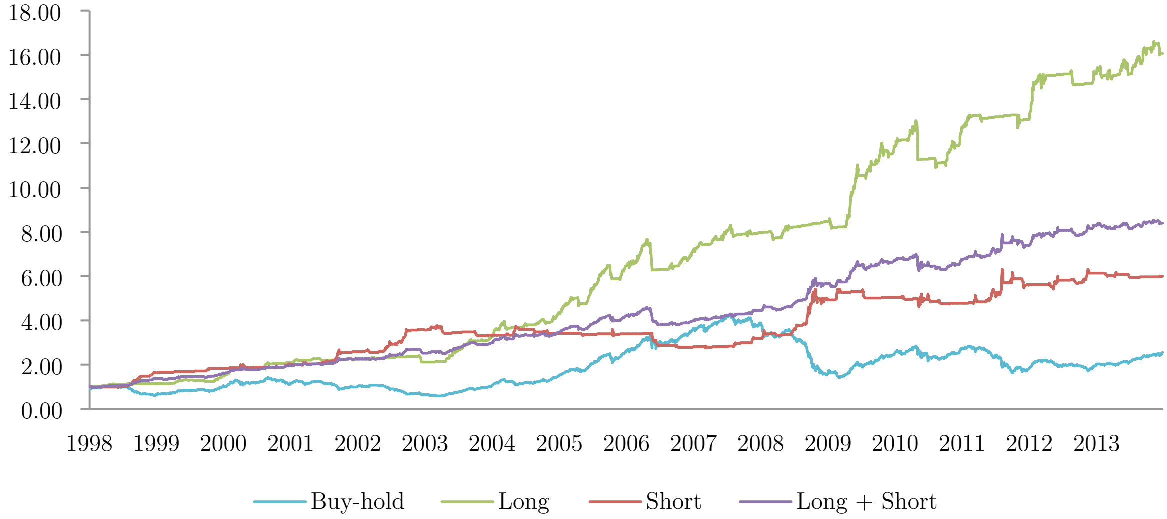

Figure 4. Cumulative daily returns for trading-range breakout (TRB) with 25-day horizon. The rule is without filter. Data sample is 1998-2013 for OSESX. The initial investment 1/1/98 is 1 NOK. Buy-hold is a 100 % position, Long is a 100 % long position from buy signals, Short is a 100 % short position from sell signals, Long + Short is a 50 % long position and 50 % short position. A neutral position implies risk-free return.

Figure 4 displays that the trading-range breakout with 25-day horizon outperforms buy-hold, and that returns from only following buy or sell signals exceed buy-hold. The returns from following buy signals are especially high. This implies that following the rule, even if it is frequently out of the market, results in outperformance relative to buy-hold. The figure suggests that the rule is able to time market positions to some extent. This is especially evident in the financial crisis of 08, as rule generates sell signals. However, the investment growth from short selling during the financial crisis is misleading, as short selling was forbidden in Norway between October 2008 and September 2009.

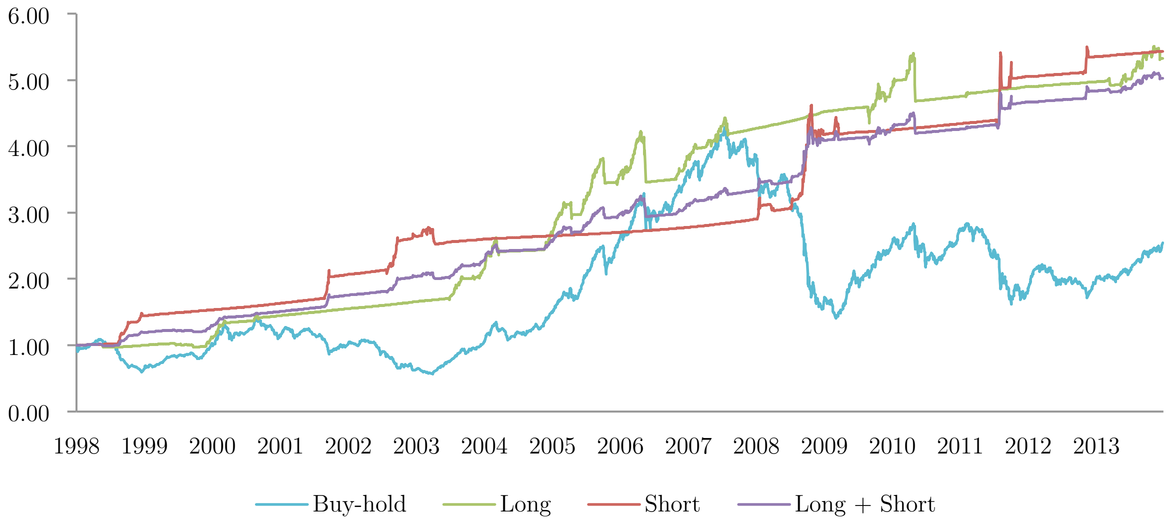

Figure 5. Cumulative daily returns for trading-range breakout (TRB) with 200-day horizon. The rule is without filter. Data sample is 1998-2013 for OSESX. The initial investment 1/1/98 is 1 NOK. Buy-hold is a 100 % position, Long is a 100 % long position from buy signals, Short is a 100 % short position from sell signals, Long + Short is a 50 % long position and 50 % short position. A neutral position implies risk-free return.

Figure 5 displays that the trading-range breakout with a 200-day horizon outperforms buy-hold, and that returns from only following buy or sell signals also exceed buy-hold. The figure suggests that the rule is able to time market positions to some extent, as the rule seldom generates sell signals in bullish markets, and avoids buy signals in the financial crisis. The investment growth from short selling during the financial crisis is misleading, as short selling was forbidden in Norway. Both rules outperform buy-hold, but the rule with 25-day horizon achieves much higher returns. An explanation for this is that the rule is more frequently in the market, and thus, the investment can grow more continuously. However, transaction costs are not considered. As the 25-day horizon rule changes position more frequently, accounting for transaction costs reduces the difference in cumulative returns between the two rules.

5.2.2 Accounting for market conditions

For the purpose of examining if the trading rules only generate excess return in periods with specific market events, the trading rule results from the subsamples are displayed in table 8. For convenience, only rules with 100-day horizon and no filter are examined.

Table 8. Test results for all rule classes on OSESX in subperiods

Period	Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
98-02	VMA	615	627	0.00113	-0.00128	0.0094	0.0124	0.569	0.571	0.00241
				(2.53)	(-2.54)					(4.42)
	FMA	56	91	0.00174	-0.00003	0.0075	0.0129	0.589	0.505	0.00178
				(2.10)	(-0.04)					(1.54)
	TRB	219	202	0.00258	-0.00362	0.0093	0.0148	0.626	0.653	0.00619
				(4.54)	(-4.37)					(6.71)
03-06	VMA	816	183	0.00001	-0.00043	0.0105	0.0098	0.669	0.437	0.00044
				(0.02)	(-0.54)					(0.54)
	FMA	60	70	-0.00044	0.00047	0.0084	0.0155	0.583	0.371	-0.00091
				(-0.39)	(0.25)					-(0.43)
	TRB	476	40	0.00016	-0.00050	0.0103	0.0096	0.685	0.450	0.00066
				(0.28)	(-0.32)					(0.42)
07-08	VMA	208	290	0.00154	-0.00114	0.0083	0.0148	0.567	0.534	0.00268
				(1.92)	(-1.10)					(2.57)
	FMA	30	30	0.00165	-0.00248	0.0066	0.0118	0.467	0.500	0.00414
				(1.24)	(-1.12)					(1.68)
	TRB	103	113	0.00234	-0.00162	0.0069	0.0192	0.573	0.549	0.00396
				(2.65)	(-0.86)					(2.05)
09-13	VMA	746	500	0.00060	-0.00120	0.0090	0.0136	0.603	0.488	0.00180
				(1.32)	(-1.75)					(2.60)
	FMA	44	50	0.00270	0.00014	0.0085	0.0160	0.682	0.440	0.00257
				(2.05)	(0.06)					(0.99)
	TRB	346	123	0.00041	-0.00247	0.0095	0.0168	0.598	0.520	0.00288
				(0.69)	(-1.60)					(1.81)

Note: Results are from daily data. Data sample is 1998-2013. Rules with 100-day horizon and no filter are displayed for all rule classes. N(buy) and N(sell) are the number of days in buy and sell periods. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of the mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97.

Testing the rules in subperiods reveals that the rules perform best during subperiod 1, where VMA and TRB are best-performing. As displayed in figure 1, subperiod 1 is a relatively flat market. For both rules, buy and sell signals generate significant excess return and buy-sell spread. The buy and sell signals appear useful, as the hit rates are relatively high. In subperiod 2, which is characterized as a bull market, none of the rules achieve significant excess return. The hit rate for buy signals is relatively high and appears useful, while the hit rate for sell signals is low. This subperiod also has relatively high risk in periods following buy signals. In subperiod 3, which is characterized as a bear market, TRB and VMA achieve positive buy-sell spread, and the hit rates are high. However, the risk in periods following sell signals is relatively high. In subperiod 4, VMA generates a positive buy-sell spread and FMA achieves excess buy return. Also, the hit rate for buy signals is high. The performance of the trading rules is not robust across subperiods, and there are strong indications that market conditions are important for performance. Further, the rules appear to only perform well during relatively flat markets, and the risk is higher in trending markets. It would be of concern if the results from the subperiods indicate that the rules only performed well in the Financial Crisis, especially if the spread originate from sell signals, as short selling were forbidden in Norway. The results from the subsamples are not as strong as for the full sample. However, there are not many indications of market events being the source of return, as the financial crisis is not the only subperiod with significant spread. In addition, returns are not only driven by sell signals in subperiod 3.

To assess if market frictions can explain return from the trading rules, the yearly break-even transaction costs are displayed for the trading rules in table 9. For convenience, only rules without filter are displayed, as the rules with filter F1 and F2 present similar results. The rules with filter F1 and F2 are found in appendix 7. High, positive break-even transaction costs will indicate that the trading rules are robust to market frictions.

Table 9. Break-even transaction costs

Rule		Break-even
(25, 0)	VMA	0.0074
	FMA	-0.0020
	TRB	0.0117
(50, 0)	VMA	0.0115
	FMA	0.0104
	TRB	0.0117
(100, 0)	VMA	0.0154
	FMA	0.0187
	TRB	0.0292
(200, 0)	VMA	0.0202
	FMA	0.0849
	TRB	0.0422

Note: Data sample is 1998-2013 for OSESX. Rules are identified as (horizon, filter). Rules without filters are displayed. The break-even is the one-way transaction costs.

All the trading rules, except one, have positive break-even transaction costs. The positive break-even costs also exceed the assumed transaction cost of 0.10 % per trade. This implies that these rules will achieve excess return after accounting for transaction costs. Primarily, it is the rules that identify long-term trends that have high break-even transaction costs. This is not surprising, as more signals are generated for rules that identify short-term trends, which results in more frequent change of position.

5.3 Correcting for data snooping

To examine if data snooping can explain excess return from the trading rules, the Reality Check is performed. The best-performing rule and the results from RC are displayed in table 10. The test is performed on all rule classes and the individual rule classes to generate the RC p-value and nominal p-value. The RC p-value results from applying the test to all rules, while the nominal p-value results from testing the best-performing rule only. The difference between the RC and the nominal p-value represents the magnitude of the data snooping bias. The mean block length is set to 20 days to reflect the dependency in OSESX.

Table 10. Test results for Reality Check bootstrap for 500 simulations

Panel I: All Rule Classes				
Best performing rule		Return	RC	Nominal
(25, 0)	VMA	0.2666	0.008	0.000
Panel II: Individual Rule Classes				
Best performing rule		Return	RC	Nominal
(25, 0)	VMA	0.2666	0.006	0.000
(50, F1)	FMA	-0.0396	1.000	0.846
(25, F2)	TRB	0.1799	0.068	0.002

Note: Data sample is 1998-2013 for OSESX. The best performance is measured as return from a 50 % long position from following buy signals and a 50 % short position from following sell-signals over a 100 % buy-hold. Rules are identified as (horizon, filter). Return is annualized. The RC and nominal are p-values.

The null hypothesis of no predictive power for the best-performing rule is rejected as the RC p-value is below 0.05. This outcome is not unexpected, as many of the trading rules outperform buy-hold, and a universe of well-performing rules increases the probability of the best-performing rule having predictive power.

To demonstrate the effect of an increased universe, the RC is also performed on the individual rule classes. VMA appears to have no problem with data snooping as the RC p-value is below 0.050. The results from TRB are less evident, as the RC p-value somewhat exceeds 0.050. The RC p-value for FMA is 1.000, revealing a bias. This is not surprising, as VMA and TRB rules perform better than FMA rules. Adding VMA and TRB to the universe of FMA decreases the RC p-value substantially, indicating that the additional rules outperform the previously best rule. This emphasizes the importance of a large universe, as the RC is sensitive to inclusion of many poor and irrelevant rules.

The nominal p-value for all rule classes supports predictive power for the best rule. This also applies for VMA and TRB as individual classes. As the difference between RC and nominal p-value represents the magnitude of data snooping, the results from the best-performing rule are not due to data snooping. However, no data snooping is a strong claim, especially without considering survivorship bias. The trading rules are well-established, and data snooping can therefore occur due to survivorship bias. Testing only historically well-performing rules is equivalent to searching for well-performing rules in a larger universe of rules. Even though the rules that are tested in this analysis are well-established, all rules do not consistently outperform in the Norwegian stock market. This indicates that the extent of survivorship bias is limited.

5.4 Simulating the stock market

In this section, results from the BLL bootstrap are displayed. First follows identification of market characteristics that may help explain the performance of the trading rules. Secondly, the null models are estimated based on the identified characteristics, and thereafter, the models are tested for misspecifications. Lastly follows the results from comparing trading rule performance in the original market to performance in the simulated markets.

5.4.1 Identifying market characteristics

To identify market characteristics in the original return series, the following aspects are examined: autocorrelation, conditional heteroscedasticity, structural breaks, and calendar effect. Table 11 displays the joint significance of autocorrelation in return and squared return.

Table 11. Ljung-Box test for autocorrelation in returns and squared returns for OSESX

Lag	Q-stat (r)	P-value	Q-stat (r^2)	P-value
5	155.02	0.0000	858.59	0.0000
10	182.76	0.0000	1187.10	0.0000
20	259.65	0.0000	1511.70	0.0000
30	285.82	0.0000	1592.00	0.0000
40	326.26	0.0000	1686.00	0.0000

Note: Data sample is 1997-2013. Q-stat is test statistic for joint significance of autocorrelation. Critical values at 5 % are as follows: 11.07 (5), 18.31 (10), 31.41 (20), 41.77 (30), and 55.76 (40). Return is denoted as r, and squared return is denoted as r^2. Complete tables of lag 1-40 are found in appendix 8 and 9.

The results in table 11 suggest that a number of lags in return and squared return have significant autocorrelation. This indicates dependency in return, and that volatility is not constant over time. Such market characteristics can help explain trading rule performance, and it is therefore considered appropriate to include AR and MA terms, and to model volatility with a GARCH model. A GARCH process allows a heavy-tailed distribution and time-varying volatility. It is assumed that a GARCH(1,1) model sufficiently captures conditional heteroscedasticity, as it is commonly used to model financial time series. The partial autocorrelation function (PACF) and autocorrelation function (ACF) for return are displayed in figure 6 and 7, and will help identify the necessary lags of AR and MA respectively.

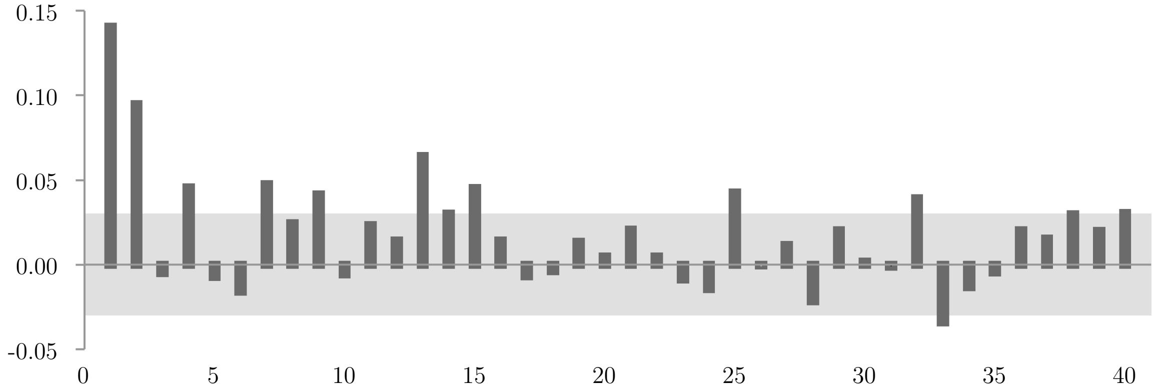

Figure 6. Partial autocorrelation in returns for OSESX. Data sample is 1997-2013. The horizontal axis is lags, and the vertical axis is PAC. The 95 % confidence band is $\pm z_{0.05/2} * SE$*. Standard error (SE) is* $[1/N]^{1/2}$.

Figure 6 displays that the time series has significant partial autocorrelation in several lags, and AR-terms are appropriate to include in the model. The first lag of PACF is highly significant, and must be included in the model to account for short-term dependency in OSESX. PACF also indicates a long-term dependency, where several of the lags can be appropriate to include. To limit the number of parameters in the model, the starting point is to include a lag for one, two and three weeks back. It is preferred to include lag 1, as it is highly significant, and lag 10 and 15, as this would account for dependency two and three weeks back approximately on the same weekday. However, lag 10 does not display significant partial autocorrelation, and is not appropriate to include in the model. For this reasoning, lag 1, 9 and 15 are applied to account for short- and long-term dependency.

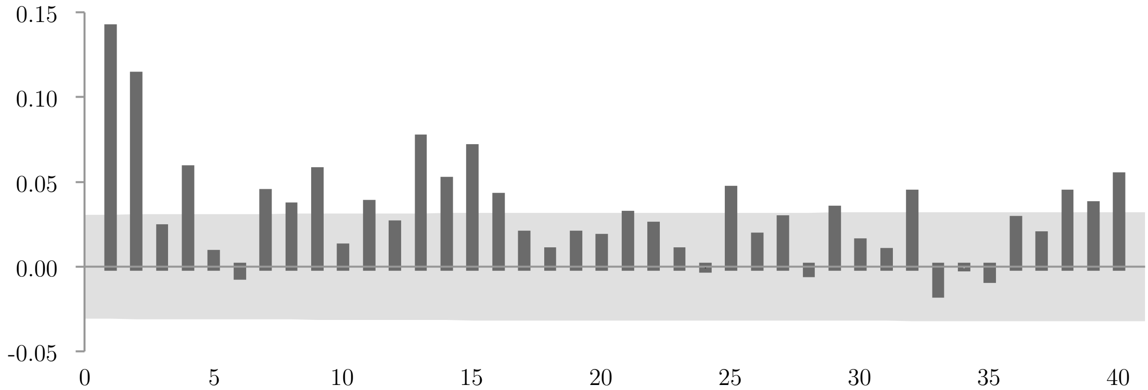

Figure 7. Autocorrelation in returns for OSESX. Data sample is 1997-2013. The horizontal axis is lags, and the vertical axis is AC. The 95 % confidence band is $\pm z_{0.05/2} * SE$*. Standard error (SE) is* $\left[\left(1 + 2 * \sum_{i=1}^{h-1} AC_i^2\right)/N\right]^{1/2}$.

Figure 7 displays that the time series has significant autocorrelation in several lags, and that MA-terms are appropriate to include in the model. The first lag of ACF is highly significant, and must be included in the model to account for short-term dependency in the series. ACF also indicates a long-term dependency, however, including more than lag 1 of MA results in a convergence problem in the estimation process. To examine if OSESX has a weekday effect, a graph displaying the cumulative daily returns for each weekday is presented in figure 8.

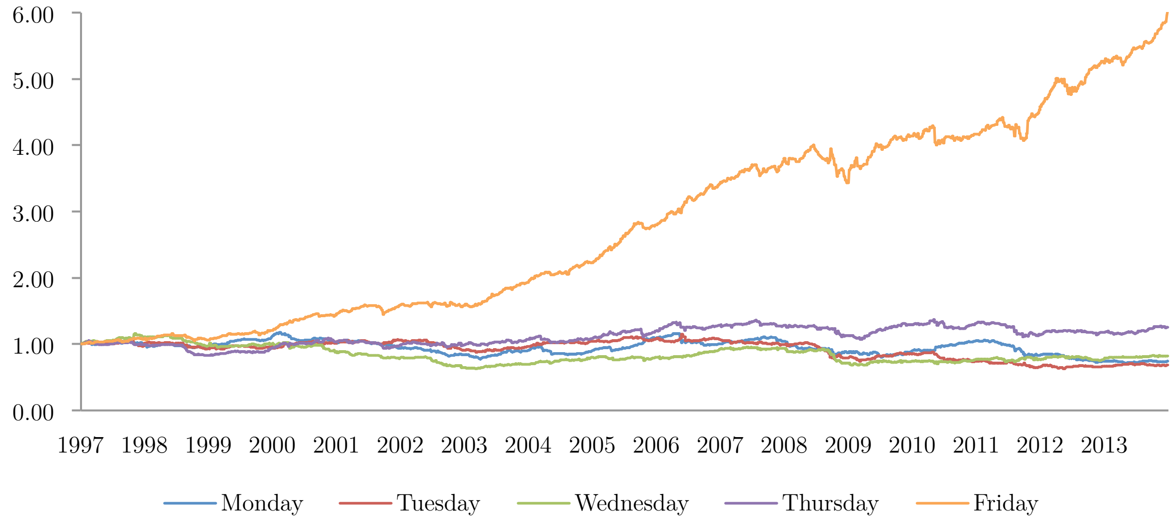

Figure 8. Cumulative daily returns on weekdays for OSESX. Data sample is 1997-2013. The initial investment 1/1/97 is 1 NOK.

According to figure 8, there seems to be an apparent Friday effect in the OSESX, as cumulative returns on Fridays exceed all other weekdays. It is therefore considered relevant to include a dummy for Friday returns in the model. In order to examine if OSESX has a month effect, a graph displaying the cumulative daily returns for each month is presented in figure 9.

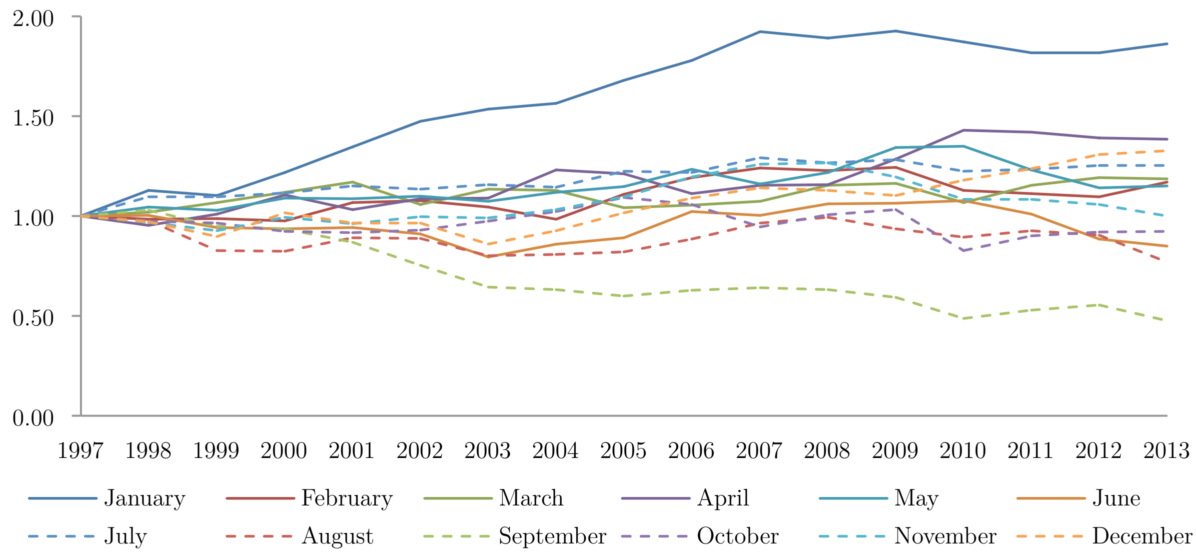

Figure 9. Cumulative daily returns on months for OSESX. Data sample is 1997-2013. The initial investment 1/1/97 is 1 NOK.

According to figure 9, there seems to also be a January effect in the OSESX, as cumulative daily return is higher in this month relative to the other months. The index also appears to underperform in September relative to the other months. However, only Friday and January effects are included as they are expected to provide sufficient foundation to examine calendar effects. If the original return series has structural breaks, the unconditional mean will change. Table 12 displays the results from testing for structural breaks in different subperiods.

Table 12. Test results for likelihood ratio test for structural break

	1997-2006	1997-2002	2003-2006	2007-2008	2009-2013
L_{UR}	13861.61	13864.04	13867.99	13863.65	13861.53
L_R	13861.28	13861.28	13861.28	13861.28	13861.28
LR	0.66	5.52	13.42	4.74	0.50

Note: Data sample is 1997-2013 for OSESX. L_{UR} is log-likelihood for unrestricted model and L_R is log-likelihood for restricted model. LR is log-likelihood ratio statistics. Restricted model is ARMA((1,9,15),1)-GARCH(1,1), and unrestricted model also contains a dummy for the given subperiod. Critical value at 5 % is 3.84.

The first column reveals that there is no significant break before and after the financial crisis manifested. The four remaining columns display that there is a break in subperiod 1-3, indicating that the unconditional mean is significantly different in subperiods. This suggests that it is appropriate to include dummies for subperiod 1-3 in the model. Subperiod 4 is applied as benchmark for the dummy variables.

To briefly summarize the points of the identification, it is appropriate to include lag 1, 9 and 15 for AR and lag 1 for MA, and model the conditional volatility through a GARCH(1,1) model. There are structural breaks between all subperiods, which indicate that a dummy should be included for the subperiods. Also, there seems to be a Friday and January effect in the OSESX, and therefore additional models that include dummies for these effects are considered interesting.

5.4.2 Estimating market models

The identification of appropriate market characteristics in OSESX gives the following three null models:

Model M1: ARMA((1,9,15),1)-GARCH(1,1) + Structural break effect
Model M2: ARMA((1,9,15),1)-GARCH(1,1) + Structural break effect + Friday effect
Model M3: ARMA((1,9,15),1)-GARCH(1,1) + Structural break effect + January effect

The models are estimated with Maximum Likelihood. Table 13 displays the estimates for models M1. Estimates for model M2 and M3 are similar to model M1, and are therefore found in appendix 10.

Table 13. Parameter estimates for model M1

ARMA((1,9,15),1)-GARCH(1,1) + Structural break effect			

$$r_t = \alpha_0 + \rho_1(r_{t-1} - \alpha_0) + \rho_9(r_{t-9} - \alpha_0) + \rho_{15}(r_{t-15} - \alpha_0) + \theta_1\varepsilon_{t-1} + D_1S_1 + D_2S_2 + D_3S_3 + \varepsilon_t,$$

$$h_t = \varphi + \gamma_1\varepsilon_{t-1}^2 + \delta_1 h_{t-1},$$

$$\varepsilon_t = v_t\sqrt{h_t},$$

α_0	D_1	D_2	D_3
0.0012	-0.0009	0.0012	-0.0016
(2.90)	(-1.58)	(2.02)	(-2.18)
ρ_1	ρ_9	ρ_{15}	θ_1
0.7327	0.0222	0.0157	-0.5971
(15.30)	(1.90)	(1.55)	(-10.56)
φ	γ_1	δ_1	
7.12E-06	1.99E-01	7.45E-01	
(12.44)	(18.17)	(64.31)	

Note: Results from daily data. Data sample is 1997-2013 for OSESX. The numbers in parentheses are t-ratios. Critical value at 5 % is 1.97. Includes dummies for subperiod 1 (S1), subperiod 2 (S2), and subperiod 3 (S3).

As displayed in table 13, current return is impacted by previous return and previous shock. The dummies for subperiod 2 and 3 are significant, indicating that the unconditional mean is different in these subperiods. Also, current conditional volatility is impacted by volatility in previous period. The estimates for model M2 and M3 are similar to M1, indicating stabile parameters. The dummies for Friday and January are significantly positive in model M2 and M3 respectively. In all models, the parameters are jointly significant and the unconditional variance is stationary, and the test results are found in appendix 11 and 12 respectively.

5.4.3 Model diagnostics

For the model to be correctly specified, the residuals must behave as white noise, which implies no autocorrelation or heteroscedasticity. As the residuals in a GARCH-model depend on conditional volatility, the residuals must be standardized. Table 14 displays joint significance for autocorrelation in standardized residuals for model M1, M2 and M3.

Table 14. Ljung-Box test: autocorrelation in standardized residuals

	Q-stat(M1)	P-value	Q-stat(M2)	P-value	Q-stat(M3)	P-value
5	3.07	0.0797	3.45	0.0631	3.09	0.0790
10	6.85	0.3353	9.53	0.1458	6.78	0.3416
20	19.26	0.2556	21.81	0.1493	18.72	0.2837
30	30.85	0.2338	31.45	0.2120	30.19	0.2598
40	42.15	0.2222	43.10	0.1936	41.61	0.2396

Note: M1 is ARMA-GARCH with structural breaks, M2 is ARMA-GARCH with structural breaks and Friday effect, and M3 is ARMA-GARCH with structural breaks and January effect. Q-stat is test statistic for joint significance of autocorrelation, and critical values for (lag) at 5 % are as follows: 11.07 (5), 18.31 (10), 31.41 (20), 41.77 (30), and 55.76 (40). Degrees-of-freedom are reduced by the number of estimated AR and MA parameters. A complete table of lag 1-40 is found in appendix 13-15.

Table 14 shows that there is no significant autocorrelation in the standardized residuals, and that the models capture the necessary autocorrelation. Table 15 displays joint significance for autocorrelation in squared standardized residuals for model M1, M2 and M3.

Table 15. Ljung-Box test: autocorrelation in squared standardized residuals

	Q-stat(M1)	P-value	Q-stat(M2)	P-value	Q-stat(M3)	P-value
5	1.24	0.7435	1.36	0.7158	1.17	0.7593
10	2.52	0.9607	2.59	0.9576	2.34	0.9688
20	6.72	0.9923	6.63	0.9929	6.58	0.9932
30	12.54	0.9947	13.46	0.9906	12.19	0.9959
40	23.62	0.9672	23.54	0.9681	22.94	0.9744

Note: M1 is ARMA-GARCH with structural breaks, M2 is ARMA-GARCH with structural breaks and Friday effect, and M3 is ARMA-GARCH with structural breaks and January effect. Q-stat is test statistic for joint significance of autocorrelation, and critical values for (lag) at 5 % are as follows: 11.07 (5), 18.31 (10), 31.41 (20), 41.77 (30), and 55.76 (40). Degrees-of-freedom are reduced by the number of estimated ARCH parameters. A complete table of lag 1-40 is found in appendix 16-18.

Table 15 shows that there is no significant autocorrelation in the squared standardized residuals, and that the models capture the necessary heteroscedasticity. Because the models remove the necessary autocorrelation and heteroscedasticity in the residuals, the models are considered correctly specified.

5.4.4 Testing the trading rules in simulated markets

In the following, the estimated p-values from testing the trading rules on the simulated price series are displayed. The p-value is the fraction of the simulated results that are higher than the results from the OSESX. To indicate that the buy signals have predictive power, the buy return in the original market should be higher than in the simulated market. This implies that the p-value must be below 0.05. To indicate that the sell signals have predictive power, the sell return in the original market should be lower than in the simulated market. This implies that the p-value must be above 0.95. To further provide support for the trading rules, the buy-sell spread in the original market should exceed the buy-sell spread in the simulated market, indicating a p-value below 0.05. Also, the volatility from following buy and sell signals in the original market should be lower than in the simulated market, indicating a p-value above 0.95.

The following notation applies to all tables in this section: Rule denotes the trading rule (horizon, filter), where horizon is number of days used to compute indicators in the trading rules. No filter is denoted as 0, the percentage band as filter F1, and the time delay as filter F2. Results for excess returns are labeled Buy and Sell, and the spread is labeled Buy-Sell. The standard deviations from following buy signals are labeled (Buy), and the standard deviations from following sell signals are labeled (Sell). For convenience, only the results from rules with no filter are displayed, and any deviations in results from filters F1 and F2 are mentioned. Table 16 displays the simulated p-values from testing the trading rules in a random walk model. Panel I displays individual rules, and Panel II displays averages for all variations of the rule. A complete table of all rules is found in appendix 19.

Table 16. Test results for random walk from 500 simulations

Rule		Buy	σ(Buy)	Sell	σ(Sell)	Buy-Sell
Panel I: Individual Rules						
(25, 0)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.862	0.760	0.984	0.002	0.264
	TRB	0.000	1.000	1.000	0.000	0.000
(50, 0)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.032	0.946	0.902	0.000	0.022
	TRB	0.000	1.000	1.000	0.000	0.000
(100, 0)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.006	1.000	0.594	0.004	0.014
	TRB	0.000	1.000	1.000	0.000	0.000
(200, 0)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.002	1.000	0.800	0.050	0.004
	TRB	0.000	0.994	1.000	0.000	0.000
Panel II: Rule Averages						
Average	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.000	1.000	0.964	0.000	0.000
	TRB	0.000	1.000	1.000	0.000	0.000

Note: Rules are identified as (horizon, filter). Rules with no filter are displayed. Numbers in the table are simulated p-values, giving the probability that the results in the simulated market are higher than the results in OSESX. Panel II is average for rule class. Complete table of rule class is found in appendix 19.

The p-values for Buy show that the trading rules generate significantly higher buy return in the original series than in a random walk. In addition, the p-values for σ(Buy) display that the buy standard deviation for most rules in the original series is significantly lower than in a random walk. This implies that random walk cannot replicate return and volatility in buy periods. Some FMA rules deviate by not achieving such results. The p-values for Sell display that the trading rules mainly generate significantly lower sell return in the original series than in a random walk. The p-values for σ(Sell) display that sell standard deviation for most rules in the original series is significantly higher than in a random walk. This implies that random walk cannot replicate return, but that it achieves lower volatility in sell periods. Again, FMA deviates somewhat from these results. The p-values for Buy-Sell show that the buy-sell spread mainly is significantly higher in the original series than in a random walk. This implies that the rules perform better in the original series than in a random walk.

The p-values for VMA and TRB strongly imply that return and volatility from the rules cannot be explained by a random walk in prices. The results are weaker for FMA, but the rule average gives the same indications as for VMA and TRB. For further analysis, the trading rules are tested in the ARMA-GARCH models, in which the conditional variance is allowed to change over time. Because the model also includes dummy variables for subperiods, the conditional mean will also differ over time. Table 17 displays the simulated p-values from testing the trading rules with no filter in model M1. A complete table of the results from the rules with filter is found in appendix 20. The results from testing the trading rules in model M2 and M3 are found in appendix 21 and 22.

Table 17. Test results for ARMA-GARCH (M1) from 500 simulations

Panel I: Individual Rules						
Rule		Buy	σ(Buy)	Sell	σ(Sell)	Buy-Sell
(25, 0)	VMA	0.732	1.000	0.908	0.000	0.334
	FMA	0.940	0.756	0.390	0.006	0.870
	TRB	0.602	1.000	0.794	0.000	0.334
(50, 0)	VMA	0.482	1.000	0.932	0.000	0.204
	FMA	0.472	0.900	0.188	0.000	0.706
	TRB	0.808	1.000	0.954	0.000	0.276
(100, 0)	VMA	0.390	1.000	0.964	0.000	0.150
	FMA	0.328	1.000	0.070	0.012	0.760
	TRB	0.704	0.998	0.984	0.000	0.100
(200, 0)	VMA	0.546	1.000	0.922	0.000	0.216
	FMA	0.128	1.000	0.172	0.126	0.434
	TRB	0.866	0.996	0.998	0.000	0.076
Panel II: Rule Averages						
Average	VMA	0.434	1.000	0.956	0.000	0.150
	FMA	0.364	1.000	0.098	0.000	0.770
	TRB	0.612	1.000	0.990	0.000	0.076

Note: M1 is ARMA-GARCH with structural breaks. Rules are identified as (horizon, filter). Rules with no filter are displayed. Numbers in the table are simulated p-values, giving the probability that the results in the simulated market are higher than the results in OSESX. Panel II is average for rule class. Complete table of rule class is found in appendix 20.

The p-values for Buy show that the trading rules do not generate significantly higher buy return in the original series than in the ARMA-GARCH process. The p-values for σ(Buy) display that the buy standard deviation for most rules in the original series is significantly lower than in the ARMA-GARCH process. This implies that the ARMA-GARCH process can replicate return, but not volatility in buy periods. The p-values for Sell display that some rules generate significantly lower sell return in the original series than in the ARMA-GARCH process. The p-values for σ(Sell) show that for most rules, the sell standard deviation is significantly in higher in the original series than in the ARMA-GARCH process. This implies that the ARMA-GARCH process can explain return, but not volatility. The p-values for Buy-Sell show that the rules do not generate significantly higher spread the original series than in the ARMA-GARCH process. This implies that the ARMA-GARCH process can replicate the buy-sell spread.

The p-values strongly imply that return from the rules can be explained by ARMA-GARCH, but that the process cannot explain volatility. The results from the ARMA-GARCH model indicate that the rules detect buy periods with lower volatility and sell periods with higher volatility. These results are not in accordance with changing risk levels as an explanation for predictability in return. The results generally do not support predictive power of the trading rules. However, there are indications that the trading rules are able to select buy periods with lower volatility. However, the fact that the ARMA-GARCH model cannot explain volatility does not imply that the rules are able to detect special patterns, as the volatility process can be more sophisticated than described in GARCH models. The GARCH models are able to capture volatility clustering, but not take into account that volatility can be impacted differently by the magnitude and direction of the price change. Thus, by applying a more advanced model for the volatility process, the BLL bootstrap may also provide an explanation for volatility.

To test if the rules have predictive power in some subperiods, the BLL bootstrap is applied to the subsamples. Table 18 displays the results for rules with 100-day horizon and without filter in model M1. Model M2 and M3, and filter F1 and F2 are expected to give similar results.

Table 18. Test results for ARMA-GARCH (M1) from 500 simulations in subperiods

Period		Buy	σ(Buy)	Sell	σ(Sell)	Buy-Sell
98-02	VMA	0.148	1.000	0.970	0.740	0.066
	FMA	0.364	1.000	0.220	0.974	0.638
	TRB	0.084	1.000	0.998	0.334	0.004
03-06	VMA	0.876	0.802	0.256	0.790	0.778
	FMA	0.754	0.846	0.116	0.024	0.900
	TRB	0.876	0.804	0.352	0.574	0.704
07-08	VMA	0.136	0.978	0.930	0.000	0.086
	FMA	0.472	0.930	0.700	0.274	0.384
	TRB	0.218	0.920	0.744	0.000	0.220
09-13	VMA	0.342	1.000	0.848	0.000	0.220
	FMA	0.118	0.942	0.150	0.000	0.502
	TRB	0.808	0.960	0.820	0.000	0.394

Note: M1 is ARMA-GARCH with structural breaks. Rules with 100-day horizon and no filter are displayed for all rule classes. Numbers in the table are simulated p-values, giving the probability that the results in the simulated market are higher than the results in OSESX.

The p-values for Buy, Sell and Buy-Sell indicate that return can be explained by the characteristics in the ARMA-GARCH process. The p-values for standard deviation are ambiguous, as some rules generate significantly lower buy standard deviation in the original series than in the ARMA-GARCH process. However, the results indicate low support for predictive power of the trading rules.

6 Conclusion

In this analysis, simple technical trading rules are tested in the Norwegian stock market represented by two indices (OBX and OSESX) between 1998 and 2013. The following research question is addressed: Can simple technical trading rules be successful in the Norwegian stock market? As successful rules must be profitable and have predictive power, both aspects are examined throughout the paper. To help answer the research question, four hypotheses are tested, where two examine profitability and two address the predictive power of the trading rules. In hypothesis 1, markets are assumed to be efficient, and technical analysis is therefore unprofitable. Further, if the trading rules appear profitable, market conditions may eliminate profits. This is the basis for hypothesis 2. The idea is that trading rule returns at best break-even after accounting for transaction costs, and that certain market trends are required for profitable rules. The latter implies that the trading rules are not robust over time, as market trends continuously change. The basis for hypothesis 3 is that extensively searching for profitable trading rules will eventually result in positive outcomes. However, this does not imply that the rules have predictive power, as it is likely a result of chance. In hypothesis 4, profitability of trading rules is explained by other aspects than predictive power. This implies that profits may not result from applying the trading rules, but rather other market characteristics, and that the trading rules are redundant. In the following, the results from testing the four hypotheses are summarized. Thereafter follows limitations to the analysis, and lastly, a conclusion to the study.

Hypothesis 1 states that technical trading rules, on average, do not outperform the market. Testing the trading rules on OBX and OSESX provide distinctive results, as the rules only perform well on OSESX. This suggests that technical trading is more valuable when applied to investments in small-cap stocks, and only OSESX is further analyzed. The results display that a short position from following sell signals generates higher average excess return than a long position from following buy signals. However, the returns following sell signals are more volatile than following buy signals or the passive strategy. The hit rate for buy signals is also higher than for sell signals for most of the trading rules. Even though the short position generates higher excess return on average, the long position from following buy signals generates highest cumulative returns. As short selling may result in infinite losses, these findings suggest that it is favorable to only utilize buy signals. According to the cumulative returns, an investment in rules that identify short-term trends is favorable to rules that identify long-term trends. However, this may be affected by transaction costs, as the rules for short-term trends require more transactions. Hypothesis 2 states that outperformance from the trading rules will disappear once market conditions are taken into account. The results reveal that reasonable transaction costs do not eliminate profits, but that the performance is not robust across subperiods. The hit rate for buy signals is relatively high in all subperiods, and primarily exceeds the hit rate for sell signals. However, the rules only generate significant returns during the first subperiod. Mainly, the performance in the subperiods indicates that the rules perform better in relatively flat markets, and poorly in bullish markets. Testing hypothesis 1 and 2 suggests that some rules can be profitable, but that the extent depends on market conditions. Hypothesis 3 states that outperformance is a result of chance. Several of the rules perform well, which increases the probability that the rules have predictive power. Thus, it is not surprising that the performance of the rules is not a result of chance. The effect of survivorship bias is also considered to be limited as not all rules outperform in the Norwegian stock market. Hypothesis 4 states that outperformance can be explained by time-varying expected return. The results suggest that the rules cannot predict return, and that the short- and long-term dependency in OSESX may explain the performance. It may be possible to utilize the long-term dependency to determine market positions, while the short-term is more difficult to exploit, as it requires more frequent transactions. It is also suggested that the calendar effects may be the source of profit, as the cumulative daily returns from Fridays are relatively high. Exploiting this effect may generate results that are comparable to the performance of the trading rules. However, this requires more frequent trades than for most of the trading rules, and transaction costs can eliminate profits. The volatility from the trading rules is not easily explained by market characteristics in OSESX, and the results suggest that the rules are able to detect periods with lower volatility. Testing hypothesis 3 and 4 suggests that the performance is not a result of chance, but that it is generated by other aspects than the predefined patterns in the trading rules. There are strong indications that returns are generated by other sources than the predefined patterns in the rules. However, as such sources can be difficult to identify and exploit, it may be useful to follow signals from technical trading rules regardless. It is important to consider the market conditions before applying the rules, as it appears that strongly trending markets can compromise the performance of the rules. Also, small investments can result in zero profits due to minimum fees.

There are some noteworthy limitations in this study. Firstly, only two simple trading rule classes are tested in this analysis. More reliable results could have been obtained with a larger number of trading rules and more complex rules. Secondly, the rules could have been tested on additional indices or stocks. This would explore other aspects of the Norwegian stock market, for example a relationship between profitability and industry. Also, the use of risk-adjusted measures of performance could provide further insight. However, these options are considered too extensive for this analysis. Thirdly, the study only accounts for transaction costs, and therefore other frictions such as taxes and regulations are not considered. However, it is assumed that the break-even transaction costs sufficiently illustrate the importance of accounting for market frictions. Also, OSESX does not have available futures. This implies that portfolios must be constructed to pursue the strategy, which results in higher transaction costs. Lastly, the volatility process in the simulated markets could be more advanced, but this is beyond the scope of this paper.

In this analysis, the importance of exploring both profitability and predictive power of trading rules is emphasized. The results provide some indications for profitability, but limit the support that this is due to predictive power of the rules. Therefore, simple technical trading rules are not considered successful in the Norwegian stock market, and the overall support for technical analysis is low. However, the potential value of technical analysis is not completely rejected. Testing more indicators and complex rules may provide further insight to the value of technical trading.

7 References

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8 Appendices

Appendix 1. Test results for variable-length moving average (VMA) on OBX

Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
Panel I: Individual Rules									
(25, 0)	2475	1510	0.00032	-0.00069	0.0129	0.0207	0.538	0.474	0.00101
			(0.89)	(-1.16)					(1.71)
(25, F1)	2471	1514	0.00030	-0.00065	0.0129	0.0207	0.537	0.473	0.00095
			(0.82)	(-1.09)					(1.60)
(25, F2)	2490	1493	0.00039	-0.00052	0.0102	0.0126	0.539	0.469	0.00091
			(1.18)	(-1.25)					(2.35)
(50, 0)	2548	1437	0.00032	-0.00074	0.0124	0.0216	0.536	0.472	0.00106
			(0.91)	(-1.18)					(1.71)
(50, F1)	2541	1444	0.00030	-0.00070	0.0124	0.0215	0.534	0.469	0.00100
			(0.85)	(-1.12)					(1.62)
(50, F2)	2552	1432	0.00033	-0.00050	0.0099	0.0129	0.538	0.469	0.00083
			(1.02)	(-1.16)					(2.10)
(100, 0)	2651	1334	0.00032	-0.00081	0.0121	0.0224	0.540	0.481	0.00113
			(0.91)	(-1.22)					(1.72)
(100, F1)	2654	1331	0.00029	-0.00076	0.0122	0.0223	0.540	0.482	0.00105
			(0.84)	(-1.14)					(1.60)
(100, F2)	2660	1321	0.00041	-0.00066	0.0100	0.0128	0.543	0.477	0.00108
			(1.28)	(-1.52)					(2.68)
(200, 0)	2744	1241	0.00025	-0.00075	0.0122	0.0229	0.543	0.489	0.00101
			(0.73)	(-1.08)					(1.46)
(200, F1)	2747	1238	0.00021	-0.00067	0.0123	0.0228	0.542	0.487	0.00088
			(0.62)	(-0.95)					(1.27)
(200, F2)	2740	1245	0.00032	-0.00055	0.0103	0.0126	0.546	0.484	0.00087
			(0.99)	(-1.25)					(2.14)
Panel II: Rule Average									
Average	2606	1378	0.00032	-0.00067	0.0117	0.0193	0.540	0.477	0.00098
Annualized			0.07943	-0.16774	0.1856	0.3066			0.24717

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). N(buy) and N(sell) are the number of total days following buy and sell signals. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

Appendix 2. Test results for variable-length moving average (VMA) on OSESX

Panel I: Individual Rules

Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
(25, 0)	2347	1638	0.00104	-0.00169	0.0086	0.0131	0.607	0.474	0.00273
			(4.22)	(-4.62)					(7.40)
(25, F1)	2337	1648	0.00104	-0.00168	0.0086	0.0131	0.607	0.473	0.00273
			(4.24)	(-4.61)					(7.41)
(25, F2)	2364	1619	0.00090	-0.00133	0.0069	0.0083	0.604	0.469	0.00223
			(4.08)	(-4.94)					(8.92)
(50, 0)	2312	1673	0.00100	-0.00158	0.0087	0.0129	0.612	0.472	0.00257
			(4.00)	(-4.38)					(7.06)
(50, F1)	2306	1679	0.00100	-0.00157	0.0087	0.0129	0.612	0.469	0.00257
			(4.01)	(-4.37)					(7.06)
(50, F2)	2323	1661	0.00099	-0.00139	0.0071	0.0081	0.616	0.469	0.00237
			(4.38)	(-5.28)					(9.59)
(100, 0)	2385	1600	0.00086	-0.00149	0.0094	0.0124	0.614	0.481	0.00235
			(3.33)	(-4.22)					(6.45)
(100, F1)	2381	1604	0.00084	-0.00146	0.0094	0.0123	0.613	0.482	0.00231
			(3.27)	(-4.14)					(6.34)
(100, F2)	2386	1597	0.00097	-0.00146	0.0074	0.0078	0.617	0.477	0.00244
			(4.26)	(-5.62)					(9.84)
(200, 0)	2478	1507	0.00065	-0.00129	0.0097	0.0122	0.603	0.489	0.00195
			(2.52)	(-3.61)					(5.26)
(200, F1)	2478	1507	0.00066	-0.00130	0.0097	0.0122	0.604	0.487	0.00196
			(2.54)	(-3.64)					(5.30)
(200, F2)	2477	1506	0.00068	-0.00112	0.0077	0.0075	0.604	0.484	0.00180
			(2.93)	(-4.34)					(7.24)
Panel II: Rule Average									
Average	2381	1603	0.00089	-0.00145	0.0085	0.0113	0.609	0.515	0.00233
Annualized			0.22331	-0.36461	0.1354	0.1795			0.58793

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). N(buy) and N(sell) are the number of total days following buy and sell signals. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

Appendix 3. Test results for fixed-length moving average (FMA) on OBX

Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
Panel I: Individual Rules									
(25, 0)	585	875	0.00066	-0.00059	0.0154	0.0159	0.562	0.475	0.00126
			(0.96)	(-1.00)					(1.51)
(25, F1)	615	855	0.00082	-0.00066	0.0151	0.0160	0.566	0.478	0.00148
			(1.24)	(-1.09)					(1.81)
(25, F2)	813	553	-0.00030	-0.00055	0.0147	0.0155	0.528	0.476	0.00024
			(-0.52)	(-0.77)					(0.29)
(50, 0)	420	538	0.00028	-0.00056	0.0151	0.0170	0.564	0.489	0.00084
			(0.35)	(-0.72)					(0.80)
(50, F1)	410	528	0.00016	-0.00062	0.0152	0.0172	0.563	0.489	0.00078
			(0.21)	(-0.78)					(0.74)
(50, F2)	517	408	-0.00067	-0.00076	0.0151	0.0183	0.518	0.478	0.00009
			(-0.94)	(-0.80)					(0.08)
(100, 0)	303	370	-0.00042	-0.00022	0.0153	0.0172	0.558	0.449	-0.00020
			(-0.46)	(-0.23)					(-0.16)
(100, F1)	303	370	-0.00045	-0.00003	0.0153	0.0169	0.558	0.441	-0.00042
			(-0.49)	(-0.03)					(-0.34)
(100, F2)	384	290	0.00039	-0.00223	0.0133	0.0203	0.565	0.497	0.00262
			(0.54)	(-1.83)					(1.91)
(200, 0)	190	213	0.00036	-0.00088	0.0132	0.0191	0.537	0.446	0.00123
			(0.36)	(-0.66)					(0.76)
(200, F1)	190	205	0.00027	-0.00068	0.0133	0.0186	0.526	0.444	0.00095
			(0.27)	(-0.51)					(0.59)
(200, F2)	180	213	0.00037	0.00010	0.0134	0.0170	0.550	0.460	0.00027
			(0.36)	(0.09)					(0.18)
Panel II: Rule Average									
Average	409	452	0.00012	-0.00064	0.0146	0.0175	0.550	0.468	0.00076
Annualized			0.03099	-0.16106	0.2314	0.2774			0.19204

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). N(buy) and N(sell) are the number of total days following buy and sell signals. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

Appendix 4. Test results for fixed-length moving average (FMA) on OSESX

Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
Panel I: Individual Rules									
(25, 0)	566	654	-0.00037	-0.00071	0.0104	0.0121	0.542	0.465	0.00034
			(-0.78)	(-1.42)					(0.53)
(25, F1)	545	644	-0.00019	-0.00065	0.0100	0.0122	0.547	0.457	0.00046
			(-0.40)	(-1.27)					(0.72)
(25, F2)	593	563	-0.00024	-0.00067	0.0089	0.0130	0.546	0.467	0.00043
			(-0.60)	(-1.17)					(0.66)
(50, 0)	341	378	0.00082	-0.00057	0.0099	0.0135	0.592	0.426	0.00139
			(1.47)	(-0.80)					(1.59)
(50, F1)	341	358	0.00081	-0.00075	0.0098	0.0138	0.595	0.439	0.00156
			(1.45)	(-1.00)					(1.73)
(50, F2)	347	354	0.00117	-0.00004	0.0088	0.0127	0.634	0.418	0.00121
			(2.32)	(-0.06)					(1.47)
(100, 0)	190	241	0.00130	-0.00015	0.0075	0.0129	0.589	0.452	0.00145
			(2.28)	(-0.18)					(1.46)
(100, F1)	184	241	0.00097	0.00003	0.0071	0.0129	0.598	0.440	0.00094
			(1.77)	(0.04)					(0.96)
(100, F2)	252	183	0.00116	-0.00068	0.0094	0.0111	0.627	0.475	0.00184
			(1.87)	(-0.82)					(1.82)
(200, 0)	110	150	0.00240	-0.00053	0.0066	0.0121	0.673	0.473	0.00294
			(3.69)	(-0.53)					(2.50)
(200, F1)	110	150	0.00251	-0.00066	0.0064	0.0121	0.673	0.487	0.00317
			(3.93)	(-0.65)					(2.72)
(200, F2)	140	120	0.00073	-0.00110	0.0079	0.0101	0.600	0.508	0.00183
			(1.06)	(-1.17)					(1.61)
Panel II: Rule Average									
Average	310	336	0.00092	-0.00054	0.0087	0.0124	0.601	0.459	0.00146
Annualized			0.23251	-0.13636	0.1376	0.1970			0.36888

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). N(buy) and N(sell) are the number of total days following buy and sell signals. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

Appendix 5. Test results for trading-range breakout (TRB) on OBX

Panel I: Individual Rules									
Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
(25, 0)	1594	825	0.00021	-0.00077	0.0132	0.0220	0.542	0.482	0.00098
			(0.51)	(-0.95)					(1.18)
(25, F1)	1541	797	0.00028	-0.00098	0.0133	0.0225	0.544	0.487	0.00126
			(0.67)	(-1.17)					(1.46)
(25, F2)	710	340	0.00047	-0.00118	0.0129	0.0261	0.552	0.497	0.00165
			(0.86)	(-0.82)					(1.10)
(50, 0)	1302	534	0.00021	-0.00184	0.0122	0.0262	0.538	0.483	0.00206
			(0.50)	(-1.59)					(1.74)
(50, F1)	1255	504	0.00020	-0.00207	0.0123	0.0268	0.539	0.490	0.00227
			(0.47)	(-1.69)					(1.83)
(50, F2)	580	210	0.00067	-0.00098	0.0124	0.0298	0.557	0.471	0.00165
			(1.16)	(-0.47)					(0.78)
(100, 0)	1114	297	0.00013	-0.00361	0.0119	0.0313	0.538	0.498	0.00374
			(0.30)	(-1.96)					(2.02)
(100, F1)	1067	297	0.00008	-0.00361	0.0121	0.0313	0.540	0.498	0.00369
			(0.18)	(-1.96)					(1.99)
(100, F2)	500	150	0.00071	-0.00121	0.0122	0.0341	0.552	0.480	0.00191
			(1.17)	(-0.43)					(0.67)
(200, 0)	929	190	-0.00011	-0.00298	0.0112	0.0341	0.524	0.516	0.00288
			(-0.23)	(-1.20)					(1.15)
(200, F1)	884	190	-0.00014	-0.00298	0.0114	0.0341	0.527	0.516	0.00284
			(-0.31)	(-1.20)					(1.13)
(200, F2)	414	110	0.00014	-0.00096	0.0120	0.0389	0.536	0.464	0.00110
			(0.22)	(-0.26)					(0.29)
Panel II: Rule Average									
Average	991	370	0.00024	-0.00193	0.0123	0.0302	0.541	0.490	0.00217
Annualized			0.06017	-0.48645	0.1947	0.4791			0.54663

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). N(buy) and N(sell) are the number of total days following buy and sell signals. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

Appendix 6. Test results for trading-range breakout (TRB) on OSESX

Panel I: Individual Rules									
Rule	N(Buy)	N(Sell)	Buy	Sell	σ(Buy)	σ(Sell)	Buy>0	Sell<0	Buy-Sell
(25, 0)	1654	936	0.00119	-0.00181	0.0089	0.0138	0.629	0.530	0.00301
			(4.29)	(-3.75)					(5.99)
(25, F1)	1599	905	0.00132	-0.00190	0.0091	0.0137	0.631	0.530	0.00322
			(4.64)	(-3.89)					(6.31)
(25, F2)	1037	486	0.00182	-0.00237	0.0086	0.0137	0.654	0.545	0.00419
			(5.71)	(-3.69)					(6.20)
(50, 0)	1384	692	0.00104	-0.00246	0.0091	0.0143	0.623	0.549	0.00350
			(3.49)	(-4.31)					(5.86)
(50, F1)	1340	684	0.00118	-0.00236	0.0094	0.0143	0.623	0.550	0.00354
			(3.83)	(-4.12)					(5.86)
(50, F2)	888	372	0.00162	-0.00322	0.0087	0.0144	0.645	0.570	0.00484
			(4.78)	(-4.21)					(6.05)
(100, 0)	1144	478	0.00128	-0.00312	0.0093	0.0148	0.637	0.577	0.00441
			(3.97)	(-4.47)					(6.02)
(100, F1)	1110	477	0.00137	-0.00316	0.0096	0.0148	0.634	0.579	0.00453
			(4.08)	(-4.52)					(6.14)
(100, F2)	778	297	0.00162	-0.00323	0.0088	0.0158	0.647	0.566	0.00486
			(4.52)	(-3.47)					(5.01)
(200, 0)	880	339	0.00107	-0.00382	0.0095	0.0159	0.630	0.602	0.00489
			(2.94)	(-4.35)					(5.31)
(200, F1)	837	339	0.00132	-0.00375	0.0099	0.0158	0.633	0.605	0.00507
			(3.43)	(-4.29)					(5.48)
(200, F2)	598	232	0.00158	-0.00322	0.0088	0.0169	0.642	0.556	0.00480
			(3.95)	(-2.87)					(4.11)
Panel II: Rule Average									
Average	1104	520	0.00137	-0.00287	0.0092	0.0149	0.636	0.563	0.00424
Annualized			0.34462	-0.72328	0.1455	0.2364			1.06790

Note: Results are from daily data. Data sample is 1998-2013. Rules are identified as (horizon, filter). N(buy) and N(sell) are the number of total days following buy and sell signals. Buy>0 and Sell<0 are the hit rates for the signals. Numbers in parentheses are t-ratios testing the difference of mean buy and mean sell return from buy-hold, and buy-sell spread from zero. Critical value at 5 % is 1.97. Panel II is the average for the rule class.

Appendix 7. Break-even transaction costs for all rules using filter F1 and F2

Rule		Break-even (F1)	Break-even (F2)
(25, F)	VMA	0.0084	0.0105
	FMA	-0.0011	-0.0014
	TRB	0.0125	0.0269
(50, F)	VMA	0.0129	0.0166
	FMA	0.0127	0.0081
	TRB	0.0125	0.0269
(100, F)	VMA	0.0170	0.0304
	FMA	0.0076	0.0267
	TRB	0.0290	0.0479
(200, F)	VMA	0.0211	0.0276
	FMA	0.0932	0.0447
	TRB	0.0431	0.0620

Note: Data sample is 1998-2013 for OSESX. Rules are identified as (horizon, filter). Rules without filters are displayed. The break-even is the one-way transaction costs.

Appendix 8. PAC and AC in returns for OSESX

	PAC	AC	Q	Prob
1	0.1405	0.1405	84.26	0.0000
2	0.0949	0.1128	138.56	0.0000
3	-0.0051	0.0227	140.76	0.0000
4	0.0457	0.0573	154.79	0.0000
5	-0.0073	0.0074	155.02	0.0000
6	-0.0159	-0.0052	155.14	0.0000
7	0.0474	0.0435	163.24	0.0000
8	0.0246	0.0355	168.63	0.0000
9	0.0415	0.0563	182.20	0.0000
10	-0.0058	0.0114	182.76	0.0000
11	0.0233	0.0372	188.69	0.0000
12	0.0144	0.0248	191.33	0.0000
13	0.0641	0.0757	215.89	0.0000
14	0.0303	0.0505	226.83	0.0000
15	0.0452	0.0699	247.73	0.0000
16	0.0144	0.0412	255.00	0.0000
17	-0.0068	0.0187	256.49	0.0000
18	-0.0037	0.0092	256.86	0.0000
19	0.0134	0.0189	258.39	0.0000
20	0.0050	0.0171	259.65	0.0000
21	0.0208	0.0304	263.62	0.0000
22	0.0048	0.0240	266.09	0.0000
23	-0.0089	0.0091	266.44	0.0000
24	-0.0146	-0.0011	266.45	0.0000
25	0.0425	0.0455	275.33	0.0000
26	-0.0001	0.0177	276.68	0.0000
27	0.0118	0.0280	280.03	0.0000
28	-0.0217	-0.0039	280.10	0.0000
29	0.0202	0.0335	284.93	0.0000
30	0.0019	0.0144	285.82	0.0000
31	-0.0012	0.0088	286.15	0.0000
32	0.0391	0.0432	294.19	0.0000
33	-0.0342	-0.0161	295.31	0.0000
34	-0.0135	-0.0001	295.31	0.0000
35	-0.0046	-0.0073	295.54	0.0000
36	0.0205	0.0277	298.86	0.0000
37	0.0155	0.0183	300.30	0.0000
38	0.0299	0.0432	308.33	0.0000
39	0.0198	0.0364	314.04	0.0000
40	0.0305	0.0533	326.26	0.0000

Note: Results are from daily data. Data sample is 1998-2013. Partial autocorrelation and autocorrelation. Q is test statistics from Ljung-box test for joint significance of autocorrelation.

Appendix 9. PAC and AC in squared returns for OSESX

	PAC	AC	Q	Prob
1	0.2442	0.2442	254.66	0.0000
2	0.1773	0.2264	473.52	0.0000
3	0.0797	0.1614	584.79	0.0000
4	0.0910	0.1685	706.13	0.0000
5	0.1098	0.1889	858.59	0.0000
6	0.0363	0.1382	940.24	0.0000
7	0.0331	0.1287	1011.00	0.0000
8	0.0708	0.1523	1110.20	0.0000
9	-0.0045	0.0957	1149.40	0.0000
10	0.0054	0.0938	1187.10	0.0000
11	0.0088	0.0812	1215.30	0.0000
12	-0.0064	0.0654	1233.60	0.0000
13	0.0504	0.1087	1284.20	0.0000
14	0.0816	0.1382	1366.10	0.0000
15	-0.0029	0.0839	1396.20	0.0000
16	0.0130	0.0886	1429.80	0.0000
17	-0.0307	0.0382	1436.10	0.0000
18	0.0310	0.0874	1468.80	0.0000
19	0.0216	0.0831	1498.50	0.0000
20	-0.0097	0.0555	1511.70	0.0000
21	0.0062	0.0645	1529.50	0.0000
22	-0.0208	0.0355	1534.90	0.0000
23	-0.0209	0.0267	1538.00	0.0000
24	0.0047	0.0388	1544.40	0.0000
25	0.0168	0.0412	1551.70	0.0000
26	0.0232	0.0572	1565.80	0.0000
27	0.0015	0.0436	1573.90	0.0000
28	0.0212	0.0571	1587.90	0.0000
29	-0.0254	0.0204	1589.70	0.0000
30	-0.0068	0.0228	1592.00	0.0000
31	0.0035	0.0237	1594.40	0.0000
32	0.0204	0.0494	1604.90	0.0000
33	0.0444	0.0736	1628.10	0.0000
34	-0.0147	0.0323	1632.60	0.0000
35	0.0285	0.0595	1647.90	0.0000
36	0.0251	0.0556	1661.20	0.0000
37	0.0083	0.0495	1671.70	0.0000
38	-0.0016	0.0407	1678.80	0.0000
39	-0.0229	0.0196	1680.50	0.0000
40	-0.0021	0.0358	1686.00	0.0000

Note: Results are from daily data. Data sample is 1998-2013. Partial autocorrelation and autocorrelation. Q is test statistics from Ljung-box test for joint significance of autocorrelation.

Appendix 10. Parameter estimates for model M2 and M3

Model M2: ARMA((1,9,15),1)-GARCH(1,1) + Structural break effect + Friday effect

$$r_t = \alpha_0 + \rho_1(r_{t-1} - \alpha_0) + \rho_9(r_{t-9} - \alpha_0) + \rho_{15}(r_{t-15} - \alpha_0) + \theta_1\varepsilon_{t-1} + D_1S_1 + D_2S_2 + D_3S_3 + D_F FRI + \varepsilon_t,$$

$$h_t = \varphi + \gamma_1\varepsilon_{t-1}^2 + \delta_1 h_{t-1},$$

$$\varepsilon_t = v_t\sqrt{h_t},$$

α_0	D_1	D_2	D_3	D_F
0.0008	-0.0008	0.0013	-0.0014	0.0022
(1.72)	(-1.35)	(2.15)	(-1.87)	(7.37)
ρ_1	ρ_9	ρ_{15}	θ_1	
0.7564	0.0187	0.0155	-0.6215	
(17.09)	(1.65)	(1.59)	(-11.76)	
φ	γ_1	δ_1		
6.93E-06	2.01E-01	7.44E-01		
(12.24)	(18.38)	(64.22)		

Model M3: ARMA((1,9,15),1)-GARCH(1,1) + Structural break effect + January effect

$$r_t = \alpha_0 + \rho_1(r_{t-1} - \alpha_0) + \rho_9(r_{t-9} - \alpha_0) + \rho_{15}(r_{t-15} - \alpha_0) + \theta_1\varepsilon_{t-1} + D_1S_1 + D_2S_2 + D_3S_3 + D_J JAN + \varepsilon_t,$$

$$h_t = \varphi + \gamma_1\varepsilon_{t-1}^2 + \delta_1 h_{t-1},$$

$$\varepsilon_t = v_t\sqrt{h_t},$$

α_0	D_1	D_2	D_3	D_J
0.0011	-0.0008	0.0013	-0.0016	0.0013
(2.54)	(-1.37)	(2.06)	(-2.14)	(2.12)
ρ_1	ρ_9	ρ_{15}	θ_1	
0.7281	0.0223	0.0162	-0.5929	
(14.77)	(1.90)	(1.59)	(-10.27)	
φ	γ_1	δ_1		
7.08E-06	1.97E-01	7.47E-01		
(12.47)	(18.14)	(64.73)		

Note: Results from daily data. Data sample is 1997-2013 for OSESX. The numbers in parentheses are t-ratios. Includes dummies for subperiod 1 (S1), subperiod 2 (S2), subperiod 3 (S3), Friday effect (FRI) and January effect (JAN).

Appendix 11. Test results for likelihood ratio test for joint significance in model M1, M2 and M3

	M1	M2	M3
L_{UR}	13922.64	13922.64	13922.64
L_R	13836.27	13950.26	13924.49
LR	172.74	227.98	176.43

Note: M1 is ARMA-GARCH with structural breaks, M2 is ARMA-GARCH with structural breaks and Friday effect, and M3 is ARMA-GARCH with structural breaks and January effect. Critical value at 5 % is 14.07 (M1), 15.51 (M2), and 15.51 (M3).

Appendix 12. Test results for Wald test on restrictions in model M1, M2 and M3

Wald (M1)	P-value	Wald (M2)	P-value	Wald (M3)	P-value
48.41	0.000	44.91	0.000	49.33	0.000

Note: M1 is ARMA-GARCH with structural breaks, M2 is ARMA-GARCH with structural breaks and Friday effect, and M3 is ARMA-GARCH with structural breaks and January effect. Critical value at 5 % is 3.84.

Appendix 13. AC in standardized residuals for model M1

	AC	Q	Prob
1	0.0164	1.15	-
2	0.0086	1.46	-
3	-0.0122	2.10	-
4	0.0146	3.00	-
5	-0.0040	3.07	0.0797
6	-0.0111	3.59	0.1657
7	0.0145	4.49	0.2134
8	0.0144	5.37	0.2510
9	-0.0018	5.39	0.3703
10	-0.0185	6.85	0.3353
11	0.0191	8.40	0.2984
12	-0.0084	8.70	0.3679
13	0.0292	12.37	0.1935
14	0.0169	13.59	0.1925
15	0.0261	16.52	0.1231
16	-0.0048	16.61	0.1648
17	-0.0065	16.79	0.2089
18	0.0146	17.70	0.2206
19	-0.0050	17.81	0.2728
20	0.0184	19.26	0.2556
21	0.0067	19.45	0.3034
22	0.0197	21.12	0.2736
23	-0.0111	21.64	0.3024
24	-0.0095	22.03	0.3390
25	0.0342	27.05	0.1693
26	-0.0137	27.86	0.1804
27	-0.0058	28.00	0.2157
28	-0.0248	30.65	0.1643
29	0.0069	30.85	0.1941
30	0.0009	30.85	0.2338
31	-0.0084	31.16	0.2647
32	0.0216	33.17	0.2297
33	-0.0209	35.04	0.2033
34	0.0017	35.05	0.2408
35	-0.0102	35.50	0.2645
36	0.0065	35.68	0.2994
37	-0.0026	35.71	0.3422
38	0.0305	39.72	0.2303
39	0.0137	40.53	0.2396
40	0.0194	42.15	0.2222

Results are from daily data. Data sample is 1998-2013. Model M1 is ARMA-GARCH with structural breaks. Q is test statistics from Ljung-box test for joint significance of autocorrelation. Degrees-of-freedom are reduced by the number of estimated AR and MA parameters.

Appendix 14. AC in standardized residuals for model M2

	AC	Q	Prob
1	0.0164	1.15	-
2	0.0116	1.72	-
3	-0.0076	1.97	-
4	0.0100	2.39	-
5	-0.0157	3.45	0.0631
6	-0.0115	4.02	0.1340
7	0.0175	5.34	0.1488
8	0.0187	6.84	0.1448
9	-0.0007	6.84	0.2329
10	-0.0251	9.53	0.1458
11	0.0209	11.40	0.1222
12	-0.0028	11.43	0.1785
13	0.0347	16.58	0.0556
14	0.0147	17.52	0.0637
15	0.0198	19.20	0.0577
16	-0.0019	19.21	0.0835
17	-0.0055	19.34	0.1128
18	0.0196	20.99	0.1020
19	-0.0076	21.23	0.1296
20	0.0117	21.81	0.1493
21	0.0091	22.17	0.1783
22	0.0212	24.09	0.1521
23	-0.0084	24.39	0.1817
24	-0.0113	24.94	0.2039
25	0.0282	28.36	0.1303
26	-0.0109	28.87	0.1487
27	-0.0031	28.91	0.1834
28	-0.0228	31.14	0.1497
29	0.0058	31.29	0.1796
30	-0.0061	31.45	0.2120
31	-0.0054	31.58	0.2481
32	0.0238	34.02	0.2002
33	-0.0165	35.20	0.1982
34	-0.0012	35.20	0.2353
35	-0.0169	36.43	0.2307
36	0.0110	36.95	0.2509
37	-0.0016	36.96	0.2910
38	0.0337	41.86	0.1667
39	0.0104	42.32	0.1844
40	0.0135	43.10	0.1936

Results are from daily data. Data sample is 1998-2013. Model M2 is ARMA-GARCH with structural breaks and Friday effect. Q is test statistics from Ljung-box test for joint significance of autocorrelation. Degrees-of-freedom are reduced by the number of estimated AR and MA parameters.

Appendix 15. AC in standardized residuals for model M3

	AC	Q	Prob
1	0.0157	1.05	-
2	0.0095	1.44	-
3	-0.0116	2.01	-
4	0.0155	3.04	-
5	-0.0034	3.09	0.0790
6	-0.0109	3.59	0.1662
7	0.0143	4.46	0.2160
8	0.0138	5.28	0.2599
9	-0.0016	5.29	0.3815
10	-0.0187	6.78	0.3416
11	0.0189	8.31	0.3063
12	-0.0086	8.62	0.3750
13	0.0285	12.10	0.2079
14	0.0159	13.18	0.2139
15	0.0258	16.02	0.1403
16	-0.0049	16.12	0.1857
17	-0.0063	16.29	0.2336
18	0.0145	17.19	0.2461
19	-0.0052	17.31	0.3009
20	0.0181	18.72	0.2837
21	0.0068	18.91	0.3336
22	0.0193	20.51	0.3048
23	-0.0106	20.99	0.3372
24	-0.0097	21.39	0.3744
25	0.0342	26.43	0.1907
26	-0.0137	27.23	0.2025
27	-0.0052	27.35	0.2413
28	-0.0246	29.95	0.1863
29	0.0073	30.18	0.2175
30	0.0014	30.19	0.2598
31	-0.0083	30.49	0.2928
32	0.0224	32.65	0.2489
33	-0.0204	34.44	0.2235
34	0.0026	34.47	0.2625
35	-0.0094	34.85	0.2898
36	0.0077	35.10	0.3232
37	-0.0018	35.12	0.3681
38	0.0307	39.18	0.2486
39	0.0136	39.98	0.2586
40	0.0195	41.61	0.2396

Results are from daily data. Data sample is 1998-2013. Model M3 is ARMA-GARCH with structural breaks and January effect. Q is test statistics from Ljung-box test for joint significance of autocorrelation. Degrees-of-freedom are reduced by the number of estimated AR and MA parameters.

Appendix 16. AC in squared standardized residuals for model M1

	AC	Q	Prob
1	0.0016	0.01	-
2	-0.0028	0.05	-
3	-0.0146	0.95	0.3286
4	0.0077	1.21	0.5473
5	0.0028	1.24	0.7435
6	-0.0064	1.42	0.8414
7	-0.0034	1.47	0.9169
8	0.0012	1.47	0.9613
9	-0.0140	2.31	0.9407
10	-0.0071	2.52	0.9607
11	0.0010	2.53	0.9801
12	-0.0187	4.03	0.9460
13	0.0074	4.26	0.9616
14	0.0104	4.73	0.9665
15	0.0106	5.21	0.9703
16	0.0004	5.21	0.9826
17	0.0138	6.03	0.9793
18	-0.0106	6.51	0.9816
19	0.0066	6.70	0.9872
20	0.0022	6.72	0.9923
21	0.0058	6.86	0.9949
22	-0.0053	6.98	0.9968
23	-0.0083	7.27	0.9975
24	-0.0106	7.75	0.9978
25	-0.0167	8.95	0.9961
26	0.0056	9.08	0.9974
27	-0.0175	10.39	0.9955
28	0.0040	10.46	0.9971
29	-0.0169	11.69	0.9954
30	-0.0140	12.54	0.9947
31	-0.0031	12.58	0.9965
32	0.0244	15.14	0.9889
33	0.0033	15.18	0.9923
34	0.0105	15.66	0.9932
35	0.0178	17.01	0.9903
36	0.0289	20.62	0.9656
37	0.0225	22.80	0.9443
38	0.0091	23.16	0.9518
39	0.0016	23.17	0.9631
40	0.0102	23.62	0.9672

Results are from daily data. Data sample is 1998-2013. Model M1 is ARMA-GARCH with structural breaks. Q is test statistics from Ljung-box test for joint significance of autocorrelation. Degrees-of-freedom are reduced by the number of estimated AR and MA parameters.

Appendix 17. AC in squared standardized residuals for model M2

	AC	Q	Prob
1	0.0041	0.07	-
2	-0.0049	0.17	-
3	-0.0146	1.08	0.2989
4	0.0069	1.28	0.5271
5	0.0042	1.36	0.7158
6	-0.0096	1.75	0.7814
7	-0.0028	1.79	0.8779
8	0.0024	1.81	0.9363
9	-0.0124	2.47	0.9291
10	-0.0051	2.59	0.9576
11	0.0019	2.60	0.9780
12	-0.0202	4.35	0.9303
13	0.0043	4.43	0.9557
14	0.0089	4.76	0.9654
15	0.0088	5.10	0.9730
16	-0.0019	5.11	0.9842
17	0.0153	6.12	0.9777
18	-0.0098	6.53	0.9813
19	0.0048	6.63	0.9879
20	0.0014	6.63	0.9929
21	0.0079	6.91	0.9947
22	0.0002	6.91	0.9970
23	-0.0069	7.11	0.9979
24	-0.0085	7.42	0.9984
25	-0.0197	9.08	0.9957
26	0.0065	9.26	0.9970
27	-0.0184	10.72	0.9942
28	0.0036	10.77	0.9962
29	-0.0185	12.24	0.9933
30	-0.0168	13.46	0.9906
31	-0.0002	13.46	0.9938
32	0.0235	15.83	0.9841
33	0.0036	15.89	0.9887
34	0.0087	16.21	0.9908
35	0.0200	17.93	0.9847
36	0.0236	20.34	0.9691
37	0.0216	22.34	0.9520
38	0.0142	23.21	0.9510
39	0.0012	23.21	0.9625
40	0.0087	23.54	0.9681

Results are from daily data. Data sample is 1998-2013. Model M2 is ARMA-GARCH with structural breaks and Friday effect. Q is test statistics from Ljung-box test for joint significance of autocorrelation. Degrees-of-freedom are reduced by the number of estimated AR and MA parameters.

Appendix 18. AC in squared standardized residuals for model M3

	AC	Q	Prob
1	0.0015	0.01	-
2	-0.0030	0.05	-
3	-0.0140	0.88	0.3471
4	0.0077	1.14	0.5668
5	0.0030	1.17	0.7593
6	-0.0062	1.34	0.8545
7	-0.0028	1.37	0.9272
8	0.0014	1.38	0.9670
9	-0.0130	2.10	0.9541
10	-0.0075	2.34	0.9688
11	0.0004	2.34	0.9849
12	-0.0186	3.81	0.9553
13	0.0078	4.08	0.9676
14	0.0098	4.48	0.9730
15	0.0105	4.96	0.9761
16	0.0006	4.96	0.9864
17	0.0138	5.77	0.9833
18	-0.0113	6.32	0.9843
19	0.0076	6.56	0.9885
20	0.0019	6.58	0.9932
21	0.0062	6.74	0.9955
22	-0.0047	6.83	0.9972
23	-0.0089	7.18	0.9978
24	-0.0105	7.65	0.9980
25	-0.0167	8.85	0.9964
26	0.0053	8.97	0.9977
27	-0.0174	10.27	0.9959
28	0.0035	10.32	0.9974
29	-0.0162	11.46	0.9961
30	-0.0130	12.19	0.9959
31	-0.0040	12.25	0.9973
32	0.0223	14.40	0.9927
33	0.0031	14.44	0.9951
34	0.0113	14.98	0.9954
35	0.0178	16.35	0.9932
36	0.0286	19.86	0.9745
37	0.0226	22.05	0.9565
38	0.0096	22.45	0.9622
39	0.0017	22.46	0.9714
40	0.0105	22.94	0.9744

Results are from daily data. Data sample is 1998-2013. Model M3 is ARMA-GARCH with structural breaks and January effect. Q is test statistics from Ljung-box test for joint significance of autocorrelation. Degrees-of-freedom are reduced by the number of estimated AR and MA parameters.

Appendix 19. Test results for random walk from 500 simulations

Panel I: Individual Rules						
Rule		Buy	σ(Buy)	Sell	σ(Sell)	Buy-Sell
(25, 0)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.862	0.760	0.984	0.002	0.264
	TRB	0.000	1.000	1.000	0.000	0.000
(25, F1)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.700	0.942	0.976	0.002	0.204
	TRB	0.000	1.000	1.000	0.000	0.000
(25, F2)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.738	1.000	0.968	0.000	0.222
	TRB	0.000	1.000	1.000	0.002	0.000
(50, 0)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.032	0.946	0.902	0.000	0.022
	TRB	0.000	1.000	1.000	0.000	0.000
(50, F1)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.040	0.944	0.956	0.000	0.010
	TRB	0.000	1.000	1.000	0.000	0.000
(50, F2)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.004	1.000	0.518	0.002	0.042
	TRB	0.000	1.000	1.000	0.002	0.000
(100, 0)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.006	1.000	0.594	0.004	0.014
	TRB	0.000	1.000	1.000	0.000	0.000
(100, F1)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.030	1.000	0.482	0.002	0.122
	TRB	0.000	0.998	1.000	0.000	0.000
(100, F2)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.008	0.980	0.904	0.268	0.010
	TRB	0.000	1.000	1.000	0.000	0.000
(200, 0)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.002	1.000	0.800	0.050	0.004
	TRB	0.000	0.994	1.000	0.000	0.000
(200, F1)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.000	1.000	0.856	0.060	0.002
	TRB	0.000	0.942	1.000	0.000	0.000
(200, F2)	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.150	1.000	0.948	0.740	0.038
	TRB	0.004	0.996	0.988	0.008	0.004
Panel II: Rule Averages						
Average	VMA	0.000	1.000	1.000	0.000	0.000
	FMA	0.000	1.000	0.964	0.000	0.000
	TRB	0.000	1.000	1.000	0.000	0.000

Note: Rules are identified as (horizon, filter). Numbers in the table are simulated p-values, giving the probability that the results in the simulated market are higher than the results in OSESX. Panel II is average for rule class.

Appendix 20. Test results for ARMA-GARCH (M1) from 500 simulations

Panel I: Individual Rules						
Rule		Buy	σ(Buy)	Sell	σ(Sell)	Buy-Sell
(25, 0)	VMA	0.732	1.000	0.908	0.000	0.334
	FMA	0.940	0.756	0.390	0.006	0.870
	TRB	0.602	1.000	0.794	0.000	0.334
(25, F1)	VMA	0.702	1.000	0.912	0.000	0.330
	FMA	0.908	0.928	0.330	0.006	0.866
	TRB	0.438	1.000	0.848	0.000	0.238
(25, F2)	VMA	0.530	1.000	0.824	0.000	0.338
	FMA	0.930	1.000	0.420	0.000	0.860
	TRB	0.200	1.000	0.918	0.000	0.056
(50, 0)	VMA	0.482	1.000	0.932	0.000	0.204
	FMA	0.472	0.900	0.188	0.000	0.706
	TRB	0.808	1.000	0.954	0.000	0.276
(50, F1)	VMA	0.470	1.000	0.942	0.000	0.188
	FMA	0.524	0.914	0.260	0.000	0.674
	TRB	0.708	1.000	0.930	0.000	0.282
(50, F2)	VMA	0.198	1.000	0.938	0.000	0.106
	FMA	0.248	1.000	0.092	0.002	0.656
	TRB	0.418	1.000	0.990	0.000	0.038
(100, 0)	VMA	0.390	1.000	0.964	0.000	0.150
	FMA	0.328	1.000	0.070	0.012	0.760
	TRB	0.704	0.998	0.984	0.000	0.100
(100, F1)	VMA	0.406	1.000	0.954	0.000	0.160
	FMA	0.486	1.000	0.054	0.012	0.872
	TRB	0.640	0.998	0.982	0.000	0.072
(100, F2)	VMA	0.112	1.000	0.980	0.000	0.052
	FMA	0.282	0.942	0.294	0.338	0.522
	TRB	0.506	1.000	0.962	0.000	0.088
(200, 0)	VMA	0.546	1.000	0.922	0.000	0.216
	FMA	0.128	1.000	0.172	0.126	0.434
	TRB	0.866	0.996	0.998	0.000	0.076
(200, F1)	VMA	0.536	1.000	0.924	0.000	0.212
	FMA	0.112	1.000	0.206	0.134	0.398
	TRB	0.714	0.970	0.998	0.000	0.058
(200, F2)	VMA	0.342	0.942	0.880	0.088	0.208
	FMA	0.544	1.000	0.430	0.728	0.576
	TRB	0.596	0.998	0.926	0.000	0.194
Panel II: Rule Averages						
Average	VMA	0.434	1.000	0.956	0.000	0.150
	FMA	0.364	1.000	0.098	0.000	0.770
	TRB	0.612	1.000	0.990	0.000	0.076

Note: M1 is ARMA-GARCH with structural breaks. Rules are identified as (horizon, filter). Numbers in the table are simulated p-values, giving the probability that the results in the simulated market are higher than the results in OSESX. Panel II is average for rule class.

Appendix 21. Test results for ARMA-GARCH (M2) from 500 simulations

Panel I: Individual Rules						
Rule		Buy	σ(Buy)	Sell	σ(Sell)	Buy-Sell
(25, 0)	VMA	0.628	1.000	0.744	0.000	0.442
	FMA	0.938	0.718	0.290	0.010	0.912
	TRB	0.538	1.000	0.678	0.000	0.380
(25, F1)	VMA	0.608	1.000	0.740	0.000	0.412
	FMA	0.880	0.896	0.244	0.006	0.890
	TRB	0.384	1.000	0.742	0.000	0.302
(25, F2)	VMA	0.440	1.000	0.668	0.000	0.370
	FMA	0.926	1.000	0.296	0.000	0.900
	TRB	0.150	1.000	0.834	0.000	0.100
(50, 0)	VMA	0.342	1.000	0.814	0.000	0.242
	FMA	0.444	0.892	0.110	0.000	0.730
	TRB	0.812	1.000	0.892	0.000	0.314
(50, F1)	VMA	0.316	1.000	0.812	0.000	0.238
	FMA	0.472	0.912	0.178	0.000	0.688
	TRB	0.696	1.000	0.846	0.000	0.316
(50, F2)	VMA	0.128	1.000	0.852	0.000	0.132
	FMA	0.208	1.000	0.044	0.006	0.700
	TRB	0.372	1.000	0.954	0.000	0.062
(100, 0)	VMA	0.240	1.000	0.886	0.000	0.156
	FMA	0.348	1.000	0.042	0.002	0.812
	TRB	0.656	1.000	0.960	0.000	0.108
(100, F1)	VMA	0.248	1.000	0.872	0.000	0.166
	FMA	0.472	1.000	0.030	0.002	0.886
	TRB	0.586	0.998	0.970	0.000	0.096
(100, F2)	VMA	0.056	1.000	0.942	0.000	0.048
	FMA	0.320	0.922	0.252	0.350	0.572
	TRB	0.466	1.000	0.912	0.000	0.126
(200, 0)	VMA	0.348	1.000	0.852	0.000	0.216
	FMA	0.104	1.000	0.114	0.130	0.490
	TRB	0.842	1.000	0.970	0.000	0.114
(200, F1)	VMA	0.316	1.000	0.856	0.000	0.200
	FMA	0.094	1.000	0.144	0.138	0.434
	TRB	0.708	0.972	0.962	0.000	0.094
(200, F2)	VMA	0.192	1.000	0.802	0.002	0.186
	FMA	0.496	0.996	0.380	0.684	0.604
	TRB	0.586	1.000	0.842	0.000	0.236
Panel II: Rule Averages						
Average	VMA	0.246	1.000	0.856	0.000	0.176
	FMA	0.376	1.000	0.030	0.000	0.824
	TRB	0.572	1.000	0.958	0.000	0.128

Note: M2 is ARMA-GARCH with structural breaks and Friday effect. Rules are identified as (horizon, filter). Numbers in the table are simulated p-values, giving the probability that the results in the simulated market are higher than the results in OSESX. Panel II is average for rule class.

Appendix 22. Test results for ARMA-GARCH (M3) from 500 simulations

Panel I: Individual Rules						
Rule		Buy	σ(Buy)	Sell	σ(Sell)	Buy-Sell
(25, 0)	VMA	0.488	1.000	0.808	0.000	0.294
	FMA	0.936	0.716	0.324	0.008	0.894
	TRB	0.428	1.000	0.736	0.000	0.300
(25, F1)	VMA	0.446	1.000	0.804	0.000	0.280
	FMA	0.890	0.920	0.274	0.008	0.870
	TRB	0.302	1.000	0.802	0.000	0.204
(25, F2)	VMA	0.304	1.000	0.736	0.000	0.280
	FMA	0.896	1.000	0.362	0.000	0.862
	TRB	0.112	1.000	0.862	0.000	0.084
(50, 0)	VMA	0.194	1.000	0.850	0.000	0.168
	FMA	0.450	0.902	0.128	0.000	0.732
	TRB	0.712	1.000	0.930	0.000	0.230
(50, F1)	VMA	0.182	1.000	0.854	0.000	0.162
	FMA	0.458	0.908	0.186	0.000	0.672
	TRB	0.594	1.000	0.900	0.000	0.222
(50, F2)	VMA	0.048	1.000	0.886	0.000	0.082
	FMA	0.226	1.000	0.052	0.010	0.682
	TRB	0.338	1.000	0.972	0.000	0.050
(100, 0)	VMA	0.138	1.000	0.904	0.000	0.124
	FMA	0.288	1.000	0.034	0.024	0.762
	TRB	0.556	1.000	0.974	0.000	0.086
(100, F1)	VMA	0.156	1.000	0.884	0.000	0.132
	FMA	0.444	1.000	0.020	0.026	0.866
	TRB	0.496	0.998	0.980	0.000	0.074
(100, F2)	VMA	0.018	1.000	0.954	0.000	0.028
	FMA	0.234	0.952	0.258	0.326	0.460
	TRB	0.402	1.000	0.924	0.000	0.110
(200, 0)	VMA	0.262	1.000	0.830	0.000	0.200
	FMA	0.088	1.000	0.132	0.128	0.406
	TRB	0.802	0.998	0.976	0.000	0.088
(200, F1)	VMA	0.254	1.000	0.840	0.000	0.198
	FMA	0.080	1.000	0.134	0.132	0.368
	TRB	0.622	0.978	0.976	0.000	0.064
(200, F2)	VMA	0.150	1.000	0.774	0.000	0.194
	FMA	0.468	0.994	0.390	0.690	0.562
	TRB	0.496	1.000	0.850	0.000	0.182
Panel II: Rule Averages						
Average	VMA	0.148	1.000	0.880	0.000	0.124
	FMA	0.302	1.000	0.038	0.000	0.774
	TRB	0.496	1.000	0.962	0.000	0.090

Note: M3 is ARMA-GARCH with structural breaks and January effect. Rules are identified as (horizon, filter). Numbers in the table are simulated p-values, giving the probability that the results in the simulated market are higher than the results in OSESX. Panel II is average for rule class.

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