Aalto University
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CAN RETAIL INVESTORS BEAT THE MARKET BY USING TECHNICAL TRADING RULES?

Evidence from the Nordic Countries

Master's Thesis
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Abstract of master's thesis

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Abstract

This thesis examines the performance of three simple technical trading rules in Nordic countries: Variable-length simple moving average (V-SMA), Fixed-length simple moving average (F-SMA), and Trading range break out (TRB). I find that technical trading rules have some predictive power. Overall, the strongest results are obtained at shorter time intervals using the V-SMA rule. Particularly the results for Iceland are strikingly strong: all the V-SMA rule tests are statistically significant. The average daily (annual) returns for conditional buy, sell and buy-sell difference are 0,093% (27%), -0,128% (-28%) and 0,221 (77%), respectively. These returns are enormous when compared to the unconditional buy-and-hold return of 0,021% (5,6%). Iceland's break-even transaction cost percent, which would eliminate trading gains, ranges from 1,1% to 11,7%, indicating that retail investors are able to beat the market even after transaction costs. The results are confirmed using a bootstrap simulation, which indicates that the results cannot be explained by the random walk. However, the results for the other countries are more mixed.

Keywords Technical analysis, technical trading rules, moving average, trading range break out, efficient market hypothesis, random walk theory, bootstrap simulation

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Tiivistelmä

Tässä tutkielmassa tarkastellaan kolmen yksinkertaisen teknisen kaupankäyntisäännön suorituskykyä Pohjoismaissa: vaihtelevapituinen liukuva keskiarvo (V-SMA), vakiopituinen liukuva keskiarvo (F-SMA) sekä kaupankäyntialueen läpimurto. Osoitan, että teknisillä säännöillä on jonkin verran ennustekykyä markkinaliikkeisiin. Yleisesti ottaen vahvimmat tulokset saadaan käyttämällä V-SMA sääntöä lyhyemmillä aikaväleillä. Erityisesti Islannin tulokset ovat hämmästyttävän vahvat: kaikki V-SMA testit ovat tilastollisesti merkittäviä. Keskimääräinen päivätuotto (vuosituotto) ehdolliselle- ostosignaalille, myyntisignaalille, ja osto- ja myyntisignaalin erotukselle on 0,093% (27%), -0,128% (-28%) ja 0,221% (77%). Verrattuna keskimääräiseen osta ja pidä -päivätuottoon 0,021% (5,6%), edellä mainitut tuotot ovat valtavia. Islannin kaupankäyntikustannusten kannattavuusraja, joka eliminoisi kaupankäyntivoitot, vaihtelee välillä 1,1% - 11,7%. Tämä osoittaa, että yksityissijoittajat pystyvät voittamaan markkinat myös kaupankäyntikustannusten jälkeen. Tulokset vahvistetaan käyttämällä bootstrap simulaatiota, joka osoittaa, ettei tuloksia voida selittää satunnaiskävelyllä. Muiden maiden tulokset ovat kuitenkin vaihtelevampia.

Avainsanat Tekninen analyysi, tekniset kaupankäyntisäännöt, liukuva keskiarvo, kaupankäyntialueen läpimurto, tehokkaiden markkinoiden hypoteesi, satunnaiskävelyn teoria, bootstrap simulaatio

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1 Introduction

1.1 Background and motivation

Despite Fama's (1965b) Efficient Market Hypothesis' dominance in the finance literature since the 1960s, many professionals and retail investors place a high value on technical analysis. Technical analysts believe that certain types of inefficiency occur in the market, allowing traders to profit from price movements. The fundamental premise is that history appears to repeat itself, at least to some extent. Because of human behavior, past patterns of price behavior tend to repeat in the future. As a result, psychology plays a significant role in forecasting. The goal is to forecast price movements by following trading signals generated by a set of trading rules and thus outperform the market. Technical rules are typically applied to take a short-term position, such as in intraday trading, but they can also be applied to take longer-term positions. The versatility of technical analysis is one of the reasons for its popularity. It can be applied to any security with historical trading data, such as stocks, futures, commodities, fixed-income securities, currencies, and so on. Furthermore, it makes no difference whether a single security or the entire index is used. Many theoretical explanations, such as noisy rational expectations models (e.g., Grossman & Stiglitz 1980; Blume et al., 1994), behavioral models (e.g., Shleifer & Summers, 1990), and herding models (e.g. Froot et al., 1992; Schmidt, 2002), as well as empirical explanations, such as central bank interference (e.g. Sweeney, 1986; Lukac et al., 1988; Davutyan & Pippenger, 1989; Levich & Thomas, 1993), order flow (e.g., Osler, 2003; Kavajecz & Odders-White, 2004), temporary market inefficiencies (e.g. Hudson et al., 1996; Bessembinder & Chan, 1998; Sullivan et al., 1999, 2003; Kwon & Kish, 2002), compensation for risk (e.g. LeBaron, 1999; Chang and Osler, 1999), and possible data snooping, are provided in academic literature for why technical analysis can be profitable. On the other hand, the other portion of academics strongly believes that the market is efficient. They believe that new information is reflected in prices quickly and instantly. Furthermore, because unpublished news is by definition unpredictable, price changes should also be unpredictable or follow a random walk. Malkiel (1999) defines the Random Walk Hypotheses as follows: “The history of stock price movements contains no useful information that will enable an investor consistently to outperform a buy-and-hold strategy in managing a portfolio”. Thus, this indicates that technical trading rules are useless. The debate has been going on for many decades, but no consensus has reached.

Despite the debate and some criticism directed at technical analysis, the popularity of trading has recently increased tremendously. According to BrokerNotes (2018), there were approximately 13,9 million online traders worldwide in 2018, with 4,9 million of them being women. The number of traders increased by 45 percent globally and 107 percent in Europe between 2017 and 2018. Such rapid growth has been driven primarily by digitalization and lower trading costs, but also by a shift in attitudes. Nowadays, a retail investor has nearly the same market access as a professional, and the trading costs are only a fraction of a percent. Furthermore, the possibility of earning a higher return than the index, as well as increased marketing of trading, make it easy to argue why trading has grown in popularity. The situation has changed dramatically in a few decades. However, the amount of work required to outperform the market is often underestimated, causing most traders to underperform.

There are thousands of indicators for technical analysis that can be examined, but the scope of this thesis is limited to three simple rules that retail investors can use: Variable-length simple moving average (V-SMA), Fixed-length simple moving average (F-SMA), and Trading range break out (TRB). Rules, for example, should not require algorithmic trading or anything else that is difficult to implement. The rules tested have been replicated from the study of Brock et al. (1992), which is widely regarded as one of the most influential modern papers on technical trading rules. They examine technical trading rules for the Dow Jones Industrial Average from 1897 to 1986 and find strongly positive and consistent results to support the technical strategies. They show that returns during buy periods are significantly and consistently larger than returns during sell periods, in addition to which they are less volatile. This thesis extends the studies of moving average- and trading range break rules to the Nordic countries. I examine whether the conditional mean returns generated by technical trading rules differ from the unconditional returns generated by the buy-and-hold strategy, as well as whether the conditional mean return of buy-signals generated by technical trading rules differs from the conditional mean return of sell-signals. In addition, I run a bootstrap simulation to confirm my findings.

1.2 Research question and hypotheses

The purpose of this thesis is to examine technical trading rules performance in the Nordic countries. More precisely, it is examined whether technical trading rules produce useful signals that retail investors can use to predict market movements and, ultimately, to win the market. My hypotheses for answering these questions are as follows:

H_0: *Simple technical trading rules do not produce useful signals.*

H_A: *Simple technical trading rules do produce useful signals.*

1.3 Contribution to prior literature

The thesis contributes to prior literature of simple technical trading rules by extending the study of Brock et al. (1992) to the Nordics. I examine whether the strong results of Brock et al. (1992) are reproducible with recent data from the Nordic countries. To the best of my knowledge, there are no prior studies focusing on the performance of these rules for the Nordic countries. Metghalchi et al. (2012) is the only paper that I am aware of that investigates some of the same Variable-length SMA rules in the Nordic countries. However, rather than reporting the rules separately, they report an average of all rules by country over a relatively short period from 1990 to 2006. Despite the lack of Nordic studies, this is not the first to investigate the performance of technical trading rules. In addition to Brock et al. (1992), Kwon and Kish (2002) for the NYSE, Coutts and Cheung (2000) for Hong Kong, Fifield et al. (2008) for emerging markets, and Metghalchi et al (2012) for Portugal have investigated the same type of rules. These and other related studies will be discussed during the thesis.

My data set is well suited for investigating this topic. First, the sample includes strong bull- and bear markets such as the early 1990s recession, the late 1990s tech bubble, the 2008 financial crisis, the 2011 European sovereign debt crisis, and most recently, the ongoing Covid-19 crisis of 2020. It is important that the sample includes both the bull- and bear markets in order to get a good picture of the overall performance of the strategy in different market situations. Second, despite the similarities between the Nordic economies, the crises mentioned above have affected countries on different scales; for example, the recession of the 1990s had the greatest impact on Finland and Sweden, while the financial crisis of 2008 nearly destroyed the Icelandic economy. Because of these differences, it is theoretically possible to identify circumstances where technical rules may perform better than in others, which Brock et al. (1992) have not detected. Third, there is a clear shortage of studies examining the performance of technical trade rules in the Nordic countries. The Dow Jones Industrial Average is by far the most studied equity index, with over a century of data available. The same high-quality and long-term time series are not available in the Nordics, which explains why there is a lack of studies that combine technical analysis and retail investors. Only recently has a point been reached where enough data is available in the Nordic countries to properly study the subject and achieve reliable results. Fourth, a sufficient amount of time has passed since the original study to re-examine the subject.

1.4 Main findings

My results indicate that technical trading rules have predictive power. Depending on the size of transaction costs, retail investors may be able to outperform the market by employing technical trading rules. The strength of the results, however, varies across tests and countries. In general, the strongest results are obtained at shorter time intervals using the V-SMA rule, such as with a moving average of 20-50 days. The results for Iceland are strikingly strong, whereas the results for the other countries are more mixed. All the tests performed on the Icelandic V-SMA rule are statistically significant, rejecting the null hypothesis that technical trading rules do not produce useful signals. The annualized return for buy days over various time horizons is 27%, while the annualized return for buy-and-hold is only 5,6%. Depending on the rule, the break-even transaction cost percent that would eliminate trading gains ranges from 1,1% to 11,7%. In general, I find that the number of buy-signals is always greater than the number of sell-signals, and that the buy returns are all positive while the sell returns are all negative. Furthermore, the market is more volatile during sell periods than during buy periods, even though the mean return on buy-signals is higher than the mean return on sell-signals, indicating that the higher mean return on buy-signals does not appear to be due to increased risk. Similar results are obtained from DJIA (Brock et al., 1992), Hong Kong (Coutts & Cheung, 2000), emerging markets (Fifield et al., 2008), and Portugal (Metghalchi et al., 2012), while more contrarian results are obtained from the UK (Hudson et al., 1996), NYSE (Kwon & Kish, 2002), and developed markets (Fifield et al., 2008). Hudson et al. (1996) and Kwon & Kish (2002) report consistent basic findings, but the strength of the results weakens in the latter sub-periods. Following Brock et al. (1992), the results are confirmed using bootstrap simulation, which indicates that the results cannot be explained by the random walk.

1.5 Limitations

This study focuses only on a relatively small number of technical rules. As a result, generalizing these findings may be premature. Furthermore, there are several limitations in this thesis. The first set of limitations relates to the quality and quantity of the data. The data used in this thesis consist of Nordic stock market indices, the majority of which have a time span of more than 30 years. It is by no means too short, but ideally, it would be even longer in order to perform a proper sub-sample analysis, or out-of-sample verification. These analyses are not addressed in this study. The daily price information of indices does not include daily dividend yields, resulting in an understatement of actual returns. However, Mills & Coutts (1995) and Bessembinder & Chan (1998) show that the exclusion of dividends should only lead to minimal bias. Another data issue might be the measurement errors arising from nonsynchronous trading. However, several studies document that spurious autocorrelations caused by nonsynchronous trading are unlikely to explain the forecast power of technical rules (e.g. Bessembinder & Chan, 1998; Ito, (1999). It is difficult to estimate the magnitude of the measurement error in a Nordic sample, which is why it is ignored.

The second set of limitations relates to the methods used in the thesis. The standard t-test assumes normal, stationary, and time-independent distributions. Brock et al. (1992). However, the distribution of stock returns is well documented to violate these assumptions in a variety of ways, including leptokurtosis, autocorrelation, conditional heteroskedasticity, and changing conditional means. I try to mitigate this issue by performing hypothesis testing with a simulated bootstrap distribution proposed by Brock et al (1992). Another well-known issue in financial research is the possibility of data snooping bias, which cannot be completely eliminated (Lo, 1994). The problem is particularly evident when examining popular technical trading rules, as in this study. As a result, there is always a slight possibility that technical analysis discovers significant patterns by chance. However, I do not address the issue by using White's (2000) reality check or the superior predictive ability test of Hansen (2005). Instead, I present results from all trading rules examined, use the longest data set available, and discuss the data snooping problem in more detail. Furthermore, I do not use risk-adjusted measures of performance, since all known methods have multiple limitations, such as the joint hypothesis problem.

1.6 Structure of the thesis

The rest of the paper is organized as follows. Section 2 presents a brief introduction to recent literature. Section 3 describes the theoretical framework of the thesis. Section 4 presents the research questions and hypotheses. Section 5 describes data and methodology. Section 6 presents the results of technical trading rules. Section 7 discusses the issue of data snooping. Finally, section 8 concludes the thesis.

2 Literature review

Technical analysis has long been used to market speculation. It is a broad term that refers to a variety of technical indicators and forecasting techniques, such as chart analysis, cycle analysis, and computerized trading systems (Park & Irwin, 2007). The oldest technique can be traced back to the late 1800s to Charles Dow. Henceforth, Technical analysis is used in a variety of markets and asset classes, including foreign exchange markets, futures markets, commodities markets, fixed-income markets, and stock markets. Moving averages, channels, filters, and momentum oscillators are popular technical indicators in academic literature. Recent research, on the other hand, has focused on more complex forecasting techniques such as visual pattern recognition and machine learning. Since the focus of the thesis is to examine simple technical trading rules, these more complex techniques are not addressed in the literature review. The aim is to provide a good overall review of studies that focus on similar types of rules as those examined in this thesis. Empirical studies of technical analysis can be categorized as early studies and modern studies based on their testing methods. It is by no means easy to place these partitions on a timeline, but roughly speaking, studies conducted before 1988 can be considered as early studies and after that as modern studies.

2.1 Early studies

One of the pioneering studies in technical analysis is by Smidt (1965a). He interviews a group of retail US commodity futures traders to find out the characteristics of amateur traders, such as the style of trading. He discovers that more than half of the respondents use charts to identify trends in a moderate or exclusive manner, and he identifies this group as 'Chartists.' Furthermore, he discovers that chartists trade more frequently and are less likely to face margin calls than non-chartists. After Fama (1965a) defined an efficient market for the first time and concluded that stock market prices follow a random walk Fama (1965b), the study of technical trading rules became more common. In addition to test statistically price independence from each other's, technical trading rules provide an empirical approach to test the random walk hypothesis. If past stock prices can be used to predict future prices and traders can profit systematically from these predictions using trading rules, then stock price changes do not follow a random walk. Perhaps this is why early studies focused on examining the various rules, such as moving averages, filters, momentum oscillators, relative strength, channels, and stop-loss orders, to name a few.

Van Horne & Parker (1967) examine three moving average rules: 100, 150, and 200 days. They choose 30 industrial stocks at random from the New York Stock Exchange between 1960 and 1967 and test the rules with five different confirmation bands: 0%, 2%, 5%, 10%, and 15%. Furthermore, they make two assumptions: the long position only, and the long and short position. They find that none of the rules outperform the buy-and-hold strategy even when transaction costs are ignored. Van Horne & Parker (1968) extend their research by introducing an exponential moving average, which emphasizes recent prices. However, the findings are consistent with previous findings: trading rules do not outperform the buy-and-hold strategy. They conclude that the results support the random walk hypothesis. Others who examine moving average rules at an early stage reach a similar conclusion. For example, James (1968) examines monthly moving averages of common stocks listed on the New York Stock Exchange from 1926 to 1960. Only a few of the decision rules outperform a simple buy-and-hold strategy. Unlike others, Cootner (1962) concludes that the stock market is not a random walk based on his statistical analysis. However, in his empirical tests, only a few rules outperformed a buy-and-hold strategy after costs, which is consistent with James (1968). Outside the stock market, Dale & Workman (1980) use Treasury bill futures at 1976-1978 and find that moving average rules are not profitable in the long run.

In addition to moving average rules, a filter rule invented by Alexander (1961) is another popularly tested rule among the early studies of technical analysis. Alexander (1961) describes the filter rule in a following way: If the daily closing price increases at least x %, buy and hold the security until its price moves down at least x % from a subsequent high, at which time simultaneously sell and go short. The position is held until the daily closing price rises by at least x % above the previous low. As a result, all price movements less than a x % are filtered out, where the name ‘filter rule’ comes from. Clearly, this rule can be tested with various filter sizes. Alexander (1961) applies various filters ranging from 5% to 50% to the Dow Jones industrial averages from 1897 to 1929 and Standard and Poor’s Industrials from 1929 to 1959. His results are promising. The smallest filters produce the highest profits, and the rules generate significant profits on average when compared to a buy-and-hold strategy. However, Alexander (1961) does not consider transaction costs. He concludes that profits would be substantially reduced, but by no means eliminated after taking care of the transaction costs. Alexander (1961) receives some criticism of his work. For example, Mandelbrot (1963) points out that Alexander overestimates the profitability of the filters. The study implicitly assumes that when the signal occurs, one can immediately buy or sell the stock at that price, resulting in bias whenever a transaction takes place. In reality, the purchase price will often be higher than low plus x % and selling price lower than high minus x %. Alexander (1964) responds to the criticism in his later paper. Many of the filter rules still show profits after corrections, but the profitability is substantially reduced. Also, Fama & Blume (1966), and Jensen & Benington (1970) show that technical rules are inferior to buy-and-hold strategy, using filters and relative strength, respectively.

Several studies examine technical trading rules outside the stock market and find superior returns compared to a buy-and-hold, see for example Smidt (1965b), Stevenson & bear (1970), Leuthold (1972), Cornell & Dietrich (1978), Sweeney (1986). Stevenson & Bear (1970) test various sized filters on the commodity futures market (soybean and corn) and find that the largest filter produces the greatest profit. They show that using a 5 percent filter, a retail investor can outperform a buy-and-hold strategy even after transaction costs. In addition, Leuthold (1972), shows superior returns compared to buy-and-hold using filter rules on the live cattle futures market. To summarize the early studies of technical trading rules, studies focusing on the stock market do not find superior returns when compared to a buy-and-hold strategy. However, on foreign exchange markets and futures markets, most of the studies find substantial profits even net of fees. Hence, it is often argued that stock markets are more efficient than foreign exchange markets or futures markets. However, this is not necessarily the case, and such a conclusion cannot be drawn solely based on early studies. First, only a small number of trading rules are often tested, making it difficult to draw broad conclusions. Second, statistical methods are deficient compared to modern studies. Quite often, early studies do not include any statistical tests of significance, or they may ignore differences in risk. For example, moving average strategies often have lower variance than a buy-and-hold strategy, but this difference is ignored. Third, results are reported as an average across all trading rules or all asset classes, despite the fact that there may be significant differences between them. Overall, testing procedures in early studies are deficient compared to modern studies.

2.2 Modern studies

Modern research is constantly evolving and attempts to address the previously mentioned shortcomings of early research. There are still differences in how well they succeed. According to Park & Irwin (2007), the first modern study can consider to be Lukac et al. (1988), who provide a more comprehensive analysis than any early study. They examine 12 different trading systems, take account transaction costs and risk, conduct out-of-sample verification for optimized trading rules, and perform a significance test. They suggest that disequilibrium models are a better description of short-run price movements than the random walk model. However, one of the most influential modern paper is Brock et al. (1992), who examine technical trading rules from 1897 to 1986 for Dow Jones Industrial Average. Several reasons for the influence can be identified. First, the time series of more than 90 years was completely exceptionally long compared to previous studies. Second, Brock et al (1992), were the first to combine technical analysis and bootstrap methodology inspired by Efron (1979), Freedman and Peters (1984a, 1984b), Efron & Tibshirani (1986). Third, perhaps the most significant reason, they find strongly positive and consistent results about the forecasting power of technical trading rules, which calls into question the random walk hypothesis and the market efficiency.

Brock et al. (1992) examine two of the most common and simplest technical trading rules; moving average and trading range break-out. Moving average rule compares the short-term moving average with the long-term moving average. A buy signal (a sell signal) is generated when the short-term moving average rises above (falls below) the long-term moving average. The trading range break-out rule on the other hand is based on the support and resistance levels where a buy (sell) signal is generated when the price exceeds the local maximum (falls below the local minimum). The results are impressive. Across all 26 rules, all buy (sell) signals generate positive (negative) returns, meaning that all buy-sell differences are positive. 10/10 buy-sell differences outperform the buy-and-hold strategy significantly for variable-length moving average, 7/10 for fixed-length moving average, and 6/6 for trading range break-out. For example, buy (sell) returns for variable-length moving average generate annual return of 12% (-7%), meaning 19% return for buy-sell difference, which is strongly favorable compared to buy-and-hold return of 5%. Return difference between buys and sells is not easily explained by risk. Even though returns during buy periods are larger than returns during sell periods, they are less volatile.

Brock et al. (1992) identify the possibility of data snooping bias that always exists in financial economics and admit that it cannot be completely corrected. However, they alleviate the problem by reporting results for all tested strategies, utilizing a very long data series, and emphasizing the robustness of results across various non-overlapping sub-periods. In addition to standard t-tests, they use model-based bootstrap method for statistical tests. Standard t-test assume normal, stationary, and time-independent distributions. However, the distribution of stock returns is known to be leptokurtic, autocorrelated, conditionally heteroskedastic and time varying. Brock et al. (1992) take these aspects into account by using distributions generated from simulated null models for stock prices. Each of the simulations is based on 500 replications. Brock et al. (1992) show consistent results about the forecasting power of technical trading rules. However, they do not take transaction costs into account, so it is hard to say whether retail investors can utilize such profitability in practice.

Brock et al. (1992) sparked a lot of discussion in the academic literature and served as an inspiration for many future studies. Bessembinder & Chan (1995) use the same rules in the Asian stock markets as Brock et al. (1992). They find that the rules are successful in Japan, Hong Kong, South Korea, Malaysia, Thailand, and Taiwan, with the predictability strongest in the last three markets. On average, 1,57% round trip transactions cost would eliminate any gain of the strategies. Bessembinder & Chan (1998) further examine the findings of Brock et al. (1992) and confirm the basic results. They find that the forecast power is not solely attributable to return measurement errors arising from nonsynchronous trading and that break-even one-way trading costs are 0,39% for the full sample and 0,22% since 1975. Bessembinder & Chan (1998) conclude that determination of the source of the technical forecast power documented by Brock et al. remains an interesting and unresolved issue. Furthermore, Sullivan et al. (1999) confirms using White's (2000) reality check bootstrap methodology that Brock et al. (1992) findings are robust to data snooping.

Other studies find that simple technical trading rules exceeds buy-and-hold strategy even after transaction costs in emerging markets Raj & Thurston (1996), Ito (1999), Ratner & Leal (1999), Gunasekarage & Power (2001) and in foreign exchange markets Levich & Thomas (1993), Lebaron (1999), Neely (2002), Saacke (2002). However, in developed markets the results are more mixed, see for example Hudson et al. (1996), Bessembinder and Chan (1998), Ito (1999). More recently is shown that moving average strategy can outperform the buy-and-hold strategy on less liquid securities. Han et al. (2013) use volatility and size deciles, while Shynkevich (2012) examines technology industry and small cap sector portfolios. In addition, Huang et al. (2019) show strong out-of-sample predictive power of daily returns on bitcoin using technical indicators.

Pulling all things together, in the early-stage trading rules are profitable in foreign exchange markets and futures markets, but not in stock markets. Modern studies on the other hand consistently beat a buy-and-hold strategy even after trading costs. Park & Irwin (2007) review a total of 95 modern studies. They report 56 studies with positive profits, 20 studies with negative results, and 19 studies with mixed results. However, some studies indicate the decline of the economic profit after the turn of the millennium (e.g. Sullivan et al., 1999, 2003; Olson, 2004.). Furthermore, as Nazario et al. (2017) point out, publication bias may have influenced the distribution of these findings. It is possible that papers with strong results may be more likely to be published than papers that do not reject the null hypothesis.

3 Theoretical framework

There are usually two common ways of how market participants try to predict market movements: technical analysis and fundamental analysis. The idea of fundamental analysis comes from the Firm-Foundation theory, according to which each company has an intrinsic value that is determined by the company's earnings potential. The intrinsic value of any company can be defined as the present value of all dollar benefits expected by the investor. What an investor can expect depends on the company's fundamentals, such as management quality, industry outlook, and financial situation. It is argued that by carefully analyzing these, the market participant can determine the true price of the security and make investment decisions based on whether the current market price is lower or higher than the true price. Fundamental analysts believe that the market is logical and will eventually reflect the true price of the security. However, no one knows how long it will take. For that reason, fundamental analysis works best for identifying long-term investment opportunities.

Technical analysis on the other hand, is often used to recognize short-term trades. Practitioners believe that the market is mostly psychological rather than logical. The basic assumption is that history seems to repeat itself, at least to some extent. Past patterns of price behavior tend to be repeated in the future. In other words, price changes are interdependent. This is thought to be due to recurring human behavior, which is not always rational. Nowadays, Behavioral finance is studying recurring irrationalities related to human behavior, but as early as the 1930s, John Maynard Keynes speculated on the impact of psychology on stock market movements. He argues that the intrinsic value of the firm-foundation theory involves too much work and is a doubtful value. Rather than focusing on intrinsic value, investors prefer to examine how the crowd of investors is likely to behave in the future and how they tend to raise their hopes during periods of optimism. The successful investor tries to estimate what the crowd does and then acts before the crowd. In other words, Keynes studies the stock market using psychological principles rather than economic valuation. For example, in his famous book The General Theory of Employment, Interest, and Money, Keynes states that most people are concerned “not with what an investment is really worth to a man who buys it ‘for keeps’, but with what the market will value it at, under the influence of mass psychology, three months or a year hence.” Keynes (2018). Next, three perspectives are introduced that form the theoretical framework of this thesis: The Random walk theory, the Dow theory, and the philosophy and rationale behind technical analysis. Furthermore, theoretical explanations for trading profits are presented.

3.1 Random walk theory

Random walk is something where future steps cannot be predicted using past information. In that case, investment advisory services-, actively managed funds-, and earnings predictions are all useless. Malkiel (1999) defines the Random Walk Hypotheses as follows: “The history of stock price movements contains no useful information that will enable an investor consistently to outperform a buy-and-hold strategy in managing a portfolio”. According to the theory, price changes are independent of each other and have a similar distribution. However, Fama (1965b) states that complete independence of successive price changes from each other is unlikely, but the amount of dependence is so small that it has no practical significance. This means that price changes in the past cannot be used to forecast future prices. Investors will not be able to consistently outperform the market unless they are willing to take on significant additional risk. In other words, all stock price forecasting methods are useless in the long run. Timing the market using technical- or fundamental analysis is not successful and results in losses. A passive buy-and-hold strategy for an index fund is the best solution for investors. The Random Walk Theory gained popularity in 1973, when Burton Malkiel published the first edition of his book A Random Walk Down Wall Street. Even prior to this, it was a common topic in academic literature as part of market efficiency. The theory provokes arguments for and against, but no consensus is reached.

3.2 Dow theory

Charles Dow, co-founder of Dow Jones and Company, journalist, founder and the first editor of the Wall Street Journal, published the first stock market average on July 3, 1884. The average composed of nine railroad and two manufacturing companies. A few years later, Dow introduced two separate indices: a 12-stock industrial index and a 20-stock rail index. Dow felt that these indices provide a good indication of the economic health and wrote his thoughts on stock market behavior on the Wall Street Journal at the turn of the century. In the later years, these series of articles were referred to as the Dow Theory (Murphy, 1999). A year after Dow's death in 1903, S.A.Nelson compiled Dow's writings into a book called The ABC of Stock Speculation, which used the term Dow theory for the first time. Dow's assistant, William Peter Hamilton, continued to make predictions for the Wall Street Journal based on Dow's principles

(Brown et al., 1998). He compiled and structured Dow's principles into a book called The Stock Market Barometer in 1922. Since then, the theory has been further developed, for example, by Robert Rhea in his 1932 book, Dow Theory. Dow theory is summarized by Hamilton and Rhea into six basic tenets: the averages discount everything, the market has three trends, major trends have three phases, the averages must confirm each other, volume must confirm the trend, and a trend is assumed to be in effect until it gives definite signal that it has reversed. Today, these principles serve as the foundation for modern technical analysis.

A lot of time has passed since the early days of the Dow Theory, and therefore it has supporters and critics. The critique that receives the most attention is by Alfred Cowles (1933), who analyzes William Peter Hamilton's editorials based on Dow Theory, published in the Wall Street Journal 1902 – 1929. Cowles (1933) analysis is one of the landmarks of random walk hypothesis and market efficiency. He provides strong evidence against Hamilton's editorials and concludes that the editorials would have produced lower earnings than a buy-and-hold strategy. After Cowles's study in 1933, many studies supported Cowles findings over the following years. However, in recent years, research methods have evolved, and researchers have revisited to Cowles's findings. For example, Brown et al. (1998) show a lack of risk adjustment. After adjustment, Dow Theory produces positive risk-adjusted returns in terms of Sharpe ratios and positive alphas for the period 1902 – 1929. There has been an ongoing debate over a century about the functionality of the Dow theory and technical analysis, see more for example Cowles (1933) and Brown et al. (1998). Nevertheless, the Dow theory forms the cornerstone of the modern technical analysis even today.

3.3 Philosophy & rationale behind technical analysis

Technical analysis is the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends (Murphy, 1999). Technical analysis is based on three assumptions:

1. Market discounts everything
2. Prices move in trends
3. History repeats itself

3.3.1 Market action discounts everything

Technical analysis is based on the idea that the market discounts everything. That is, all factors that can affect price (fundamentally, politically, psychologically, or otherwise) are reflected in market price. As a result, a study of price action is the only thing that is required to gain all available information. The main principle of what technical analysis claims is that price action should reflect changes in supply and demand; if demand exceeds supply, prices should rise, and vice versa, if supply exceeds demand, prices should fall. This same principle applies to all economic and fundamental forecasts. The technician (an individual who uses technical analysis) reverses the chain of thought; if prices are rising, demand must exceed supply, implying that the market's psychological fundamentals are bullish. If prices fall, the market's psychological fundamentals must be bearish. Overall, technical analysis is indirectly investigating the fundamentals of the market. Price actions, charts, and technical indicators do not cause market movements on their own. They simply reflect the market's psychology in a bullish or bearish market.

3.3.2 Prices move in trends

Technical analysis is based on the concept of a trend, which is the opposite view than the Random walk theory, where price changes are viewed independent. The aim is to identify market trends and trend changes at the earliest possible stage. A price is expected to follow a previous trend rather than move in the opposite direction. An uptrend can be identified when the price is consistently making higher highs and higher lows. On the other hand, a downtrend occurs when the price is making lower lows and lower highs. Market trend can be identified using different timescales, such as short-, intermediate-, and long-term. Therefore, it is possible to have trends within trends. Technical indicators are critical for identifying, defining, and confirming market trends. For this reason, many technical indicators are trend following, such as Moving Average, Moving Average Convergence Divergence (MACD), On-Balance Volume (OBV), Relative Strength Index (RSI), and Bollinger Bands.

3.3.3 History repeats itself

According to technical analysis, the price trend seems to repeat itself at least to some extent. It is said that price changes are interdependent, and that by carefully analyzing them, conclusions about the future can be drawn. When discussing technical analysis, the validity of using past price data to predict the future is often raised as a concern. It is important to remember that every known forecasting method, from weather forecasting to fundamental analysis, is entirely based on the study of past data, because there is no such thing as 'future data'. The first step in forecasting company's or economy's future is to gather observations from the past. Technical analysis is just another form of time series analysis. The rationale behind the repetition of history is quite straightforward. Technical analysis argue that market participants consistently react to price movements in a surprisingly similar manner. During market uptrends, participants become greedy and are willing to buy despite the high price. Similarly, in downtrends, participants want to sell despite low and unappealing prices. Most of the research in technical analysis and market operation is related to the study of human psychology. For example, chart patterns identified over the last century are based on human psychological behavior and thus reflect the prevailing psychology of the rising or falling market. If the patterns have worked well in past, it is assumed that they will continue to work well in the future.

3.4 Explanations for trading profits

Lo (1994) points out that the absence of theory, as well as the attitude that if something works, it does not matter why it works, can increase the possibility of data snooping bias. Therefore, it is important to discuss some explanations for why traders can outperform the market. Although there is no widely accepted theoretical model that explains technical trading profits, several theoretical and empirical explanations have been proposed, including the noisy rational expectations model (Grossman & Stiglitz 1980; Blume et al., 1994, behavioral models (Shleifer & Summers, 1990), herding models (Froot et al., 1992; Schmidt, 2002), central bank intervention (Sweeney, 1986; Lukac et al., 1988; Davutyan & Pippenger, 1989; Levich & Thomas, 1993), order flow (Osler, 2003; Kavajecz & Odders-White, 2004), temporary market inefficiencies (Hudson et al., 1996; Bessembinder & Chan, 1998; Sullivan et al., 1999, 2003; Kwon & Kish, 2002), and compensation for risk (LeBaron, 1999; Chang and Osler, 1999).

3.4.1 Noisy rational expectations model

According to the traditional model of market efficiency, the equilibrium price completely represents all available information and responds instantly to new information. The fundamental premise is that participants are rational and have similar beliefs about information. The noisy rational expectations model, on the other hand, suggests that because of noise in the current equilibrium price, the current price does not fully reveal all available information. As a result, price adapts gradually to new information, making profitable trading possible. Grossman and Stiglitz (1980) show that an information efficient market is impossible. They argue that if current price truly reflects all available information, there is no possibility to make arbitrage profits and therefore, no incentive to obtain and evaluate expensive information. As a consequence, the market collapse. Another example of Noisy rational expectations model is Blume et al. (1994) who examine the informational role of volume. They develop an equilibrium model in which the total supply is fixed, and traders are given signals of varying quality. They show that volume contains important information for technical analysis, that is not available from the price. In addition, their model provides predictions about the types of firms for which technical analysis will be particularly useful. As a result, Blume et al. (1994) provide one explanation for why technical analysis exists.

3.4.2 Behavioral models

Behavioral models often have two kind of investors: arbitrageurs and noise traders. Arbitrageurs represents sophisticated, or 'smart money' investors, who have rational expectations about asset returns. On the other hand, investors that trade with irrational beliefs are referred to as noise traders (Shleifer and Summers, 1990). In the context of technical analysis, noise traders can be trend chasers, who buy when prices rise, following a positive feedback, and sell when prices fall, following a negative feedback. Positive feedback leads to an increase in demand, which in turn raises prices even further. Arbitrageurs or 'smart money' can short sell, if they think that price exceeds its fundamental value. However, due to the limits of arbitrage, this may not lead to a fall in price (Shleifer & Vishny, 1997). Arbitrageurs always bear the risk that the price increases more if noise traders become even more optimistic. As a result, the sophisticated investors are unable to completely mitigate the impact of noise traders. In fact, they might want, and it might even be advantageous, to jump on the train which amplifies the impact in the short run. A similar phenomenon occurred in January 2021 in the case of GameStop. Overall, behavioral models suggest that if trading strategies are based on noise, psychology, or popular models rather than news or fundamental factors, profits of technical analysis could be possible even in the long run.

3.4.3 Herding Models

In general, herding refers to behavior where individuals behave together without a unified agreement. Several studies have modeled herd behavior in the context of technical analysis. Froot et al. (1992) show that the herding of short-term speculators, i.e., technical traders, can lead to informational inefficiency despite fully rational agents. They develop a model, which assumes that some rational speculators prefer to trade over short horizons and examines the implications of short-term trading. A couple of reasons can be identified, why rational traders choose to trade over a short period. First, some speculators, for example, portfolio managers of an actively managed fund, may need to prove that they are skilled investors and can beat the market. They cannot wait and show their clients returns that will only come after 10 years. Second, long-term investment strategies could be prohibitively expensive for certain speculators. If speculators lock up their funds in long-term investments and then run out of credit, they will be unable to take advantage of potential investing opportunities. Froot et al. (1992) find that traders who have short horizon may herd on the same information and make profits. Also, they find that multiple herding equilibria exists, and it can even be optimal to study information that is completely unrelated to fundamentals, like technical analysis. Since a large number of traders use technical analysis, Froot et al (1992) suggest that it could be enough to produce positive profits for those who already know how to use it. They argue that the more popular the use of technical analysis is, the stronger the effect would be.

Also, Schmidt (2002) examine why technical trading may be successful. She uses a simple agent-based model for market dynamics and shows that herding behavior will shift the share price in a favorable direction if technical traders are able to influence market liquidity. In other words, when technical traders decide to buy an asset, based on some signal, they increase the demand for the asset and as a result, the price goes up. This may provoke the regular traders to buy until the price notably exceeds the fundamental value, which amplifies the effect and moves the price in the direction favorable to technical strategy.

3.4.4 Empirical explanations

Many studies especially in the foreign exchange markets show that trading profits are related to central bank intervention (e.g. Sweeney, 1986; Levich & Thomas, 1993, LeBaron, 1999; Saacke, 2002). Saacke (2002) explains the logic as follows: Without central bank intervention, the exchange rate would jump to a new equilibrium level after an exogenous shock to fundamentals. In order to reduce volatility, central banks try to prevent exchange rate fluctuations. As a result, they postpone the exchange rate adjustment, which may be picked up and exploited by trend-following forecasters. Saacke (2002) shows that technical trading rules are unusually profitable on days on which interventions occur. Furthermore, LeBaron (1999) reports that removing periods when the Federal Reserve is active reduces exchange rate predictability significantly. Another empirical explanation for trading profits is order flows that cluster at round numbers. According to Osler (2003) requested execution rates for stop-loss and take-profit orders cluster at round numbers. Take-profit orders are more likely to be executed at round numbers (ending in 00) than stop-loss orders, which may result in the price behaviors predicted by technical analysts. Similar explanation is provided by Kavajecz & Odders-White (2004) who use limit order books in the NYSE.

Furthermore, several studies show that technical rules outperform the market prior to the 1990s, but the significance diminishes or disappears in later sub-periods (e.g. Hudson et al., 1996; Bessembinder & Chan, 1998; Sullivan et al., 1999, 2003; Kwon & Kish, 2002). Two possible explanations are given for the temporary market inefficiencies: First, the technical trading gains may be profitable to the first users that invented the rule. However, as the rule becomes more widely known, the new information may already be incorporated into prices, making the rule ineffective. Many market anomalies have vanished as they have come to widespread awareness, which supports this argument. Second, there may have been some structural change in the market which cause temporal inefficiency. For example, Sullivan et al. (1999) argue that cheaper computing power, lower transaction costs, and increased liquidity in the stock market may have increased the speed of market price movements and therefore reduced the profitability of technical trading rules.

Finally, technical trading profits may be compensation for risk. Although many studies show that technical trading strategies have lower risk and higher risk-adjusted returns, measured by the Sharpe ratio, compared to a buy-and-hold strategy (e.g. LeBaron, 1999; Chang and Osler, 1999). Both the Sharpe ratio and the CAPM are popular risk-adjusted performance measures used in studies of technical trading rules, but each has its own set of limitations. Even though investors are more concerned about downside volatility, the Sharpe ratio makes no distinction between the variability of returns and the variability of losses. CAPM on the other hand has a well-known joint hypothesis problem. Most studies using CAPM assume a constant risk premium over time. In general, a constant risk premium fails to explain technical trading returns (See more e.g. Sweeney, 1986; Lukac et al., 1988; Levich & Thomas, 1993). The results for time-varying risk premiums are more mixed. Okunev and White (2003) discover that time-varying risk premiums are ineffective at explaining technical trading profits. Sapp (2004), on the other hand, provides contradictory evidence.

4 Research questions and hypotheses

Despite the intensified debate on market efficiency, the Efficient Market Hypothesis has long been the dominant paradigm in financial markets. According to the Random walk theory, the history of stock price movements contains no useful information that will enable an investor consistently to outperform a buy-and-hold strategy Malkiel (1999). All stock price forecasting methods are useless in the long run. Timing the market using technical analysis, or fundamental analysis is not successful and only leads to losses. The market price already reflects all the information that is available and therefore, the expected return for technical trading rules of past prices should be zero compared to the buy-and-hold strategy. As a result, a passive buy-and-hold strategy for an index fund is the best solution for investors.

This thesis examines the performance of technical trading rules in the Nordic countries. The research question delivered from the Random walk theory is: Do technical trading rules provide useful signals that retail investors can use to predict market movements in Nordics. Technical trading rules must be simple enough that retail investors can use them. Hence, I examine whether the moving average and the trading range break-out strategies are profitable. More precisely, I investigate whether the returns of these strategies outperform the buy-and-hold strategy and whether the mean buy differs from the mean sell at a 5% significance level.

My null and alternative hypotheses are:

H_0: Simple technical trading rules do not produce useful signals.

$$X(b) - X(s) = 0,$$
$$X(b) - X(h) = 0,$$
$$X(s) - X(h) = 0$$

H_A: Simple technical trading rules do produce useful signals.

$$X(b) - X(s) \neq 0,$$
$$X(b) - X(h) \neq 0,$$
$$X(s) - X(h) \neq 0$$

where $X(b)$, $X(s)$, and $X(h)$ are mean buy, mean sell and mean return for the buy-and-hold strategy, respectively.

5 Data and methodology

5.1 Data

The data used in this thesis consist of Nordic stock market indices over a 25-year period (Finland – OMX Helsinki, Sweden – OMX Stockholm, Norway – Oslo OBX, Denmark – OMX Copenhagen, and Iceland – OMX Iceland). The Nordic market can be considered efficient because it is less vulnerable to political instability and government intervention than many other markets. Daily price information on the indices is retrieved from the Datastream including open, high, low, and close prices from each index. I try to gather the longest possible time series in order to include varying economic circumstances while avoiding sample selection bias as much as possible. The sample size varies slightly depending on the index; Sweden has the longest sample period at 33 years, while Denmark has the shortest at 25 years. Overall, the sample period includes the early 1990s recession, the late 1990s tech bubble, the 2008 financial crisis, the 2011 European sovereign debt crisis, and, most recently, the ongoing Covid-19 crisis of 2020. Using the daily observations, I calculate daily log return for each index using the following formula:

$$r_t = log_e\left(\frac{P_{t+1}}{P_t}\right) \tag{1}$$

, where r_t is the daily log return on the index and P_t denotes the value of the price index in day t. From now on this is referred to as an unconditional return to distinguish it from a conditional return of a technical strategy. Daily price information does not include daily dividend yields, but it should not affect the results that much. After reviewing the literature, Mills & Coutts (1995) show that the exclusion of dividends should only lead to minimal bias. Table 1 presents summary statistics for unconditional 1- and 10-day returns, as well as key information about return distributions such as the Kendall-Stuart measure of skewness, kurtosis, and the Shapiro-Wilk test for normality. Table 1 also includes a test for autocorrelations with up to 5 lags.

Table 1: Summary statistics for unconditional 1- and 10-day returns

The table contains summary statistics for unconditional 1- and 10-day returns. Returns are measured as log differences of the level of each index. 10-day returns are based on nonoverlapping 10-day periods. The mean is equally weighted average of all 1- and 10-day observations over the sample period. Std, Min and Max denote the standard deviation, the minimum return, and the maximum return, respectively. Skew is the Kendall-Stuart measure of skewness and Kurtosis is the Kendall-Stuart measure of kurtosis. Norm stands for the Shapiro-Wilk test for normality, where H0: x is normally distributed. p(i) shows the Box-Ljung test for autocorrelation for up to 5 lags. P-values are reported in parentheses. Bold numbers indicate significance at the 5% level for a two-tailed test.

Panel A: Daily Returns					
	Finland	Sweden	Norway	Denmark	Iceland
Start date	2.1.1987	31.12.1986	2.1.2987	29.12.1995	31.12.1992
End date	22.12.2020	22.12.2020	22.12.2020	22.12.2020	22.12.2020
N	8862	8864	8862	6517	7298
Mean	0,00026	0,00033	0,00025	0,00038	0,00021
Std.	0,01546	0,0128	0,01454	0,01059	0,01609
Min	-0,17404	-0,11805	-0,23996	-0,10583	-1,096
Max	0,14563	0,09883	0,11123	0,082013	0,051345
Skew	-0,43986	-0,19458	-0,97788	-0,49203	-45,18497
Kurtosis	12,68596	9,59145	18,70518	9,10921	2990,556
Norm	**0,89591***	**0,92919***	**0,88995***	**0,93762***	**0,24105***
	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)
p(1)	**15,185***	**14,255***	3,793	**19,114***	3,252
	(0,0001)	(0.0002)	(0,0515)	(0,0000)	(0.07135)
p(2)	**15,415***	**16,572***	**10,163***	**19,940***	**12,159***
	(0,0004)	(0,0003)	(0,0062)	(0,0000)	(0,0023)
p(3)	**17,437***	**17,803***	**12,197***	**20,035***	**12,207***
	(0,0006)	(0,0005)	(0,0067)	(0,0002)	(0,0067)
p(4)	**22,858***	**19,125***	**14,453***	**27,041***	**13,194***
	(0,0001)	(0,0007)	(0,0060)	(0,0000)	(0,0104)
p(5)	**23,999***	**21,202***	**18,695***	**32,714***	**15,290***
	(0,0002)	(0,0007)	(0,0022)	(0,0000)	(0,0092)

Panel B: 10-Day Returns					
	Finland	Sweden	Norway	Denmark	Iceland
Mean	0,00190	0,00298	0,00197	0,00275	0,00095
Std.	0,04642	0,03753	0,04430	0,03241	0,05375
Min	-0,23983	-0,17679	-0,29249	-0,18774	-1,15338
Max	0,22967	0,15200	0,21111	0,08809	0,10407
Skew	-0,53593	-0,68746	-1,32074	-1,19833	-14,27029
Kurtosis	6,72733	5,68567	10,15578	7,49808	297,17910
Norm	**0,94881***	**0,95897***	**0,90621***	**0,93799***	**0,40967***
	(0,0000)	(0,0000)	(0,0000)	(0,0000)	(0,0000)
p(1)	3,465	0,954	**4,955***	**6,185***	**18,529***
	(0,0630)	(0,3290)	(0,0260)	(0,0130)	(0,0000)
p(2)	**7,630***	1,140	**6,274***	**7,100***	**20,992***
	(0,0220)	(0,5660)	(0,0430)	(0,0290)	(0,0000)
p(3)	**11,257***	1,734	**8,543***	7,171	**26,088***
	(0,0100)	(0,6300)	(0,0360)	(0,0670)	(0,0000)
p(4)	**11,538***	2,647	8,876	7,817	**72,491***
	(0,0210)	(0,6190)	(0,0640)	(0,0990)	(0,0000)
p(5)	**11,740***	3,069	9,032	8,001	**74,378***
	(0,0390)	(0,6890)	(0,1080)	(0,1560)	(0,0000)

In panel A, the results of the daily returns are presented. Denmark has the highest average daily return of 0,038% (10,4% per annum) and it is associated with the lowest risk (SD of 1,06%), while Iceland has the lowest average daily return of 0,021% (5,6% per annum) with the highest associated risk (SD of 1,61%). Annualized returns are estimated using 260 trading days per year. The mean daily returns are broadly consistent with the prior literature: 0,029% for NYSE (Kwon & Kish, 2002), 0,026% for UK (Hudson et al., 1996), 0,023% for Austria (Metghalchi et al., 2007), 0,020% for Portugal (Metghalchi et al., 2012), and 0,017% for DJIA (Brock et al., 1992). In contrast, Coutts & Cheung (2000) report much higher daily returns of 0,074%, for the Hong Kong stock exchange from 1985 to 1996, while Fifield et al. (2008) show returns ranging from -0,04% to 0,08% for emerging markets. Return distributions are skewed to the left and strongly leptokurtic for all countries as expected. This is hardly surprising given that the subject of non-normality return distribution is well documented in the past. The Shapiro-Wilk test for normality confirms this finding. P-values reported in parentheses are less than 0,05 for all countries, indicating that the null hypothesis, that x is normally distributed, can be rejected. The Box-Ljung test for autocorrelation reveals a strong dependence on daily returns for all countries. The null hypothesis that daily returns are independent of one another can be rejected 23 times out of 25.

Panel B shows the results for 10-day nonoverlapping returns. Iceland's average return remains the lowest when compared to other countries, and it is associated with the highest risk. With the exception of Iceland, 10-day return distributions are even more skewed to the left. Furthermore, a reduction in kurtosis is detected for all countries. The Box-Ljung test for autocorrelation reveals some evidence of dependence. The null hypothesis of return independence can be rejected 14 out of 25 times.

5.2 Technical trading rules

There are thousands of different technical trading strategies that investors use trying to beat the market. Some of them are very complex while others can be super simple. It is possible and even assumed that some strategies have not come to the public. The purpose of this thesis is to examine whether it is possible for retail investors to obtain useful signals using simple technical trading rules and thus beat the market. The rules must be simple enough for retail investors to understand, and should not, for example, require complicated algorithm trading. Therefore, replicating the analysis of Brock et al. (1992), this thesis focuses only on the most common trading rules; moving average- and trading range break-out strategies. Next, the trading rules examined by the thesis are introduced below.

5.2.1 Moving-average strategies

Moving average trading strategies are the most used because their ease. The purpose of the moving averages is to smooth out the volatile series and give an idea of the trend behind the price series. The Simple Moving Average at day t for the past L days is defined as follows:

$$SMA_{t,L} = \frac{1}{L}(P_t + P_{t-1} + \cdots + P_{t-L+2} + P_{t-L+1}) \quad (2)$$

, where $SMA_{t,L}$ is the simple moving average at time t of the last L observed prices and P_t denotes the closing value of each price index on day t. In this thesis, the SMA with a larger L is referred to as long-term, while the SMA with a smaller L is referred to as short-term. The larger L, the slower the SMA adapts and the more volatility is smoothed out.

Variable length simple moving average (V-SMA). Following Brock et al. (1992) the Variable length simple moving average trading strategy (V-SMA) is examined. The strategy compares the short-term moving average of the index price to the long-term moving average. A buy signal (a sell signal) is generated when the short-term moving average rises above (falls below) the long-term moving average. If the short SMA is above the long SMA, then the next day is marked as a “Buy” signal. In this case, the trader is in the market at the next day and buys the index at the previous day’s closing price. The position is kept open until the opposite signal is generated. The position length varies, hence the name Variable-length SMA. On the other hand, if long MA is above the short MA, then the next day is marked as a “Sell” signal and the trader will sell the index at the closing price. The next day’s return will be the difference between the logarithm of next day’s closing price and the previous day’s closing price. The mean buy and sell returns, $X(b)$ and $X(s)$, are defined as follows:

$$X(b) = \frac{1}{N_b}\sum R_b \quad (3)$$

$$X(s) = \frac{1}{N_s}\sum R_s \quad (4)$$

, where N_b and N_s are the total number of buy and sell days, respectively. R_b and R_s are the daily returns of buy and sell days, respectively. Clearly, this strategy can be implemented using a variety of lengths for both the short-term and long-term moving averages. Furthermore, it is possible to use a %-confirmation band, which reduces the number of trades and therefore also the trading costs. In this case, the signal is only confirmed if the short-term MA crosses the long-term MA far enough (x% of the long-term MA). The rationale behind the confirmation band is to eliminate false signals that may occur if both short- and long-term moving averages move close to each other. The SMA model with a %-confirmation band is given by:

$$\begin{aligned} &Pos_{t+1} = BUY, \quad\quad if\ SMA_t^s > (1+b)SMA_t^l \\ &Pos_{t+1} = Pos_t,\ if\ (1-b)SMA_t^l \leq SMA_t^s \leq (1+b)SMA_t^l \\ &Pos_{t+1} = SELL, \quad\quad if\ SMA_t^s < (1-b)SMA_t^l \end{aligned} \tag{5}$$

, where SMA_t^s is the short-term MA, SMA_t^l is the long-term MA, and b is the confirmation band. This thesis examines the following strategies: (1, 20), (1, 50), (1, 100), (1, 150), (1, 200), (2, 200), (5, 150) and (5, 200). The first number represents the strategy's short-term moving average, while the second number represents the strategy's long-term moving average. In addition to these, a third number, which refers to the confirmation band, can be introduced. For example (1, 20, 0.01) denotes that the short-term moving average is 1 day, the long-term is 20 days, and the band is 1%. All strategies are examined with and without a 1% confirmation band. The passive buy-and-hold strategy serves as a benchmark.

The fixed length simple moving average (F-SMA). This thesis also examines the fixed length simple moving average trading strategy (F-SMA). The signal is generated in the same manner as the V-SMA rule described above, but the position is always closed after a fixed time. During that time, all other signals are ignored. Following Brock et al. (1992), a 10-day fixed period is used.

5.2.2 Trading range break-out (TRB)

The trading range break-out (TRB) strategy is based on the support and resistance levels where a buy (sell) signal is generated when price exceeds the local maximum (falls below the local minimum). Following Brock et al. (1992) the local maximum and minimum are based on the previous 50, 150 and 200 days. In addition, the thesis examines the rule using the previous

20 days. When a break occurs, a 10-day holding period return is calculated. Similarly to moving average strategies, TRB is examined with and without a 1% band. The TRB model with a %-confirmation band is given by:

$$
\begin{aligned}
&Pos_{t+1} = BUY, && if\ P_t > (1+b)\max\{P_{t-1}, P_{t-2}, \dots, P_{t-n}\} \\
&Pos_{t+1} = Pos_t, && if (1-b)\min\{P_{t-1}, \dots, P_{t-n}\} \leq P_t \leq (1+b)\max\{P_{t-1}, \dots, P_{t-n}\} \\
&Pos_{t+1} = SELL, && if\ P_t < (1-b)\min\{P_{t-1}, P_{t-2}, \dots, P_{t-n}\}
\end{aligned} \tag{6}
$$

TRB is based on the idea of support and resistance levels, according to which market participants can be divided into three categories:

- The longs,
- The shorts,
- The uncommitted

The longs have bought contracts from the market, near to the support level at price $P_{support}$ and own them at time $t = 0$. The shorts have committed to sell side at the same time $t = 0$, near to same price $P_{support}$. The uncommitted are those who have either left the market before $t = 0$, or have not decided which side to take. If the price starts to rise from the support level $P_{support}$, the following will happen: The longs are happy, but wish they had bought more contracts. They want to buy more contracts if the price returns close to the support level. The shorts understand that they may be wrong about the market. They hope the price will return close to $P_{support}$ so they could close their positions with minimal losses. The uncommitted think they have missed the train and all potential winnings. They plan to buy contracts if the price returns close to $P_{support}$. As a result, all three groups plan to buy contracts if the price returns close to the support level. Even though the psychological aspect of trading is simplified in this example, it is easy to argue where it leads. According to the law of supply and demand, increased buying pressure at the price level $P_{support}$ forces the price to increase and therefore the price level $P_{support}$ is called the support level.

However, if the price falls below the support level, everyone's reaction will change. If some market participants are for some reason unconvinced, leaving demand too low, the price will fall below the support level $P_{support}$. The longs think they have made a mistake. They can either accept their losses or wait and hope the price to return close to level $P_{support}$ so they could sell the contracts with minimum losses. The shorts are glad they have made the right choice. They hope to have taken a larger position and plan to short-sell more if the price returns close to $P_{support}$. The uncommitted think they missed a good short opportunity. They plan to short-sell if the price returns to $P_{support}$. Instead of buying at the old support level $P_{support}$, and thus making the price bounce back up, everyone is selling from the same level. The law of supply and demand say that the price will go down. The old support level becomes the new resistance because of human psychology. Technical analysis is fundamentally the study of human behaviour rather than a mechanical process.

6 Results

This section presents the results of several technical trading rules examined in the Nordics. To save space, only the results from Finland (Panel A) and Iceland (Panel B) are presented and communicated. The results from the other Nordic countries can be found in the appendix (Panel C, D and E). Iceland was chosen for its uniqueness; the results differ radically from others, whereas Finland was chosen as a proxy for other countries as well; the results are quite similar to the remaining countries. Rules examined are replicated from Brock et al. (1992) unless otherwise stated.

6.1 Results for variable length SMA strategies

Panel A of Table 2 presents the results of the Variable-length simple moving average (V-SMA) trading rules in Finland. The first column shows the test examined. Brock et al. (1992) examine the same tests except for the shortest (1, 20). The second and third columns show the number of buy- and sell-signals for each test. The number of buy-signals always outnumbers the number of sell-signals. It is an indication that the market is rising, which is often seen in the stock market when a sufficiently long time series is used. Several other studies have come up with the same conclusion, including Brock et al. (1992) using Dow Jones Industrial Average, Hudson et al. (1996) using UK stock prices, Coutts & Cheung (2000) using Hong Kong Stock Exchange, Kwon & Kish (2002) using NYSE, and Metghalchi et al. (2012) using Portuguese stock market. The fourth and fifth columns show the conditional standard deviation of buy- and sell-signals. Consistent with the papers of Brock et al. (1992), Kwon & Kish (2002), Metghalchi et al. (2007), Metghalchi et al. (2012), the conditional standard deviation is always larger for sell-signals than for buy-signals indicating that the market is more volatile during sell periods than during buy periods. As an evidence, the mean standard deviation of sell-signals 0,01868 is larger compared to buy-signals 0,01345. Others who have tested the V-SMA rule, Hudson et al. (1996), Bessembinder & Chan (1998), Ito (1999), Coutts & Cheung (2000), and Fifield et al. (2008), do not report the conditional standard deviation figures. The sixth and seventh columns labeled by ‘Buy’ and ‘Sell’ respectively, show the conditional mean daily returns of buy and sell signals. Again, consistent with the recent literature, the buy returns are all positive and the sell returns are all negative, meaning that the buy-sell difference on the eighth column is always positive. The average daily returns for conditional buy and sell days are 0,062% and -0,030%, respectively. Using 260 trading days per year, the annualized return for conditional buy is approximately 17.5% and -7.50% for conditional sell. These figures are remarkably similar to those found in recent literature. Brock et al. (1992) report the conditional mean daily buy return of 0,042% and sell return of -0,025% for DJIA, while Hudson et al. (1996) report 0,057% and -0,021% for UK, respectively. More extreme mean daily figures are presented from Hong Kong: 0,155% and -0,152% (Coutts & Cheung, 2000).

The mean daily returns generated by V-SMA rules are compared to the unconditional mean daily buy-and-hold return of 0,026% (7% annualized) reported in Table 1. Standard t-statistics are reported in parentheses and computed as:

$$t = \frac{X(r)-X(h)}{\sqrt{\frac{\sigma_r^2}{N_r}+\frac{\sigma_h^2}{N_h}}} \tag{7}$$

where subscript $_r$ refers to conditional buy (sell) days and $_h$ to unconditional days. That is, $X(r)$, N_r and σ_r^2 represent the conditional mean return during buy (sell) days, the number of buy (sell) signals and the variance of buy (sell) signals, respectively. X(h), N_h and σ_h^2 represent the mean daily return of buy-and-hold, the number of returns for the entire sample period and the variance of the entire sample period. Using a standard two-tailed test, the null hypothesis that conditional returns are equal to unconditional returns can be rejected in both cases 4/12 times at the 5% level. It is worth noting that the significant results occur mainly when long-term MA is relatively short, such as 20 or 50 days. 'Buy-Sell' is the difference of mean return between the conditional buy and sell signals. For the buy-sell spread, the t-statistic is computed as:

$$t = \frac{X(b)-X(s)}{\sqrt{\frac{\sigma_b^2}{N_b}+\frac{\sigma_s^2}{N_s}}} \tag{8}$$

where $X(b)$, N_b and σ_b^2 represent the mean daily return, the number of signals and the variance during buy days, respectively. $X(s)$, N_s and σ_s^2 represent the mean daily return, the number of signals and the variance during sell days, respectively. All of the buy-sell differences are positive. The null hypothesis that the buy-sell difference is zero can be rejected 8/12 times at the 5% level. The mean spread between the buy and sell returns is 0,092% (27% annually). Except for the (5,150), the addition of the percent band increases the spread between the buy and sell returns. The results are similar to those of Brock et al. (1992), but not as strong. They report that all buy-sell differences are highly significant, and the buy-sell difference is always larger when percent band is introduced. Furthermore, all their sell returns and 6/10 of buy returns are significant at the 5% level. Also, Coutts & Cheung (2000) report strong results from Hong Kong and Metghalchi et al. (2012) from Portugal. A stark contrast to these, Ito (1999) shows that on average V-SMA rules do not generate significant forecasting power when using Datastream U.S. index or Dow Jones Index during 1980 - 1996. Also, Hudson et al. (1996), Bessembinder & Chan (1998), and Kwon & Kish (2002) get more mixed results from UK, DJIA and NYSE, respectively. All of these studies split their sample into sub-periods and show that results lose significance as the sub-periods approach the present, Hudson et al. (1996) during 1981 – 1994, Bessembinder & Chan (1998) during 1976-1991, and Kwon & Kish (2002) during 1985-1996.

The t-stat formulas presented above differ slightly from those used by Brock et al. (1992). Griffionen (2003) points out that Brock et al. (1992) do not use the correct t-test statistic. The variance of their test statistic is smaller than what they observed resulting in too conservative results, i.e., the corrected results would be even more significant, see more Griffionen (2003). In this thesis, the corrected t-test statistics are used. The last two columns in Table 2 present the fraction of buy-signals and sell-signals greater than zero. Under the assumption of random walk theory, the history of stock price movements should not contain any useful information. In other words, the fraction of buy- and sell-signals greater than zero should be equal. The fraction of buys greater than zero ranges from 51% to 53% while the fraction of sells ranges from 45% to 47%. Brock et al. (1992) use a binominal test to show that these differences are significant. In this thesis, the binominal test is excluded from consideration and only the percentages above are reported.

Panel B of Table 2 reports the results of the V-SMA trading rules for Iceland. The results are stunning. All of the t-tests for different rules are highly significant, rejecting null hypothesis 12/12 times. The average daily returns for conditional buy, sell and buy-sell difference are 0,093%, -0,128% and 0,221%, respectively. Annualized returns are approximately 27%, -28% and 77%, respectively. Compared to annualized unconditional buy-and-hold return mentioned earlier in Table 1 (5,6%), these returns are on a completely different scale. What factors could account for such wide variation in comparison to Finland and other Nordic countries? One important difference to highlight between Iceland and the other Nordic countries is how they managed to survive on Financial crisis. They survived poorly compared to others. Iceland nationalized its three largest banks in October 2008, which collapsed and sent the foreign investors out of Iceland. The Icelandic krona fell 50% in one week, and the Stock market crashed more than 95%. Many businesses went bankrupt, housing prices fell, and mortgage rates more than doubled. Table 1 backs up this claim by demonstrating that Iceland has the lowest buy-and-hold return and the highest volatility among Nordic countries. It also has the lowest maximum and minimum daily returns, and its return distribution is the most heavily skewed to the left. Despite these differences, the number of buy signals reported in Panel B of Table 2 is always greater than the number of sell signals, and the conditional standard deviation for sell signals is always greater than the conditional standard deviation for buy signals, 0.02798 and 0,00746 respectively. As in Finland, the fraction of buy-signals greater than zero is greater than the fraction of sell-signals. In addition, the larger buy-sell difference is recognized when a percent band is used. The results of other Nordic countries can be found in the appendix. To conclude the significance of the buy-sell difference for all countries examined: Finland: 8/12, Iceland: 12/12, Sweden: 4/12, Norway: 4/12 and Denmark: 11/12 rules are significant at the 5% level.

Table 2: Traditional test results for the V-SMA trading rules

The table contains results of the Variable-length simple moving average (V-SMA). Panel A reports results for Finland and Panel B for Iceland. The rest of the countries are reported in the appendixes. Test (short, long, band) denotes short-term, long-term moving average and the percentage difference needed to generate a signal, respectively. 'N(Buy)' and 'N(Sell) are the number of buy and sell signals, respectively. 'σ(Buy)' and 'σ(Sell)' are standard deviations of buy and sell signals, respectively. 'Buy' and 'Sell' denote the mean of buy and sell signals, respectively. 'Buy-Sell' is the difference of mean buy and sell signals. Numbers in parentheses are standard two-tailed t-statistics for testing the difference of the mean buy and mean sell from the unconditional 1-day buy-and-hold return, and 'buy-sell' from zero. Bold numbers are statistically significant at the 5% level. The last row reports average across all 12 rules.

Panel A: Finland

Test	N(Buy)	N(Sell)	σ(Buy)	σ(Sell)	Buy	Sell	Buy-Sell	Buy > 0	Sell > 0
(1, 20, 0)	5061	3782	0.01344	0.01780	**0.00084***	**-0.00052***	**0.00136***	0.5317	0.4617
					(2.30634)	(-2.34133)	(3.92441)		
(1, 20, 0.01)	3942	2844	0.01386	0.01913	**0.00094***	**-0.00063***	**0.00157***	0.5350	0.4560
					(2.44140)	(-2.26716)	(3.71789)		
(1, 50, 0)	5119	3694	0.01332	0.01805	**0.00082***	**-0.00052***	**0.00134***	0.5259	0.4672
					(2.23991)	(-2.32039)	(3.83252)		
(1, 50, 0.01)	4507	3106	0.01340	0.01875	**0.00091***	**-0.00052***	**0.00142***	0.5294	0.4623
					(2.48536)	(-2.09071)	(3.64259)		
(1, 150, 0)	5331	3382	0.01333	0.01856	0.000524	-0.00022	**0.00075***	0.5168	0.4728
					(1.06518)	(-1.35686)	(2.03590)		
(1, 150, 0.01)	5004	3059	0.01317	0.01900	0.00055	-0.00027	**0.00082***	0.5164	0.4698
					(1.16957)	(-1.39976)	(2.10709)		
(5, 150, 0)	5339	3374	0.01354	0.01832	0.00060	-0.00034	**0.00093***	0.5175	0.4715
					(1.34335)	(-1.69067)	(2.55259)		
(5, 150, 0.01)	5000	3070	0.01364	0.01873	0.00055	-0.00026	**0.00081***	0.5150	0.4723
					(1.12807)	(-1.38944)	(2.07577)		
(1, 200, 0)	5370	3293	0.01337	0.01869	0.00040	-0.00007	0.00048	0.5155	0.4725
					(0.56941)	(-0.91993)	(1.27315)		
(1, 200, 0.01)	5071	2972	0.01347	0.01921	0.00044	-0.00005	0.00049	0.5151	0.4724
					(0.70900)	(-0.81131)	(1.23268)		
(2, 200, 0)	5374	3289	0.01337	0.01869	0.00041	-0.00007	0.00048	0.5153	0.4728
					(0.58188)	(-0.93445)	(1.29534)		
(2, 200, 0.01)	5056	2973	0.01349	0.01922	0.00047	-0.00015	0.00062	0.5158	0.4679
					(0.81353)	(-1.07388)	(1.55307)		
Average			0.01345	0.01868	0.00062	-0.00030	0.00092		

Panel B: Iceland									
Test	N(Buy)	N(Sell)	σ(Buy)	σ(Sell)	Buy	Sell	Buy-Sell	Buy > 0	Sell > 0
(1, 20, 0)	4378	2901	0.00728	0.02385	**0.00101***	**-0.00098***	**0.00199***	0.5473	0.4474
					(3.67418)	(-2.47643)	(4.36832)		
(1, 20, 0.01)	2853	1619	0.00767	0.03099	**0.00134***	**-0.00158***	**0.00292***	0.5661	0.4466
					(4.76312)	(-2.25368)	(3.72098)		
(1, 50, 0)	4528	2721	0.00729	0.02454	**0.00101***	**-0.00107***	**0.00208***	0.5479	0.4443
					(3.66788)	(-2.53098)	(4.30786)		
(1, 50, 0.01)	3849	1995	0.00739	0.02833	**0.00117***	**-0.00145***	**0.00262***	0.5630	0.4446
					(4.31442)	(-2.50413)	(4.05723)		
(1, 150, 0)	4941	2208	0.00750	0.02687	**0.00090***	**-0.00123***	**0.00213***	0.5422	0.4457
					(3.18669)	(-2.38814)	(3.65773)		
(1, 150, 0.01)	4724	1976	0.00744	0.02828	**0.00088***	**-0.00132***	**0.00221***	0.5432	0.4459
					(3.11362)	(-2.30957)	(3.42289)		
(5, 150, 0)	4933	2216	0.00753	0.02681	**0.00087***	**-0.00115***	**0.00202***	0.5415	0.4477
					(3.03397)	(-2.26387)	(3.47790)		
(5, 150, 0.01)	4699	1964	0.00747	0.02834	**0.00085***	**-0.00130***	**0.00214***	0.5425	0.4465
					(2.94292)	(-2.25571)	(3.30563)		
(1 ,200, 0)	5187	1912	0.00750	0.02875	**0.00078***	**-0.00121***	**0.00199***	0.5342	0.4582
					(2.64312)	(-2.07799)	(2.98950)		
(1, 200, 0.01)	4957	1721	0.00748	0.03016	**0.00081***	**-0.00148***	**0.00229***	0.5364	0.4497
					(2.79260)	(-2.24312)	(3.11501)		
(2, 200, 0)	5185	1914	0.00751	0.02874	**0.00076***	**-0.00117***	**0.00194***	0.5337	0.4598
					(2.57937)	(-2.02284)	(2.91324)		
(2, 200, 0.01)	4951	1730	0.00749	0.03009	**0.00083***	**-0.00140***	**0.00223***	0.5369	0.4532
					(2.85274)	(-2.15341)	(3.04565)		
Average			0.00746	0.02798	0.00093	-0.00128	0.00221		

6.2 Results for fixed length SMA strategies

Panel A of Table 3 reports the results of the Fixed-length simple moving average (F-SMA) trading rules in Finland, where the position is always closed after a fixed 10-day holding period ignoring any other signals during that time. Consistent with the V-SMA rules, the number of buy-signals generated is always greater than the number of sell-signals. Also, the standard deviation of sell-signals is always higher than the standard deviation of buy-signals, averaging 0,05504 and 0,04069, respectively. In fixed SMA rules, the conditional 10-day returns are compared to the unconditional 10-day return reported in panel B of Table 1 (0,19%). Standard t-tests are reported in the parenthesis. As with the V-SMA rule, the buy returns are positive and greater than the unconditional 10-day return, averaging 0,45%. Similarly, sell returns are negative and drop below the unconditional 10-day return, averaging -0,15%. According to the null hypothesis, the buy-sell difference should be zero to not provide any useful signals. The null hypothesis can be rejected 4/12 times at the 5% level. All of the differences are positive, averaging 0.60%. The average difference without a band is 0,61% and with a band 0,59%. Average return differences are quite prominent compared to the unconditional mean 10-day return of 0,19%. Similarly, in V-SMA rules, the fraction of buys greater than zero is bigger than the fraction of sells greater than zero.

Results are quite consistent with the ones of Brock et al. (1992) from DJIA and Hudson et al. (1996) from the UK, but not as strong. Brock et al. (1992) report 0/10 significant returns for buy-signals, 5/10 for sell-signals, and 7/10 for buy-sell difference. The same figures reported by Hudson et al. (1996) are 3/5 for buy, 5/5 for sell, and 5/5 for buy-sell. Consistent with my findings, Brock et al. (1992) find that all buy-sell differences are positive, all the buys (sells) are greater (smaller) than the unconditional mean 10-day return. Also, the fraction of buys greater than zero is bigger than the fraction of sells greater than zero. Bessembinder & Chan (1998) use the same rules as Brock et al. (1992). They show that F-SMA rules are significant on average. Again, contrary to these, Ito (1999) does not find any significant results from the Datastream U.S. index or Dow Jones Index during 1980 - 1996. Others do not report the F-SMA rule at all and are therefore ignored.

The results of the F-SMA rules in Iceland are reported in Panel B of Table 3. Again, the results are striking and much stronger than in Finland. All the buy rules and buy-sell differences are highly significant. The average buy-sell difference is 1,84%, which is huge compared to the unconditional mean 10-day return of 0,095%. For the sells 5/12 rules are significant. Other findings are consistent with the results of Finland; the fraction of buys greater than zero exceeds the fraction of sells greater than zero, but on a larger scale, likewise the conditional standard deviation of sells is always higher than for buys. The results of other Nordic countries can be found in the appendix. To conclude the significance of the buy-sell difference for all countries examined: Finland: 4/12, Iceland: 12/12, Sweden: 2/12, Norway: 2/12 and Denmark: 9/12 rules are significant at the 5% level. Overall, my results, as well as the recent literature, indicate that F-SMA rules have some predictive power, but not as strong as the V-SMA rules.

Table 3: Traditional test results for the F-SMA trading rules

The table contains results of the Fixed-length simple moving average (F-SMA). Panel A reports results for Finland and Panel B for Iceland. The rest of the countries are reported in the appendixes. Cumulative returns are calculated for fixed 10-day periods after signals. Test (short, long, band) denotes short-term, long-term moving average and the percentage difference needed to generate a signal, respectively. 'N(Buy)' and 'N(Sell) are the number of buy and sell signals, respectively. 'σ(Buy)' and 'σ(Sell)' are standard deviations of buy and sell signals, respectively. 'Buy' and 'Sell' denote the mean of buy and sell signals, respectively. 'Buy-Sell' is the difference of mean buy and sell signals. Numbers in parentheses are standard t-statistics for testing the difference of the mean buy and mean sell from the unconditional 10-day buy-and-hold return, and 'buy-sell' from zero. Bold numbers are statistically significant at the 5% level. The last row reports average across all 12 rules.

Panel A: Finland

Test	N(Buy)	N(Sell)	σ(Buy)	σ(Sell)	Buy	Sell	Buy-Sell	Buy > 0	Sell > 0
(1, 20, 0)	502	383	0.04044	0.05288	0.00610	-0.00365	**0.00974***	0.5916	0.4987
					(1.75667)	(-1.77967)	(2.99822)		
(1, 20, 0.01)	462	342	0.04244	0.05301	**0.00751***	-0.00273	**0.01024***	0.6190	0.5234
					(2.22694)	(-1.41946)	(2.94073)		
(1, 50, 0)	522	360	0.04023	0.05394	0.00564	-0.00370	**0.00934***	0.5920	0.4917
					(1.58984)	(-1.72691)	(2.79281)		
(1, 50, 0.01)	485	354	0.04210	0.05413	0.00555	-0.00129	**0.00684***	0.5897	0.5226
					(1.47730)	(-0.97503)	(1.97899)		
(1, 150, 0)	538	334	0.04090	0.05467	0.00361	-0.00154	0.00515	0.5743	0.5060
					(0.72559)	(-1.02104)	(1.48387)		
(1, 150, 0.01)	525	326	0.04045	0.05485	0.00485	-0.00059	0.00544	0.5962	0.5184
					(1.24934)	(-0.73041)	(1.54753)		
(5, 150, 0)	532	340	0.04128	0.05399	0.00378	-0.00172	0.00550	0.5714	0.5118
					(0.79186)	(-1.09173)	(1.60320)		
(5, 150, 0.01)	516	323	0.04003	0.05695	0.00497	-0.00186	0.00683	0.5950	0.5077
					(1.30313)	(-1.06625)	(1.88439)		
(1, 200, 0)	534	333	0.04058	0.05532	0.00316	-0.00107	0.00423	0.5618	0.5195
					(0.53347)	(-0.87315)	(1.20733)		
(1, 200, 0.01)	533	312	0.03823	0.05759	0.00254	0.00006	0.00248	0.5704	0.5385
					(0.27810)	(-0.51152)	(0.67857)		
(2, 200, 0)	535	332	0.04031	0.05573	0.00252	-0.00006	0.00257	0.5551	0.5301
					(0.26216)	(-0.57091)	(0.73097)		
(2, 200, 0.01)	523	318	0.04126	0.05746	0.00366	0.00030	0.00335	0.5660	0.5503
					(0.73448)	(-0.44765)	(0.90827)		
Average			0.04069	0.05504	0.00449	-0.00149	0.00598		

Panel B: Iceland

Test	N(Buy)	N(Sell)	σ(Buy)	σ(Sell)	Buy	Sell	Buy-Sell	Buy > 0	Sell > 0
(1, 20, 0)	423	305	0.02581	0.07637	**0.00813***	**-0.00882***	**0.01695***	0.6430	0.4984
					(3.05282)	(-2.03338)	(3.72543)		
(1, 20, 0.01)	357	219	0.03215	0.08442	**0.00934***	-0.01056	**0.01990***	0.6583	0.4703
					(3.20729)	(-1.90500)	(3.34359)		
(1, 50, 0)	455	270	0.02504	0.08085	**0.00809***	**-0.01062***	**0.01871***	0.6659	0.4444
					(3.09284)	(-2.17986)	(3.69936)		
(1, 50, 0.01)	416	237	0.02625	0.08597	**0.00958***	-0.00887	**0.01845***	0.6611	0.4810
					(3.64293)	(-1.65619)	(3.21928)		
(1, 150, 0)	492	223	0.02514	0.08830	**0.00719***	**-0.01188***	**0.01907***	0.6565	0.4350
					(2.72737)	(-2.05529)	(3.16681)		
(1, 150, 0.01)	486	213	0.02487	0.09079	**0.00792***	-0.00982	**0.01774***	0.6708	0.4648
					(3.05049)	(-1.64790)	(2.80571)		
(5, 150, 0)	493	222	0.02523	0.08851	**0.00700***	**-0.01153***	**0.01852***	0.6511	0.4459
					(2.64034)	(-1.99145)	(3.06286)		
(5, 150, 0.01)	480	207	0.02574	0.09164	**0.00719***	-0.01037	**0.01756***	0.6542	0.4589
					(2.70359)	(-1.69548)	(2.71118)		
(1, 200, 0)	512	198	0.02545	0.09342	**0.00627***	-0.01181	**0.01808***	0.6348	0.4646
					(2.33089)	(-1.84066)	(2.68557)		
(1, 200, 0.01)	512	180	0.02496	0.09754	**0.00734***	**-0.01064***	**0.01798***	0.6582	0.4500
					(2.81063)	(-1.53719)	(2.44508)		
(2, 200, 0)	510	200	0.02547	0.09298	**0.00628***	-0.01165	**0.01793***	0.6353	0.4650
					(2.33290)	(-1.83378)	(2.68800)		
(2, 200, 0.01)	508	181	0.02609	0.09733	**0.00703***	-0.01239	**0.01941***	0.6555	0.4254
					(2.64150)	(-1.77727)	(2.64987)		
Average			0.02601	0.08901	0.00761	-0.01075	0.01836		

6.3 Result for trading range break out strategies

Results for the TRB rules are presented in Table 4. Panel A reports the results on Finland while Panel B on Iceland. Results for other Nordic countries are presented in the Appendix. As a reminder of TRB rules, a buy signal is generated when the price exceeds the local maximum. The same applies the other way around. A sell signal is generated when the price falls below the local minimum. Following a signal, a 10-day holding period return is calculated. Previous 20, 50, 150, and 200 days are used as a local maximum and minimum. In Finland, the average 10-day return for conditional buy and sell days are 0,87% and -0,92%, respectively. For buys, 3/8 rules are significant at the 5% level, rejecting the null hypothesis of equality between the conditional return and the unconditional return. For sells, 2/8 rules are significant. The conditional standard deviation is again much larger for the sell-signals than for the buy-signals. The average buy-sell return is 1,79%. 7 out of 8 rules are significant at the 5% level, rejecting the null hypothesis of equality with zero.

Again, compared to Brock et al. (1992) the results are quite consistent. They report a total of 6 TRB rules, where 3 out of 6 buy-signals are significant, one sell-signal is significant, and all the buy-sell differences are significant. The average 10-day return for conditional buy and sell are 0,63% and -0,24%, respectively. The only clear difference is their average buy-sell difference, which is on a smaller size of 0,86%. However, it can be due to the smaller overall volatility of the sample size. In addition, Hudson et al. (1996) report surprisingly similar results from the UK, while results from the Hong Kong (Coutts & Cheung, 2000) are strikingly strong. Hudson et al. (1996) report the conditional average 10-day returns as follows: 0,70% for buy, -0,43% for sell, and 1,12% for buy-sell. They show significant results over the full sample, but again the strength of the results weaken in the latter periods. Coutts & Cheung (2000) report that all their TRB rules are significant, while Bessembinder & Chan (1998) show in contrast, that their results of TRB rules are not significant on average.

In Iceland, the results are again a bit stronger. All the rules for buy-sell differences are significant, averaging 2,8%. The average return for buy- and sell-signals are 1,2% and -1,6% respectively. 7/8 rules are significant for buy-signals, while 3/8 are significant for sell-signals. It is worth noting that in Sweden and Denmark there are no significant rules for buy-sell differences, while in Norway 6/8 rules are significant, indicating that overall, the significance of TRB rules varies quite heavily depending on the market as well as across studies.

Table 4: Traditional test results for the TRB rules

The table contains results of the Trading range break (TRB). Panel A reports results for Finland and Panel B for Iceland. The rest of the countries are reported in the appendixes. Cumulative returns are calculated for fixed 10-day periods after signals. Test (short, long, band) denotes short-term, long-term moving average and the percentage difference needed to generate a signal, respectively. 'N(Buy)' and 'N(Sell) are the number of buy and sell signals, respectively. 'σ(Buy)' and 'σ(Sell)' are standard deviations of buy and sell signals, respectively. 'Buy' and 'Sell' denote the mean of buy and sell signals, respectively. 'Buy-Sell' is the difference of mean buy and sell signals. Numbers in parentheses are standard t-statistics for testing the difference of the mean buy and mean sell from the unconditional 10-day buy-and-hold strategy, and 'buy-sell' from zero. Bold numbers are statistically significant at the 5% level. The last row reports average across all 8 rules.

Panel A: Finland									
Test	N(Buy)	N(Sell)	σ(Buy)	σ(Sell)	Buy	Sell	Buy-Sell	Buy > 0	Sell > 0
(1, 20, 0)	359	253	0.04193	0.05162	**0.00737***	-0.00390	**0.01127***	0.6323	0.4941
					(2.01900)	(-1.61092)	(2.86826)		
(1, 20, 0.01)	206	179	0.04507	0.05876	0.00708	-0.00146	0.00854	0.6262	0.5140
					(1.47621)	(-0.72189)	(1.58185)		
(1, 50, 0)	275	162	0.03869	0.05317	0.00724	-0.00390	**0.01114***	0.6145	0.4815
					(1.90042)	(-1.30118)	(2.32725)		
(1, 50, 0.01)	148	108	0.04436	0.06428	0.00817	-0.00779	**0.01596***	0.6351	0.4630
					(1.58050)	(-1.51920)	(2.22265)		
(1, 150, 0)	177	82	0.03732	0.05870	0.00701	**-0.01250***	**0.01951***	0.6271	0.3415
					(1.59191)	(-2.15992)	(2.76222)		
(1, 150, 0.01)	93	59	0.04005	0.06787	0.01040	-0.01224	**0.02265***	0.6667	0.3729
					(1.91613)	(-1.57652)	(2.31945)		
(1, 200, 0)	157	67	0.03609	0.06213	**0.00980***	**-0.01497***	**0.02477***	0.6369	0.3134
					(2.41131)	(-2.17783)	(3.05164)		
(1, 200, 0.01)	83	46	0.03990	0.07154	**0.01246***	-0.01660	**0.02906***	0.6627	0.3261
					(2.26999)	(-1.73528)	(2.54406)		
Average			0.04043	0.06101	0.00869	-0.00917	0.01786		

Panel B: Iceland									
Test	N(Buy)	N(Sell)	σ(Buy)	σ(Sell)	Buy	Sell	Buy-Sell	Buy > 0	Sell > 0
(1, 20, 0)	306	184	0.03218	0.04305	**0.00993***	-0.00385	**0.01378***	0.7190	0.5109
					(3.31492)	(-1.28051)	(3.75603)		
(1, 20, 0.01)	133	90	0.04270	0.05374	0.00851	-0.00752	**0.01602***	0.6391	0.5556
					(1.79884)	(-1.40950)	(2.36774)		
(1, 50, 0)	251	126	0.02438	0.05036	**0.01206***	-0.00504	**0.01711***	0.7490	0.5159
					(4.42019)	(-1.22045)	(3.60664)		
(1, 50, 0.01)	110	57	0.02883	0.06597	**0.01262***	**-0.01722***	**0.02984***	0.6818	0.5088
					(3.43919)	(-2.02717)	(3.25712)		
(1, 150, 0)	208	66	0.02399	0.06188	**0.01251***	-0.01386	**0.02637***	0.7692	0.4091
					(4.45916)	(-1.88113)	(3.38263)		
(1, 150, 0.01)	84	32	0.03007	0.08011	**0.01438***	**-0.03166***	**0.04604***	0.6786	0.3750
					(3.50234)	(-2.28005)	(3.16745)		
(1, 200, 0)	196	54	0.02413	0.06721	**0.01293***	-0.01577	**0.02870***	0.7755	0.4630
					(4.55484)	(-1.78572)	(3.08392)		
(1, 200, 0.01)	78	26	0.03041	0.08804	**0.01385***	**-0.03562***	**0.04947***	0.6667	0.3462
					(3.24575)	(-2.10413)	(2.81020)		
Average			0.02959	0.06379	0.01210	-0.01632	0.02842		

6.4 Break-even transaction costs

Slightly depending on the rule and country, traditional tests provide an indication that conditional returns are statistically different from the unconditional buy-and-hold return, and that conditional buy return is different from conditional sell. Especially Iceland's results are statistically strong. To address the question, whether a retail investor can beat the market after transaction costs, I calculate the break-even transaction cost, which would eliminate the gains from trading. Since I do not have data for bid-ask spreads, a simplified approach is performed as follows: Let's assume a long-only strategy where investors are in the market when the "Buy" signal occurs and otherwise out of the market. This allows forgetting short-sale constraints, or any costs incurred during a short-sale. First, I calculate the annualized return difference between the mean conditional buy and the passive buy-and-hold strategy likewise the annual number of trades required to achieve this. After that, I simply calculate the break-even costs per trade by dividing the annualized return difference by the number of trades per year. In each country, only the rules that differ statistically from the returns of the buy-and-hold strategy are examined.

Panel A of Table 5 reports the results on Finland while Panel B on Iceland. The first column identifies the rule examined. The second column reports the return difference between the conditional buy and the unconditional buy-and-hold strategy. The third column reports the annualized excess return generated in each rule. Column 'Total trades' reports the total number of trades including opening and closing the position, while the column 'Trades per year' reports the average number of trades per year. Finally, the column 'Break-even costs %' reports the one-way break-even %. If the actual trading cost is below the break-even %, the investor will beat the passive buy-and-hold strategy. For Iceland, all rules except TRB (1, 20, 0.01) differ significantly from the buy-and-hold strategy and are therefore considered. The break-even transaction costs range from 1,1% to 11,7% for V-SMA, 0,4% to 1,0% for F-SMA, and 1,2% to 7,1% for TRB. For example, in the V-SMA (1, 50, 0.01) rule, the total number of trades is 118, averaging 4,2 trades per year. The return difference between mean conditional buy and the conditional buy-and-hold is 0,096%. Using 260 trading days per year, the annualized return difference is ~28,3%. Finally, the break-even cost is 6,7% per trade (28,3% / 4,2). Using the same method for Finland, the break-even transaction costs range from 0,6% to 2,4% for V-SMA, 0,6% for F-SMA, and 0,7% to 6,4% for TRB.

Transaction costs depend largely on the number of trades required. In F-SMA and TRB rules the position is always closed after 10-days, which increases the number of trades compared to V-SMA and reduces the break-even point. In both countries, the F-SMA rule generates the lowest break-even percentage. However, the relevant question is, are these break-even percentages large or small? Break-even transaction costs vary depending on the rule and on the market examined. Bessembinder & Chan (1995) report an average V-SMA round-trip break-even cost of 2,6% in Asian stock markets, while Knez & Ready (1996) estimate a one-way transaction cost of 0,26% using DJIA. Also, Bessembinder & Chan (1998) examine DJIA. They report break-even one-way transaction cost averaging 0,39% for the full 1926 to 1991 sample, and 0,22% for the 1976 to 1991 sub-sample. Ito (1999) examine the break-even round-trip transaction costs for emerging markets (Indonesia, Mexico, and Taiwan) and for developed markets (Japan, U.S and Canada). The averages for emerging markets are much higher, ranging from 3,27% to 4,64%, compared to developed markets ranging from 0,65% to 2,24%. Finally, Domowitz et al. (2002) examine the one-way explicit and implicit costs for 42 countries from 1996 through 1998. Explicit costs include commissions and fees, while implicit costs are estimated by comparing the trade price to a benchmark price of the day. They report an average one-way total equity cost of 0,713%. However, the estimates vary greatly depending on the country.

Nowadays, a retail investor has almost the same access to the market as a professional and the trading costs are only a fraction of a percent, something like 0,1% or some cases even below. This, of course, does not represent the whole time period used in the thesis, but rather only the current situation. Even after using a very conservative estimate of 0,2% - 0,3% one-way transaction cost, the break-even percentages reported in Table 5 are mostly larger, indicating that retail investors can beat the market, at least most times, even after transaction costs. The F-SMA rule is on the limit of whether it can be profitable after transaction costs or not.

Table 5: Break-even transaction costs

The table contains the break-even transaction costs that eliminate all gains from technical trading. Panel A reports the break-even cost % from Finland, while Panel B from Iceland. The long-only strategy and the rules that are statistically significant are examined. 'Rule' identifies the rule examined. 'Difference' reports the return difference between the conditional mean buy and the unconditional buy-and-hold strategy. 'Annual excess return %' reports the annualized excess return generated in each rule. 'Total trades' reports the total number of trades, while the 'Trades per year' reports the average number of trades per year. 'Break-even costs %' reports the one-way break-even %.

Panel A: Finland

Rule	Difference	Annual excess return (%)	Total trades	Trades per year	Break-even cost (%)
V-SMA					
(1, 20, 0)	0,00058	16,3 %	858	25,2	0,6 %
(1, 20, 0,01)	0,00068	19,3 %	454	13,4	1,4 %
(1, 50, 0)	0,00056	15,7 %	489	14,4	1,1 %
(1, 50, 0,01)	0,00065	18,4 %	265	7,8	2,4 %
F-SMA					
(1, 20, 0,01)	0,00561	15,7 %	924	27,2	0,6 %
TRB					
(1, 20, 0)	0,00547	15,2 %	718	21,1	0,7 %
(1, 200, 0)	0,00790	22,7 %	314	9,2	2,5 %
(1, 200, 0,01)	0,01056	31,4 %	166	4,9	6,4 %

Panel B: Iceland					
Rule	**Difference**	**Annual excess return (%)**	**Total trades**	**Trades per year**	**Break-even cost (%)**
V-SMA					
(1, 20, 0)	0,00080	23,1 %	614	21,9	1,1 %
(1, 20, 0,01)	0,00113	34,1 %	218	7,8	4,4 %
(1, 50, 0)	0,00080	23,1 %	326	11,6	2,0 %
(1, 50, 0,01)	0,00096	28,3 %	118	4,2	6,7 %
(1, 150, 0)	0,00069	19,6 %	120	4,3	4,6 %
(1, 150, 0,01)	0,00067	19,0 %	58	2,1	9,2 %
(5, 150, 0)	0,00066	18,7 %	64	2,3	8,2 %
(5, 150, 0,01)	0,00064	18,1 %	46	1,6	11,0 %
(1 ,200, 0)	0,00057	16,0 %	106	3,8	4,2 %
(1, 200, 0,01)	0,00060	16,9 %	46	1,6	10,3 %
(2, 200, 0)	0,00055	15,4 %	86	3,1	5,0 %
(2, 200, 0,01)	0,00062	17,5 %	42	1,5	11,7 %
F-SMA					
(1, 20, 0)	0,00718	20,4 %	846	30,2	0,7 %
(1, 20, 0,01)	0,00839	24,3 %	714	25,5	1,0 %
(1, 50, 0)	0,00714	20,3 %	910	32,5	0,6 %
(1, 50, 0,01)	0,00863	25,0 %	832	29,7	0,8 %
(1, 150, 0)	0,00624	17,6 %	984	35,1	0,5 %
(1, 150, 0,01)	0,00697	19,8 %	972	34,7	0,6 %
(5, 150, 0)	0,00605	17,0 %	986	35,2	0,5 %
(5, 150, 0,01)	0,00624	17,6 %	960	34,3	0,5 %
(1 ,200, 0)	0,00532	14,8 %	1 024	36,6	0,4 %
(1, 200, 0,01)	0,00639	18,0 %	1 024	36,6	0,5 %
(2, 200, 0)	0,00533	14,8 %	1 020	36,4	0,4 %
(2, 200, 0,01)	0,00608	17,1 %	1 016	36,3	0,5 %
TRB					
(1, 20, 0)	0,00898	26,2 %	612	21,9	1,2 %
(1, 50, 0)	0,01111	33,3 %	502	17,9	1,9 %
(1, 50, 0,01)	0,01167	35,2 %	220	7,9	4,5 %
(1, 150, 0)	0,01156	34,8 %	416	14,9	2,3 %
(1, 150, 0,01)	0,01343	41,5 %	168	6,0	6,9 %
(1, 200, 0)	0,01198	36,3 %	392	14,0	2,6 %
(1, 200, 0,01)	0,01290	39,6 %	156	5,6	7,1 %

6.5 Bootstrap

Standard t-statistic assume normal, stationary, and time independent distributions. However, many studies show that stock returns are not normally distributed. In fact, there are many known violations from this assumed distribution such as leptokurtosis, autocorrelation, conditional heteroskedasticity, and changing conditional means, Brock et al. (1992). For this reason, in addition to the standard t-statistic, I use a bootstrap method to test the hypothesis and to make results more robust. Bootstrapping is a resampling technique used to estimate statistics on a population by sampling a dataset with replacement. Bradley Efron unified different ideas of resampling procedure and connected the simple nonparametric bootstrap, for independent and identically distributed (IDD) observations, see more Efron (1979). This first method is nowadays commonly called the nonparametric IDD bootstrap. In general, the bootstrapping procedure will produce a large number of simulated samples based on the original sample. It enables the calculation of standard errors, confidence intervals, and hypothesis testing without assuming any underlying data distribution Chihara & Hesterberg (2011).

The standard approach is to take one sample of size n from the population and calculate population estimates from it, such as the sample mean. Due to sampling variability, the sample mean is rarely the same as the population mean. For this reason, the standard error is calculated and after that, assuming an underlying distribution and using laws of probability, the sampling distribution and hypothesis testing can be performed. The theory says that if the population has a Normal distribution, then the sampling distribution is also Normal. However, in many settings the assumption that population has a Normal distribution is hard to make, such as in the case of stock returns. In addition, sometimes there is no known model for the population. In these situations, one possible solution is to use a bootstrap. Bootstrapping process draws random samples from the original dataset. Next, I will explain how it works:

1. Bootstrapping process randomly selects one data point from the original dataset. Each data point has an equal probability of being selected.
2. The process continues until the bootstrapped dataset is the same size as the original dataset.
3. The process can select a data point more than once. This is called bootstrapping 'with replacement'.
4. The whole process is repeated N-times. Each bootstrapped dataset has its own set of sample statistics (sample mean, median, standard deviation etc.)

5. Bootstrapped sample statistics can be now arranged from smallest to largest and the smallest and largest 2,5 percent can be removed. The remaining part represents a 95% bootstrap percentile confidence interval.
6. Original sample statistics can be compared to a bootstrapped confidence interval and hypotheses test can be performed.

In most cases, the bootstrap distribution has approximately the same shape and spread as the sampling distribution, but it is centered at the original statistic value rather than the parameter value. It is important to understand that bootstrapping does not create new data. Bootstrapping assumes that the original sample is a good proxy for the real population and creates many possible samples that could have drawn from it. In addition, the bootstrap allows to calculate standard errors for statistics for which do not have formulas and to check Normality for statistics that theory does not easily handle. Hesterberg (2011).

6.5.1 Results for Random Walk Bootstrap

The random walk bootstrap is defined as:

$$log_e P_t = log_e P_{t-1} + \varepsilon_t \tag{9}$$

, where residuals of the natural logarithm difference, also known as returns, are resampled 500 times with replacement. Resampled returns are exponentiated back to price series by using the original price as the first index value. As a result, I have 500 simulated price series in which I test the same trading rules as before and compare them to the results of the original sample. Brock et al. (1992) show that extending the replications beyond 500 adds only a little additional value. For this reason, 500 replications are chosen. Table 6 presents the summarized results of 500 simulations from the Random walk bootstraps in Finland. As before, the first column shows the test examined. The second column indicates that all numbers in the table represent the proportion of the results of the 500 simulations that are greater than the result obtained with the original OMX Helsinki price index. Original results are reported earlier in panel A of tables 2-4. Columns labeled Buy, Sell, and Buy-Sell reports the results for returns, while σ(Buy) and σ(Sell) reports the results for standard deviations. The last two columns report the results for the number of buy- and sell-signals generated, respectively.

In the columns labeled 'Buy' and 'Buy-Sell', the fraction reported can be considered as the simulated p-value. When the fraction is below 0.05 the results are significant. Correspondingly in the column 'Sell', the simulated p-value is obtained by 1 – Fraction > OMXH, so the results are significant when the fraction is over 0.95. For example, in the (1, 50, 0) V-SMA rule, the number in the column labeled 'Buy' is 0.004. This means that only 0,4% i.e., 2 out of 500 simulated mean V-SMA returns of buy-signals are greater than those from the original sample. In the column labeled 'Sell', the number is 1.00, meaning that all the simulated mean returns are greater than those from the original sample. In other words, none of the returns generated by using the random walk simulated series are as small as the real ones, while in the column Buy-Sell none of the simulated mean returns are larger than those from the original sample.

For the V-SMA rule, the fraction of standard deviation greater than from the original series is always either 1.00 (for buy-signals) or 0.00 (for sell signals) which is interesting, but also consistent with the results of Brock et al. (1992). For example, in the (1, 50, 0) V-SMA rule, at the same time, the conditional mean return of OMXH is higher, but the standard deviation is lower than from the simulated series. In contrast to sell periods, the conditional mean return is lower, but the standard deviation is higher than from the simulated series. This strongly indicates that the higher mean return on buy-signals does not appear to be due to increased risk. Table 6 also reports the results for the F-SMA and TRB rules. The results are very similar to those from the V-SMA and for this reason, are not communicated. In panel B of Table 6 the average results are presented across all rules in Finland. The first row labeled 'Fraction > OMXH' follows the same format as Panel A and reports the average proportion across all eight rules reported in Panel A. The average results are slightly weaker than the individual ones, mainly because of the results of the 200-days moving average. This is consistent with the standard results, where the results weaken when the long-term moving average increases. The second row 'Simulated average' reports the average number across all 8 rules from the 500 random walk simulations and the third row 'OMXH' reports the average number across all 8 rules from the original OMX Helsinki price series. The average buy- and buy-sell return from the original index is always higher, while the average sell return is always lower than the simulated one.

In table 7, the same bootstrap process is done and reported for Iceland. In column Buy, all the simulated p-values are under 0,05. Practically none of the simulated mean returns of buy-signals are greater than those from the original OMXI price series. When moving to the Sell column, almost nothing changes. All p-values are less than 0,05 except for a few values of the TRB rule. Finally, all the p-values for Buy-sell column are also under 0,05. In terms of standard deviation, the results are quite consistent compared to Finland. For the V-SMA rule, the fraction of standard deviation greater than from the original series is always 1.00 for buy-signals. Consistent with Finland, the conditional mean return of OMXI is higher at the same time. For sell-signals, a little more variation is observed compared to Finland. Panel B of table 8 reports the average results for Iceland. The first row, Fraction > OMXI confirm the findings of the individual rules; the results are highly significant and consistent with the traditional results. All the p-values are under 0,05, except the TRB rule, which is marginally above the 5% threshold (0,0505). Second and third row report the simulated average and the average of the original OMXI series. Consistent with Finland, the average Buy and Buy-sell for the original series is always larger than the simulated average. Likewise, the average Sell for the original series is always smaller than the simulated average.

To conclude random walk bootstraps, the results are consistent with the traditional tests reported in tables 2-4 and confirms that the results from the original sample cannot be explained by the random walk. Brock et al. (1992) also test three other null models, which are not included in this thesis: the autoregressive process of order one (AR(1)), the generalized autoregressive conditional heteroskedasticity in-mean model (GARCH-M), and the Exponential GARCH (EGARCH). All these null models failed to explain the returns generated from the original sample.

Table 6: Results of 500 Simulations from Random Walk Bootstraps in Finland

Panel A reports the results of random walk bootstraps in Finland where the residuals of the natural logarithm difference are resampled 500 times with replacement, while Panel B reports the averages. 'Test' shows the test examined. 'Result' indicates that the numbers reported at the table are the proportion of the simulated results that is greater than the result of the original index. 'Buy', 'Sell' and 'Buy-sell' report the proportion for returns, while σ(Buy) and σ(Sell) report the proportion for standard deviations. 'Nbuy' and 'Nsell' report the proportion for the number of buy and sell signals, respectively. 'Simulated average' on Panel B reports the average across all 8 rules from the 500 random walk simulations, while 'OMXH' reports the average from the original OMX Helsinki price series.

Panel A: Finland

Test		Result	Buy	σ(Buy)	Sell	σ(Sell)	Buy-sell	Nbuy	Nsell
(1,20,0)	V-SMA	Fraction > OMXH	**0.00400**	1.00000	**1.00000**	0.00000	**0.00000**	0.01000	0.99000
	F-SMA	Fraction > OMXH	**0.03800**	1.00000	**1.00000**	0.00200	**0.00000**	0.03000	0.96600
	TRB	Fraction > OMXH	**0.02400**	0.98600	**0.99200**	0.01400	**0.00200**	0.00400	0.76400
(1,20,0.01)	V-SMA	Fraction > OMXH	**0.00200**	1.00000	**1.00000**	0.00000	**0.00000**	0.06600	0.99400
	F-SMA	Fraction > OMXH	**0.00800**	0.97600	**0.98800**	0.00200	**0.00000**	0.08400	0.99200
	TRB	Fraction > OMXH	0.06200	0.65800	0.88200	0.00000	**0.03600**	0.95800	0.72400
(1,50,0)	V-SMA	Fraction > OMXH	**0.00400**	1.00000	**1.00000**	0.00000	**0.00000**	0.09400	0.90600
	F-SMA	Fraction > OMXH	**0.04800**	1.00000	**0.99600**	0.00000	**0.00200**	0.04800	0.94600
	TRB	Fraction > OMXH	**0.04000**	0.99800	**0.96400**	0.01400	**0.01200**	0.00200	0.67400
(1,50,0.01)	V-SMA	Fraction > OMXH	**0.00800**	1.00000	**1.00000**	0.00000	**0.00000**	0.11300	0.91000
	F-SMA	Fraction > OMXH	0.06800	0.99200	0.94800	0.00000	**0.01800**	0.17600	0.86800
	TRB	Fraction > OMXH	**0.04600**	0.71200	**0.99200**	0.00000	**0.00200**	0.70400	0.72000
(1,150,0)	V-SMA	Fraction > OMXH	0.08800	1.00000	**0.98600**	0.00000	**0.01200**	0.19400	0.80400
	F-SMA	Fraction > OMXH	0.24200	1.00000	**0.95600**	0.00000	**0.03600**	0.16800	0.82200
	TRB	Fraction > OMXH	0.08000	0.99800	**1.00000**	0.00400	**0.00400**	0.06000	0.62400
(1,150,0.01)	V-SMA	Fraction > OMXH	0.08600	1.00000	**0.98800**	0.00000	**0.00400**	0.20000	0.81800
	F-SMA	Fraction > OMXH	0.08400	0.99800	0.92400	0.00200	**0.03600**	0.18200	0.81400
	TRB	Fraction > OMXH	**0.03000**	0.95000	**0.98800**	0.00000	**0.00400**	0.61800	0.50000
(1,200,0)	V-SMA	Fraction > OMXH	0.24000	1.00000	0.92200	0.00000	0.05400	0.23200	0.76800
	F-SMA	Fraction > OMXH	0.29800	1.00000	0.94200	0.00000	0.06400	0.25800	0.73800
	TRB	Fraction > OMXH	**0.01400**	1.00000	**1.00000**	0.00200	**0.00200**	0.08800	0.59800
(1,200,0.01)	V-SMA	Fraction > OMXH	0.18200	1.00000	0.90800	0.00000	0.06000	0.26000	0.79800
	F-SMA	Fraction > OMXH	0.38800	1.00000	0.84800	0.00000	0.19400	0.22000	0.80600
	TRB	Fraction > OMXH	**0.01200**	0.95000	**0.99800**	0.00000	**0.00000**	0.59800	0.58200

Panel B: Averages

	Result	Buy	σ(Buy)	Sell	σ(Sell)	Buy-sell	Nbuy	Nsell
Rule average V-SMA	Fraction > OMXH	0,07675	1.00000	**0.97550**	0.00000	**0.01625**	0.14613	0.87350
	Simulated average	0.00025	0.01549	0.00028	0.01542	-0.00003	4599	3623
	OMXH	0.00068	0.01342	-0.00035	0.01865	0.00103	4926	3267
Rule average F-SMA	Fraction > OMXH	0,14675	0.99575	**0.95025**	0.00075	**0.04375**	0.14575	0.86900
	Simulated average	0.00218	0.04643	0.00258	0.04636	-0.00040	479	380
	OMXH	0.00449	0.04067	-0.00181	0.05455	0.00668	513	343
Rule average TRB	Fraction > OMXH	**0,03850**	0.90650	**0.97700**	0.00425	**0.00775**	0.37900	0.64825
	Simulated average	0.00207	0.00004	0.00232	0.04611	-0.00025	174	125
	OMXH	0.00869	0.04043	-0.00917	0.06101	0.01786	187	120

Table 7: Results of 500 Simulations from Random Walk Bootstraps in Iceland

Panel A reports the results of random walk bootstraps in Iceland where the residuals of the natural logarithm difference are resampled 500 times with replacement, while Panel B reports the averages. 'Test' shows the test examined. 'Result' indicates that the numbers reported at the table are the proportion of the simulated results that is greater than the result of the original index. 'Buy', 'Sell' and 'Buy-sell' report the proportion for returns, while σ(Buy) and σ(Sell) report the proportion for standard deviations. 'Nbuy' and 'Nsell' report the proportion for the number of buy and sell signals, respectively. 'Simulated average' on Panel B reports the average across all 8 rules from the 500 random walk simulations, while 'OMXI' reports the average from the original OMX Iceland price series.

Panel A: Iceland

Test		Result	Buy	σ(Buy)	Sell	σ(Sell)	Buy-sell	Nbuy	Nsell
(1,20,0)	V-SMA	Fraction > OMXI	**0.00000**	1.00000	**1.00000**	0.07600	**0.00000**	0.24000	0.76000
	F-SMA	Fraction > OMXI	**0.00000**	0.82400	**0.99600**	0.06000	**0.00000**	0.59600	0.38600
	TRB	Fraction > OMXI	**0.00000**	0.49600	0.93400	0.21800	**0.00600**	0.34800	0.42600
(1,20,0.01)	V-SMA	Fraction > OMXI	**0.00000**	1.00000	**1.00000**	0.01800	**0.00000**	0.38800	0.81200
	F-SMA	Fraction > OMXI	**0.00000**	0.51600	**1.00000**	0.04000	**0.00000**	0.66400	0.86800
	TRB	Fraction > OMXI	**0.00600**	0.16600	0.92800	0.09600	**0.02600**	0.74800	0.36200
(1,50,0)	V-SMA	Fraction > OMXI	**0.00000**	1.00000	**0.99800**	0.06600	**0.00000**	0.43600	0.56000
	F-SMA	Fraction > OMXI	**0.00000**	0.92400	**0.99800**	0.03800	**0.00000**	0.41000	0.57400
	TRB	Fraction > OMXI	**0.00000**	0.87800	0.89400	0.13000	**0.00600**	0.10400	0.05600
(1,50,0.01)	V-SMA	Fraction > OMXI	**0.00000**	1.00000	**1.00000**	0.04800	**0.00000**	0.21400	0.49800
	F-SMA	Fraction > OMXI	**0.00000**	0.80600	**0.99400**	0.04400	**0.00000**	0.49200	0.51200
	TRB	Fraction > OMXI	**0.00000**	0.30600	**0.97000**	0.06000	**0.01000**	0.19200	0.15000
(1,150,0)	V-SMA	Fraction > OMXI	**0.00000**	1.00000	**1.00000**	0.06400	**0.00000**	0.37800	0.62200
	F-SMA	Fraction > OMXI	**0.00000**	0.91000	**0.99800**	0.04800	**0.00000**	0.40600	0.58600
	TRB	Fraction > OMXI	**0.00000**	0.89400	0.94600	0.07000	**0.02000**	0.01800	0.04800
(1,150,0.01)	V-SMA	Fraction > OMXI	**0.00000**	1.00000	**1.00000**	0.06800	**0.00000**	0.21000	0.47000
	F-SMA	Fraction > OMXI	**0.00000**	0.93800	**0.99200**	0.04600	**0.00000**	0.31400	0.50600
	TRB	Fraction > OMXI	**0.00000**	0.24600	**0.98400**	0.03600	**0.01000**	0.14200	0.06000
(1,200,0)	V-SMA	Fraction > OMXI	**0.00000**	1.00000	**1.00000**	0.05600	**0.00000**	0.24200	0.75400
	F-SMA	Fraction > OMXI	**0.00200**	0.89800	**1.00000**	0.04800	**0.00000**	0.30600	0.68400
	TRB	Fraction > OMXI	**0.00000**	0.85200	**0.96000**	0.05600	**0.02400**	0.02200	0.05000
(1,200,0.01)	V-SMA	Fraction > OMXI	**0.00000**	1.00000	**1.00000**	0.04600	**0.00000**	0.17600	0.67200
	F-SMA	Fraction > OMXI	**0.00000**	0.95600	**0.99600**	0.03600	**0.00000**	0.20200	0.72400
	TRB	Fraction > OMXI	**0.00000**	0.22800	**0.98000**	0.03200	**0.01200**	0.16200	0.06600

Panel B: Averages

	Result	Buy	σ(Buy)	Sell	σ(Sell)	Buy-sell	Nbuy	Nsell
Rule average V-SMA	Fraction > OMXI	**0,00000**	1.00000	**0.99975**	0.05525	**0.00000**	0.28550	0.64350
	Simulated average	0.00021	0.01465	0.00023	0.01417	-0.00002	4244	2230
	OMXI	0.00099	0.00744	-0.00129	0.02772	0.00228	4427	2132
Rule average F-SMA	Fraction > OMXI	**0,00025**	0.84650	**0.99675**	0.04500	**0.00000**	0.42375	0.60500
	Simulated average	0.00183	0.04404	0.00212	0.04159	-0.00029	447	240
	OMXI	0.00798	0.02621	-0.01038	0.08721	0.01836	457	231
Rule average TRB	Fraction > OMXI	**0,00075**	0.50825	0.94950	0.08725	**0.01425**	0.21700	0.15225
	Simulated average	0.00198	0.03851	0.00219	0.03542	-0.00021	154	68
	OMXI	0.01210	0.02959	-0.01632	0.06379	0.02842	171	79

7 Discussion

7.1 Data snooping

Data snooping is especially problematic in financial research and cannot be eliminated entirely (Lo, 1994). In practice, historical data available in financial research is limited, but the number of possible rules to examine is massive. When using the same data set over and over again, there is always the possibility that any results obtained may be due to luck. This is data snooping, and it can be loosely defined as finding patterns in the data that do not actually exist. For a more specific definition, White (2000) defines it as follows: "data snooping occurs when a given set of data is used more than once for purposes of inference or model selection". Given enough time, imagination, and computer power, almost any pattern can be pushed out of any data set. The situation is made problematic by the fact that if researchers do not find statistically significant results, that study will not be published. This leads in a clear incentive for the researcher to find statistically significant results. As a result, data is examined much more comprehensively than what is observed from the publications. Data snooping biases are most likely to occur when a large amount of data exist, and many researchers use the same data set. In addition, the absence of theory or controls and the attitude that if something works, it does not matter why it works, can lead to biased estimates (Lo, 1994). These conditions are met, in particular, when examining popular technical trading rules, and thus are inevitably present in this study.

Some potential solutions can be identified to mitigate the problem, but no complete solution exist. The best solution is to perform a controlled experiment and not to use any data, but it is rarely a practical solution for financial research. One solution is to replicate a previous study on a new set of data, Lo & MacKinlay (1990). Although, a considerable amount of time must have elapsed since the original study in order to achieve a reasonable sample size. The easiest solution is to use White's Reality Check bootstrap methodology or methods extended from it. White's Reality Check bootstrap assesses data snooping by evaluating the performance of the best trading rules among a series of multiple strategies with a certain confidence level and provides data snooping adjusted p-values, see more from White (2000). Others who extended White's reality check are 'superior predictive ability' (SPA) test of Hansen (2005) and the stepwise SPA test of Hsu et al. (2010).

Despite of empirical results that support technical analysis by many studies, such as Brock et al. (1992), Coutts & Cheung (2000), Savin et al. (2007), Fifield et al. (2008), Metghalchi et al. (2012), and Huang et al. (2019), their evidence is easily criticized for data snooping bias. Sullivan et al. (1999) apply White's Reality Check bootstrap and use the same data set as Brock et al. (1992) to examine the potential effects of data snooping in their findings. They find that certain trading rules exceed the benchmark evaluated by using mean return and Sharpe ratio, even after adjusting for data snooping bias. The best rule examined by Brock et al. (1992), the 50-day V-SMA with a 1% confirmation band produces an annual mean return of 9,4% and a bootstrap reality check p-value of zero. This strongly indicates that findings of Brock et al. (1992) are robust to data snooping biases, and that there are trading rules that perform even better than ones examined by Brock et al. (1992). However, Sullivan et al. (1999) have an additional 10 years of data for DJIA at their disposal and they test whether the results hold out-of-sample. They report that over the 10-year out-of-sample period (1987 – 1996), the best-performing trading rule did not generate an economically and statistically significant return.

A few conclusions can be drawn from the results. First, it is possible that the amount of 7 846 trading rules, that Sullivan et al. (1999) consider as 'full universe of trading rules', should be even larger. If that is the case, the bootstrap reality check p-value is biased towards zero, indicating that the results of Brock et al. (1992) could be, after all, a result of data snooping. However, Sullivan et al. (1999) consider this unlikely. Second, it is possible that technical trading rules have outperformed the market in the past, but more recently the markets may have become more efficient and hence the trading opportunities have disappeared.

8 Conclusion

Even though the Efficient Market Hypothesis is well established in financial theory, an increasing number of professionals and retail investors place emphasis on technical analysis when making investment decisions. The same applies in academic literature; one portion of academics strongly believes that the market is efficient, while others not. The debate between the two groups has intensified further with the publication of academic studies supporting technical trading rules, such as Brock et al. (1992), Coutts & Cheung (2000), Fifield et al. (2008), and Metghalchi et al. (2012). This thesis examines the performance of three simple technical trading rules that retail investors can use: Variable-length simple moving average (V-SMA), Fixed-length simple moving average (F-SMA), and Trading range break out (TRB). I largely follow the methodology of Brock et al. (1992) and extend their study to the Nordics. In addition to standard t-tests, I perform hypothesis testing with a simulated bootstrap distribution.

I find that technical rules have predictive power, which indicates that depending on transaction costs, retail investors may be able to outperform the buy-and-hold strategy. In general, the strongest results are obtained using the V-SMA rule and a relatively short time period, such as 20-50 days. Particularly the results for Iceland are strikingly strong. All of the V-SMA rule tests are statistically significant, rejecting the null hypothesis that technical trading rules do not produce useful signals. The average daily (annual) returns for conditional buy, sell and buy-sell difference are 0,093% (27%), -0,128% (-28%) and 0,221 (77%), respectively. These returns are enormous when compared to the unconditional buy-and-hold return of 0,021% (5,6%). Iceland’s break-even transaction cost percent, which would eliminate trading gains, ranges from 1,1% to 11,7%, indicating that retail investors are able to beat the market even after transaction costs. On the other hand, the results for other countries are not as strong and consistent. No single rule is significant in all countries, implying that even if the rule works in one market, it may not work in another. Moreover, before drawing broad conclusions about the net of cost performance, a proper out-of-sample verification should be performed. Due to lack of data, an out-of-sample test is ignored in this study. The results mostly align with those in earlier studies in simple technical trading rules from DJIA (Brock et al., 1992), Hong Kong (Coutts & Cheung, 2000), emerging markets (Fifield et al., 2008), and Portugal (Metghalchi et al., 2012). On the other hand, some studies report that the strength of the results weakens as the sub-periods approach the present (Hudson et al., 1996; Bessembinder & Chan, 1998; Kwon & Kish, 2002).

Although there is no widely accepted theoretical model that explains technical trading profits, several theoretical and empirical explanations have been proposed, including the noisy rational expectations model (Grossman & Stiglitz 1980; Blume et al., 1994, behavioral models (Shleifer & Summers, 1990), herding models (Froot et al., 1992; Schmidt, 2002), central bank intervention (Sweeney, 1986; Lukac et al., 1988; Davutyan & Pippenger, 1989; Levich & Thomas, 1993) order flow (Osler, 2003; Kavajecz & Odders-White, 2004), temporary market inefficiencies (Hudson et al., 1996; Bessembinder & Chan, 1998; Sullivan et al., 1999, 2003; Kwon & Kish, 2002),, compensation for risk (LeBaron, 1999; Chang and Osler, 1999), and possible data snooping. Nevertheless, more research is needed on these issues since they are still controversial. For future studies, it is also critical to address the limitations identified in this study, even though they may be challenging. First, a proper out-of-sample verification should be conducted. The best performing trading rules should be identified in the first half of the sample period and validated on the rest of the sample. However, a sufficient amount of quality data is required to ensure reliable results, which may be challenging depending on the market. Second, the performance of trading rules should be adjusted for risk and transaction costs in order to reflect reality. Taking risk into account is difficult because all known methods have limitations, such as the joint hypothesis problem. Estimating transaction costs can also be challenging since data for bid–ask spreads was not widely available until recently. Third, the possibility of data snooping and return distribution normality violations should be given special consideration, particularly in topics relating to technical trading rules. Furthermore, recent research indicates that the performance of technical analysis can vary across asset classes, markets and over time. Therefore, future studies could examine the performance and practices of technical in a broad cross-section of speculative markets, while also taking psychological factors into account. This, combined with continuous technological development, would provide a much better picture of the actual use and effectiveness of technical trading strategies.

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Appendix

Table 2: Traditional test results for the V-SMA trading rules: Panels C-E

The table contains results of Variable-length simple moving average (V-SMA) rules for Sweden, Norway and Denmark. Test (short, long, band) denotes short-term, long-term moving average and the percentage difference needed to generate a signal, respectively. 'N(Buy)' and 'N(Sell) are the number of buy and sell signals, respectively. 'σ(Buy)' and 'σ(Sell)' are standard deviations of buy and sell signals, respectively. 'Buy' and 'Sell' denote the mean of buy and sell signals, respectively. 'Buy-Sell' is the difference of mean buy and sell signals. Numbers in parentheses are standard two-tailed t-statistics for testing the difference of the mean buy and mean sell from the unconditional 1-day buy-and-hold return, and 'buy-sell' from zero. The last row reports average across all 12 rules.

Panel C: Sweden

Test	N(Buy)	N(Sell)	σ(Buy)	σ(Sell)	Buy	Sell	Buy-Sell	Buy > 0	Sell > 0
(1, 20, 0)	5366	3479	0.01008	0.01606	0.00070	-0.00022	**0.00092***	0.5389	0.4740
					(1.94808)	(-1.78705)	(3.01786)		
(1, 20, 0.01)	4068	2435	0.01019	0.01778	**0.00080***	-0.00037	**0.00117***	0.5455	0.4669
					(2.24028)	(-1.82198)	(2.97224)		
(1, 50, 0)	5712	3103	0.00969	0.01706	**0.00071***	**-0.00038***	**0.00109***	0.5341	0.4734
					(2.04931)	(-2.11973)	(3.29263)		
(1, 50, 0.01)	5019	2574	0.00956	0.01799	**0.00073***	**-0.00050***	**0.00123***	0.5326	0.4650
					(2.09629)	(-2.18330)	(3.24380)		
(1, 150, 0)	5812	2903	0.00959	0.01762	0.00047	-0.00001	0.00048	0.5262	0.4843
					(0.78279)	(-0.94190)	(1.36585)		
(1, 150, 0.01)	5473	2579	0.00947	0.01827	0.00056	-0.00004	0.00060	0.5293	0.4796
					(1.26020)	(-0.94728)	(1.57014)		
(5, 150, 0)	5785	2930	0.00979	0.01734	0.00054	-0.00013	0.00066	0.5279	0.4812
					(1.11409)	(-1.30627)	(1.92075)		
(5, 150, 0.01)	5466	2585	0.00966	0.01801	0.00052	-0.00005	0.00057	0.5278	0.4809
					(1.00864)	(-0.99744)	(1.50597)		
(1, 200, 0)	5918	2747	0.00978	0.01776	0.00047	-0.00008	0.00055	0.5264	0.4791
					(0.78181)	(-1.10994)	(1.52173)		
(1, 200, 0.01)	5629	2461	0.00972	0.01831	0.00047	-0.00010	0.00057	0.5264	0.4697
					(0.74016)	(-1.09548)	(1.45692)		
(2, 200, 0)	5926	2739	0.00986	0.01770	0.00044	0.00000	0.00044	0.5251	0.4816
					(0.59127)	(-0.90783)	(1.22041)		
(2, 200, 0.01)	5629	2468	0.00976	0.01815	0.00041	-0.00008	0.00050	0.5253	0.4737
					(0.46750)	(-1.04472)	(1.27686)		
Average			0.00976	0.01767	0.00057	-0.00016	0.00073		

Panel D: Norway									
Test	N(Buy)	N(Sell)	σ(Buy)	σ(Sell)	Buy	Sell	Buy-Sell	Buy > 0	Sell > 0
(1, 20, 0)	5253	3589	0.01154	0.01806	**0.00074***	**-0.00047***	**0.00121***	0.5130	0.4932
					(2.20813)	(-2.12157)	(3.54456)		
(1, 20, 0.01)	3998	2566	0.01175	0.02015	**0.00077***	**-0.00087***	**0.00164***	0.5165	0.4899
					(2.15877)	(-2.62242)	(3.73705)		
(1, 50, 0)	5482	3331	0.01119	0.01885	0.00061	-0.00037	**0.00098***	0.5091	0.4971
					(1.67298)	(-1.72339)	(2.73469)		
(1, 50, 0.01)	4731	2691	0.01130	0.02025	0.00065	-0.00050	**0.00115***	0.5124	0.4946
					(1.77010)	(-1.78795)	(2.71462)		
(1, 150, 0)	5694	3019	0.01122	0.01946	0.00040	-0.00014	0.00054	0.5098	0.4925
					(0.71467)	(-1.00529)	(1.41016)		
(1, 150, 0.01)	5320	2702	0.01129	0.02016	0.00038	-0.00010	0.00048	0.5088	0.4948
					(0.59380)	(-0.84136)	(1.15203)		
(5, 150, 0)	5698	3015	0.01150	0.01915	0.00041	-0.00015	0.00056	0.5091	0.4939
					(0.73005)	(-1.04559)	(1.46401)		
(5, 150, 0.01)	5341	2687	0.01151	0.01979	0.00045	-0.00017	0.00062	0.5115	0.4924
					(0.92972)	(-1.01126)	(1.50509)		
(1, 200, 0)	5610	3053	0.01131	0.01925	0.00035	-0.00009	0.00044	0.5119	0.4864
					(0.46592)	(-0.88598)	(1.15424)		
(1, 200, 0.01)	5344	2739	0.01123	0.01993	0.00036	-0.00011	0.00047	0.5112	0.4874
					(0.49796)	(-0.88443)	(1.14928)		
(2, 200, 0)	5605	3058	0.01149	0.01905	0.00036	-0.00010	0.00046	0.5110	0.4882
					(0.50046)	(-0.93263)	(1.22255)		
(2, 200, 0.01)	5345	2749	0.01141	0.01974	0.00038	-0.00015	0.00053	0.5102	0.4882
					(0.61448)	(-0.97326)	(1.30283)		
Average			0.01139	0.01949	0.00049	-0.00027	0.00076		

Panel E: Denmark

Test	N(Buy)	N(Sell)	σ(Buy)	σ(Sell)	Buy	Sell	Buy-Sell	Buy > 0	Sell > 0
(1, 20, 0)	4057	2441	0.00865	0.01320	0.00065	-0.00009	**0.00074***	0.5267	0.5059
					(1.43455)	(-1.58722)	(2.47967)		
(1, 20, 0.01)	2809	1507	0.00881	0.01526	0.00065	-0.00033	**0.00098***	0.5240	0.5030
					(1.27123)	(-1.70735)	(2.28821)		
(1, 50, 0)	4288	2180	0.00830	0.01409	0.00064	-0.00015	**0.00079***	0.5289	0.4986
					(1.43444)	(-1.61824)	(2.42607)		
(1, 50, 0.01)	3595	1672	0.00828	0.01513	0.00061	-0.00014	0.00076	0.5252	0.4946
					(1.21359)	(-1.33469)	(1.91165)		
(1, 150, 0)	4517	1851	0.00863	0.01451	0.00064	-0.00029	**0.00093***	0.5320	0.4824
					(1.43521)	(-1.84088)	(2.57563)		
(1, 150, 0.01)	4268	1614	0.00856	0.01515	0.00064	-0.00038	**0.00102***	0.5333	0.4845
					(1.40441)	(-1.91228)	(2.56442)		
(5, 150, 0)	4523	1845	0.00873	0.01439	0.00063	-0.00025	**0.00088***	0.5328	0.4802
					(1.35127)	(-1.76418)	(2.46054)		
(5, 150, 0.01)	4261	1602	0.00871	0.01501	0.00059	-0.00031	**0.00090***	0.5311	0.4838
					(1.09146)	(-1.73901)	(2.24871)		
(1, 200, 0)	4539	1779	0.00877	0.01456	0.00059	-0.00022	**0.00081***	0.5292	0.4823
					(1.13591)	(-1.61425)	(2.18458)		
(1, 200, 0.01)	4345	1634	0.00871	0.01493	0.00062	-0.00028	**0.00091***	0.5305	0.4780
					(1.29758)	(-1.69527)	(2.30966)		
(2, 200, 0)	4537	1781	0.00877	0.01456	0.00060	-0.00025	**0.00085***	0.5294	0.4818
					(1.21137)	(-1.70885)	(2.31743)		
(2, 200, 0.01)	4346	1642	0.00873	0.01484	0.00062	-0.00023	**0.00085***	0.5297	0.4805
					(1.25526)	(-1.57768)	(2.17674)		
Average			0.00864	0.01464	0.00062	-0.00024	0.00087		

Table 3
Traditional test results for the F-SMA trading rules: Panels C-E

The table contains results of Fixed-length simple moving average (F-SMA) rules. Panel A reports results for Finland and Panel B for Iceland. The rest of the countries are reported in the appendixes. Cumulative returns are calculated for fixed 10-day periods after signals. Test (short, long, band) denotes short-term, long-term moving average and the percentage difference needed to generate a signal, respectively. 'N(Buy)' and 'N(Sell) are the number of buy and sell signals, respectively. 'σ(Buy)' and 'σ(Sell)' are standard deviations of buy and sell signals, respectively. 'Buy' and 'Sell' denote the mean of buy and sell signals, respectively. 'Buy-Sell' is the difference of mean buy and sell signals. Numbers in parentheses are standard t-statistics for testing the difference of the mean buy and mean sell from the unconditional 10-day buy-and-hold strategy, and 'buy-sell' from zero. The last row reports average across all 12 rules.

Panel C: Sweden									
Test	**N(Buy)**	**N(Sell)**	**std buy**	**std sell**	**Buy**	**Sell**	**Buy-Sell**	**Buy > 0**	**Sell > 0**
(1,20,0)	529	356	0,03299	0,04329	0,00375	0,00209	0,00166	0,5917	0,5562
					0,40700	-0,33659	0,61290		
(1,20,0,01)	487	308	0,03008	0,04724	0,00498	0,00046	0,00452	0,6181	0,5552
					1,07865	-0,84605	1,49720		
(1,50,0)	574	308	0,03020	0,04783	0,00499	-0,00095	0,00594	0,6028	0,5260
					1,12719	-1,30770	**1,97694**		
(1,50,0,01)	544	294	0,03192	0,05004	0,00488	-0,00168	0,00656	0,6158	0,5068
					1,02349	-1,46571	**2,03641**		
(1,150,0)	581	291	0,02994	0,04905	0,00441	-0,00041	0,00482	0,5938	0,5326
					0,81248	-1,07882	1,54045		
(1,150,0,01)	572	283	0,03065	0,04898	0,00421	-0,00093	0,00514	0,6136	0,5300
					0,68417	-1,23155	1,61493		
(5,150,0)	579	293	0,03089	0,04780	0,00425	-0,00005	0,00429	0,5924	0,5358
					0,70607	-0,98688	1,39717		
(5,150,0,01)	569	276	0,03383	0,05269	0,00360	0,00205	0,00155	0,6116	0,5797
					0,32833	-0,27130	0,44585		
(1,200,0)	596	271	0,03146	0,04824	0,00350	0,00085	0,00265	0,5872	0,5351
					0,28790	-0,66718	0,82698		
(1,200,0,01)	584	261	0,03366	0,05169	0,00302	0,00133	0,00169	0,6079	0,5556
					0,02082	-0,47916	0,48342		
(2,200,0)	593	274	0,03147	0,04809	0,00340	0,00108	0,00233	0,5868	0,5365
					0,23607	-0,59965	0,73129		
(2,200,0,01)	582	264	0,03355	0,04984	0,00358	0,00123	0,00235	0,5911	0,5606
					0,32074	-0,52720	0,69788		
Average			0,03172	0,04873	0,00405	0,00042	0,00362		

Panel D: Norway									
Test	**N(Buy)**	**N(Sell)**	**std buy**	**std sell**	**Buy**	**Sell**	**Buy-Sell**	**Buy > 0**	**Sell > 0**
1,20,0	525	360	0,04064	0,04935	0,00237	0,00139	0,00098	0,5714	0,5556
					0,17203	-0,19315	0,31037		
1,20,0.01	469	325	0,03682	0,05132	0,00441	-0,00087	0,00528	0,5864	0,5415
					1,07814	-0,88659	1,59357		
1,50,0	551	331	0,03572	0,05584	0,00384	-0,00138	0,00522	0,5662	0,5589
					0,87558	-0,98257	1,52232		
1,50,0.01	525	306	0,03503	0,05425	0,00400	-0,00086	0,00486	0,5562	0,5654
					0,95083	-0,82308	1,40553		
1,150,0	566	306	0,03449	0,05845	0,00371	-0,00198	0,00569	0,5689	0,5458
					0,83785	-1,08025	1,56278		
1,150,0.01	561	291	0,03396	0,05524	0,00435	-0,00463	0,00898	0,5615	0,5223
					1,14911	**-1,85329**	**2,53552**		
5,150,0	568	304	0,03581	0,05721	0,00261	0,00004	0,00258	0,5599	0,5625
					0,30251	-0,53713	0,71350		
5,150,0.01	556	285	0,03594	0,05839	0,00360	-0,00021	0,00380	0,5755	0,5614
					0,76120	-0,57902	1,00581		
1,200,0	563	304	0,03515	0,05782	0,00232	0,00012	0,00220	0,5648	0,5493
					0,16268	-0,51049	0,60493		
1,200,0.01	555	289	0,03483	0,05905	0,00329	-0,00307	0,00635	0,5874	0,5329
					0,62689	-1,33345	**1,68317**		
2,200,0	561	306	0,03540	0,05742	0,00226	0,00023	0,00203	0,5615	0,5556
					0,13620	-0,48323	0,56252		
2,200,0.01	559	286	0,03593	0,05808	0,00315	-0,00009	0,00325	0,5886	0,5490
					0,55485	-0,55258	0,86496		
Average			0,03581	0,05604	0,00333	-0,00094	0,00427		

Panel E: Denmark									
Test	**N(Buy)**	**N(Sell)**	**std buy**	**std sell**	**Buy**	**Sell**	**Buy-Sell**	**Buy > 0**	**Sell > 0**
1,20,0	414	236	0,02652	0,04080	0,00388	0,00058	0,00330	0,5918	0,5932
					0,61965	-0,73827	1,11562		
1,20,0.01	354	196	0,02854	0,04672	0,00536	-0,00194	0,00731	0,6045	0,5663
					1,31929	-1,31534	**1,99301**		
1,50,0	430	217	0,02569	0,04289	0,00411	-0,00008	0,00419	0,5930	0,5899
					0,76249	-0,89179	1,32262		
1,50,0.01	402	202	0,02722	0,04473	0,00507	-0,00037	0,00544	0,5846	0,5396
					1,24493	-0,92056	1,58651		
1,150,0	454	183	0,02741	0,04256	0,00539	-0,00412	0,00951	0,6233	0,5082
					1,46097	**-2,02622**	**2,79918**		
1,150,0.01	443	176	0,02804	0,04613	0,00585	-0,00162	0,00747	0,6208	0,5568
					1,68247	-1,18127	**2,00565**		
5,150,0	453	184	0,02743	0,04252	0,00528	-0,00380	0,00908	0,6159	0,5272
					1,39828	-1,93703	**2,67917**		
5,150,0.01	442	168	0,02813	0,04444	0,00508	-0,00229	0,00737	0,6018	0,5655
					1,26089	-1,37851	**2,00125**		
1,200,0	450	182	0,02750	0,04283	0,00495	-0,00339	0,00834	0,6133	0,5220
					1,21139	-1,79745	**2,43314**		
1,200,0.01	451	171	0,02774	0,04829	0,00571	-0,00291	0,00862	0,6231	0,5439
					1,62165	-1,45080	**2,20034**		
2,200,0	451	181	0,02748	0,04279	0,00520	-0,00407	0,00927	0,6164	0,5138
					1,35194	**-1,99127**	**2,69958**		
2,200,0.01	444	176	0,02615	0,04599	0,00651	-0,00242	0,00893	0,6419	0,5341
					2,11756	-1,40091	**2,42561**		
Average			0,02732	0,04422	0,00520	-0,00220	0,00740		

Table 4
Traditional test results for the TRB rules: Panels C-E

The table contains results of the Trading range break (TRB) rules. Panel A reports results for Finland and Panel B for Iceland. The rest of the countries are reported in the appendixes. Cumulative returns are calculated for fixed 10-day periods after signals. Test (short, long, band) denotes short-term, long-term moving average and the percentage difference needed to generate a signal, respectively. 'N(Buy)' and 'N(Sell) are the number of buy and sell signals, respectively. 'σ(Buy)' and 'σ(Sell)' are standard deviations of buy and sell signals, respectively. 'Buy' and 'Sell' denote the mean of buy and sell signals, respectively. 'Buy-Sell' is the difference of mean buy and sell signals. Numbers in parentheses are standard t-statistics for testing the difference of the mean buy and mean sell from the unconditional 10-day buy-and-hold strategy, and 'buy-sell' from zero. The last row reports average across all 8 rules.

Panel C: Sweden									
Test	**N(Buy)**	**N(Sell)**	**std buy**	**std sell**	**Buy**	**Sell**	**Buy-Sell**	**Buy > 0**	**Sell > 0**
1,20,0	391	230	0,03055	0,04968	0,00456	0,00400	0,00056	0,6061	0,5739
					0,79204	0,29100	0,15407		
1,20,0.01	189	154	0,03315	0,05305	0,00379	0,00569	-0,00190	0,5926	0,5779
					0,29985	0,60942	-0,38714		
1,50,0	309	141	0,02640	0,05171	0,00695	0,00422	0,00273	0,6375	0,5957
					2,02602	0,27345	0,59335		
1,50,0.01	132	105	0,02773	0,05425	0,00471	0,00734	-0,00263	0,5909	0,5905
					0,63762	0,80224	-0,45198		
1,150,0	226	68	0,02463	0,06081	0,00756	-0,00086	0,00842	0,6460	0,5441
					2,21599	-0,51295	1,11442		
1,150,0.01	83	54	0,02369	0,06493	0,00690	0,00210	0,00480	0,6265	0,5741
					1,35633	-0,09822	0,52066		
1,200,0	205	55	0,02810	0,06578	0,00645	0,00529	0,00116	0,6390	0,5636
					1,48974	0,25839	0,12768		
1,200,0.01	73	48	0,02477	0,06759	0,00692	0,01132	-0,00441	0,6301	0,6250
					1,24630	0,84849	-0,43299		
Average			0,02738	0,05847	0,00598	0,00489	0,00109		

Panel D: Norway									
Test	**N(Buy)**	**N(Sell)**	**std buy**	**std sell**	**Buy**	**Sell**	**Buy-Sell**	**Buy > 0**	**Sell > 0**
1,20,0	364	220	0,03935	0,04890	0,00561	-0,00476	0,01036	0,6154	0,5136
					1,42799	-1,86067	**2,66464**		
1,20,0.01	217	153	0,03832	0,06041	0,00605	-0,00696	0,01301	0,6175	0,4837
					1,36112	-1,74994	**2,35179**		
1,50,0	261	126	0,03478	0,05309	0,00472	-0,00840	0,01312	0,6015	0,5000
					1,05039	**-2,09129**	**2,52438**		
1,50,0.01	149	91	0,03146	0,06463	0,00635	-0,00784	0,01419	0,5973	0,5055
					1,47176	-1,41473	1,95809		
1,150,0	188	52	0,03646	0,06500	0,00422	-0,01949	0,02372	0,5479	0,4231
					0,73775	**-2,34970**	**2,52340**		
1,150,0.01	97	42	0,03172	0,08264	0,00646	-0,02612	0,03258	0,5979	0,4286
					1,26467	**-2,18808**	**2,47702**		
1,200,0	171	40	0,03603	0,07151	0,00359	-0,02360	0,02720	0,5439	0,3250
					0,51682	**-2,24268**	**2,33677**		
1,200,0.01	87	33	0,02963	0,09063	0,00545	-0,02474	0,03019	0,5747	0,3939
					0,99196	-1,68545	1,87584		
Average			0,03472	0,06710	0,00531	-0,01524	0,02055		

Panel E: Denmark									
Test	**N(Buy)**	**N(Sell)**	**std buy**	**std sell**	**Buy**	**Sell**	**Buy-Sell**	**Buy > 0**	**Sell > 0**
1,20,0	284	152	0,02718	0,04480	0,00477	0,00319	0,00158	0,6127	0,5987
					0,98423	0,11438	0,39741		
1,20,0.01	111	93	0,02797	0,05055	0,00776	-0,00033	0,00810	0,5946	0,5269
					1,70269	-0,57199	1,37775		
1,50,0	219	81	0,02468	0,05776	0,00599	0,00355	0,00244	0,6164	0,5802
					1,54197	0,12178	0,36722		
1,50,0.01	82	53	0,02818	0,06319	0,00699	-0,00133	0,00832	0,5854	0,5094
					1,26188	-0,46556	0,90282		
1,150,0	165	38	0,02458	0,06139	0,00701	0,00293	0,00408	0,6606	0,6053
					1,85385	0,01746	0,40250		
1,150,0.01	63	31	0,02847	0,06675	0,00698	-0,00061	0,00759	0,5873	0,5484
					1,11072	-0,27895	0,60649		
1,200,0	155	30	0,02508	0,06652	0,00622	0,00193	0,00429	0,6323	0,6000
					1,45699	-0,06739	0,34866		
1,200,0.01	60	22	0,02898	0,07608	0,00579	-0,00999	0,01578	0,5667	0,4545
					0,76834	-0,78343	0,94806		
Average			0,02689	0,06088	0,00644	-0,00008	0,00652		