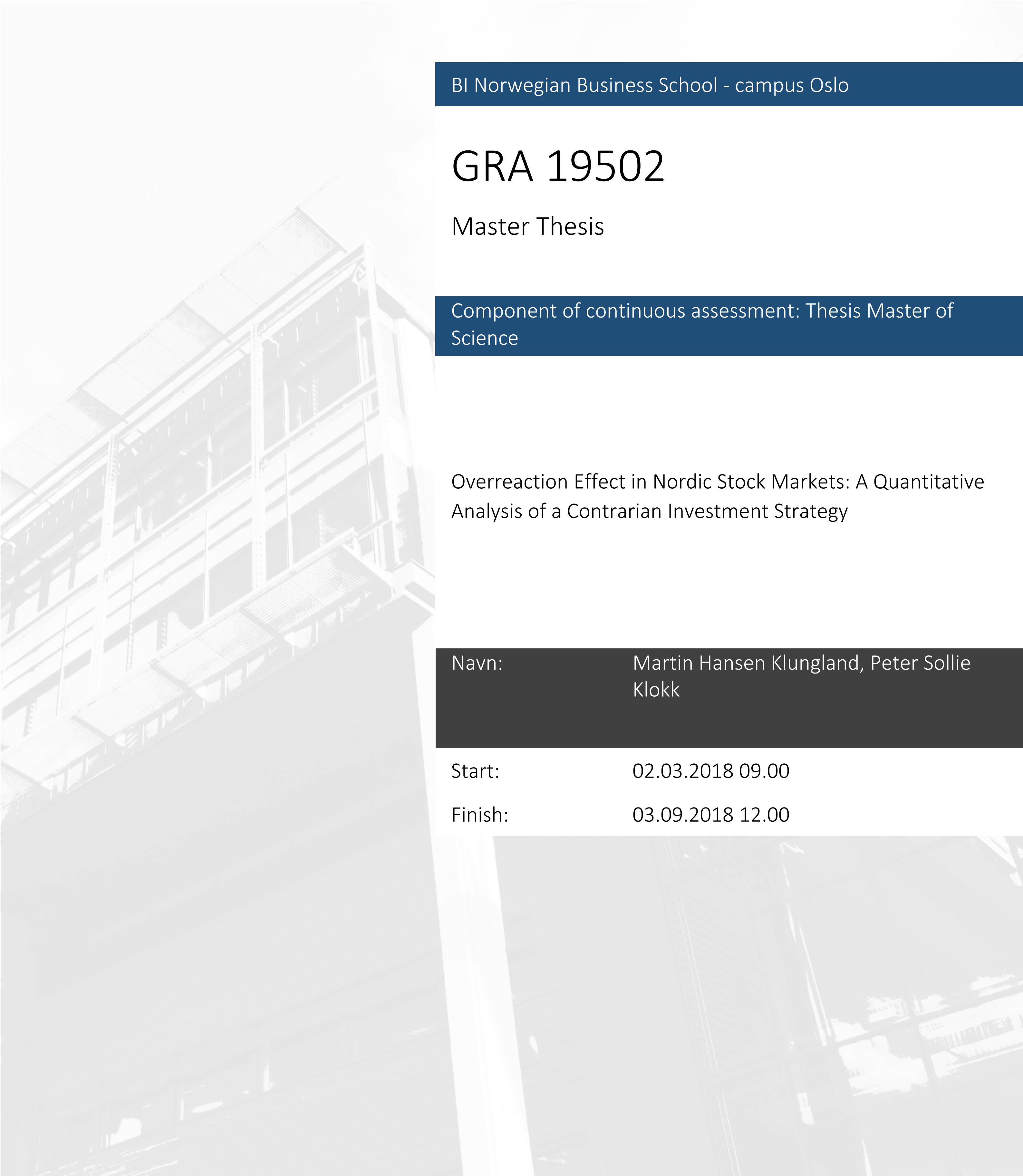

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Overreaction Effect in Nordic Stock Markets: A Quantitative Analysis of a Contrarian Investment Strategy

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Overreaction Effect in Nordic Stock Markets

- A Quantitative Analysis of a Contrarian Investment Strategy -

Martin Hansen Klungland and Peter Sollie Klokk

Supervisor: Associate Professor Siv Jønland Staubo

MSc in Business | Master Thesis | Major in Finance

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I have already made up my mind, don't confuse me with facts
Philip A. Fisher

Most people get interested in stocks when everyone else is. The time to get interested is when no one else is

Warren Buffet

Abstract

Research in behavioral finance suggests that investors are prone to violate Bayes' theorem and thus irrationally conform to various heuristics. This challenges the Efficient Market Hypothesis and is reflected in the stock market through overreactions and subsequent price reversals. Our thesis investigates whether such overreactions are affecting stock prices in four Nordic stock markets and sectors, and if such overreactions can be theoretically exploited through a contrarian strategy; selling portfolios of prior winner stocks whilst simultaneously buying portfolios of loser stocks. We also address critique targeted at the Overreaction Hypothesis, such as the January effect. The empirical proof from the Nordics is consistent with what the Overreaction Hypothesis predicts; statistically significant stock price reversals are predictable both on market- and sector level, exclusively based on historical return data, suggesting a significant weak-form market inefficiency.

Keywords: Overreaction Hypothesis, Market Efficiency, Behavioral Finance, Heuristics, Irrationality, Experimental Psychology.

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The work presented in this thesis would not have been possible without our close association with many people. We express our thankfulness to all those who have contributed, directly or indirectly to make this Master thesis possible.

We would like to extend our sincere gratitude and appreciation to our supervising Professor, Siv J. Staubo for her dedicated help, advice, inspiration, encouragement and continuous support throughout our Master's thesis. We are proud to say that we have emerged from this dissertation with enhanced knowledge and a broader understanding of the dynamics of financial markets than what we did a year ago.

Martin Hansen Klungland

Peter Sollie Klokk

Contents

Introduction

This thesis examines the presence of the overreaction effect in the Nordic Stock Markets during the period from 1996 throughout 2017. We will inspect whether a zero-portfolio containing a short position in the best performing stocks and a long position in the worst performing stocks will manage to outperform the market in subsequent periods. This study is largely based on the research of De Bondt and Thaler (1985), who found that recent losers on average outperformed recent winners by 24,6% over a 36 months' period. The 1985-paper by De Bondt and Thaler acted as evidence against the entrenched Efficient Market Hypothesis (EMH), and gave birth to the Overreaction Hypothesis (OH).

The theory of the overreaction phenomenon is widely discussed and debated with varying conclusions and findings depending on investigated market, test-period and methodology (e.g. Brown and Warner (1985) in the US, Antoniou and Galariotis (2006) in the UK). However, the exploration in the Nordic markets has been limited.

In this paper, we utilize weekly return data from four Nordic stock exchanges to rank stocks in accordance with their abnormal movements. We divide stocks in quintiles, where the loser and winner portfolios are constructed contingent upon being top and bottom 20% in their respective markets and sectors, measured by abnormal returns during a three-year formation period. Portfolio returns are measured as the average return of stocks that are included in winner and loser portfolios. That is, stock returns are equally weighted within each portfolio.

The empirical evidence from our results is consistent with the overreaction hypothesis; we find substantial weak form market inefficiencies in all Nordic markets and investigated sectors.

During the period from 1996 until 2017, loser portfolios outperform the market by on average 15,1%, three years' post-formation. Winner portfolios, on the other hand, earn about 26,9% less than the market, implying a contrarian return equal to 42%. Similarly, for sectors we experience an average return for the winner portfolios of 21,5% below the market, whereas the loser portfolio outperforms by 14,7%, indicating a contrarian return equal to 36,2%.

This thesis proceeds with the following structure: Section 2 elucidates on the emergence of behavioral finance, and how this perspective contrasts the efficient market hypotheses. Section 3 contains an in-depth review of previous literature on the overreaction hypothesis, including both empirical findings and critical views from other researchers in the field. Section 4 elaborates on data and descriptive statistics, followed by a thorough review of our selected methodology in section 5. Section 6 highlights results and findings in accordance with our formulated hypotheses, accompanied by possible explanations and other considerations relevant to the results, for both markets and sectors. Lastly, Section 7 concludes our findings and discusses directions for future research within the field of behavioral finance.

Theory

2.1 Efficient Market Hypothesis

The EMH achieved an immensely important role as one of the most seminal edifice of neoclassical economics in the 1960s, and has been an integral part of financial theory ever since. The father of the EMH, Eugene Fama (1970) identified three levels of market efficiency. However, as the strongest form of market efficiency implies exploitation of insider information, which is outside the scope of this paper. Hence, we will not discuss this further. The weakest form of market efficiency confines itself to entail historical price information on the security, thereby invoking the assumption that such information already is reflected in the market price of the security. Thus, no market participant would be able to generate abnormal returns by simply utilizing historical price information.

The semi-strong form of market efficiency posits that all relevant and publicly available information is quickly absorbed and reflected in the market price, implying that investors are incapable of earning excess returns relative to the market portfolio without utilizing insider information.

The EMH is fundamentally dependent upon three arguments, which rely on gradually punier assumptions. First, all investors are presumed to be rational decision makers, whom value securities coherently. Second, should irrational investors partake in the market, the following noise is explicitly random – and therefore cancel each other out. Thirdly, if these irrational investors trade similarly, rational arbitrageurs eradicate their influence on market prices (Shleifer, 2000). Despite the broad acknowledgement of the EMH, the theory has received progressively increased criticism. The last years' success of quantitative trading algorithms, such as high frequency trading, has proved to increase market efficiency; implying that the markets in fact were not truly efficient (Virgilio, 2015); (Haferkorn, 2017).

2.2 Behavioral Finance

Behavioral finance is a term that emerged into public consciousness in the mid-1990s, and is a blunt contradiction to the well-established EMH and its underlying assumptions. Being a relatively new field, behavioral finance seeks to enrich standard economic models by studying how psychology influence investors and their decisions. Research within this field has led to several Nobel prizes; the latest awarded to Richard Thaler in 2017 for his contributions to behavioral economics.

2.2.1 Development

Robert Shiller (1981), one of the founding fathers and profound influencers of behavioral finance, was one of the first researchers to challenge the foothold of the EMH. The assumptions made in his initial research was that dividends are the fundamental driver of stock prices; stock prices are equal to the present value of future real dividends, discounted by a constant real discount rate (Shiller, 1981). Shiller found that stock prices are far too volatile to be justified by subsequent changes in dividends, implying violations of the EMH. Shiller interpreted this unfounded variability as an irrational aspect of market participants' decision making. The pursuit of explaining this irrationality became the birth of behavioral finance.

Unlike classical economics, behavioral finance invokes research from the social sciences. Amongst the most influential, Daniel Kahneman and Amos Tversky impacted the field immensely through their research on how psychological and cognitive factors affect decision making. Kahneman and Tversky's (1979) "Prospect Theory" offer possible explanations to many puzzles in the field of finance. Arguably most prominent, the researchers found that investors value gains and losses non-linearly; a loss of value constitute a greater sense of pain compared to the experienced joy created by an equivalent gain. Despite holding a doctorate in psychology, not economics, Kahneman received the Nobel Prize in Economics in 2002 for his contributions to behavioral economics.

2.2.2 The Overreaction Hypothesis

The Overreaction Hypothesis (OH) originates from the research of De Bondt and Thaler (1985), which is the main source of inspiration for this thesis. De Bondt and Thaler found that investors in the US stock market systematically overreacted to unexpected news. This consistent overreaction was interpreted as evidence for weak-form inefficiency in the US stock market. Ultimately, the OH states that "*extreme movements in stock prices will be followed by subsequent price movements in the opposite direction"* (De Bondt & Thaler, 1985). Due to the initial controversy of the implications of their research, De Bondt and Thaler were labeled as outcasts by fellow researchers. Regardless, behavioral finance has become more accepted; to the extent that large mutual funds specialize in exploiting behavioral patterns in the market.

Proponents of the OH deem the overreactions to be a consequence of human foibles when processing information. Shefrin (2002) argues that the *representativeness* heuristic is one of the more important principles affecting financial decisions. The heuristic proclaims that the majority of individuals disregard prior probabilities and neglects base rate frequencies, and is therefore a contradiction to Bayes' theorem (Kahneman & Tversky, 1974). An overreaction must be reviewed relative to a reaction that is considered appropriate and rational. We deem Bayes' theorem to sufficiently represent rational reactions towards new information released to the market:

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)} \tag{2.1}$$

Bayes' theorem (1763) states that investors process information rationally, in accord with equation (2.1), and therefore review their predictions correctly by applying conditional probability to account for past and current information. By conforming to the representativeness heuristic and thus violating Bayes' law, investors become exaggeratedly pessimistic about past losers and excessively optimistic about past winners. This implies that one of the sides in equation (2.1) is attributed an unwarranted amount of weight, relative to the other. We interpret cognitive biases (i.e. representativeness) as an underlying assumption of the OH; by violating Bayes' law, investors systematically misinterpret information, and thus conduct systematic errors. If this is true, investors cannot be deemed rational and therefore violates the assumption of rationality underlying the EMH.

Following the logic above, investors' systematic errors lead to an inevitable mispricing of securities in the market; security prices become prone to deviate from their fundamental value as new information is available. Specifically, past losers become undervalued, whilst past winners are overvalued. Per the OH, this mispricing is not permanent, and will be followed by a subsequent price movement in the opposite direction. When this reversion occurs, loser stocks outperform the market while winner stocks underperform, creating the possibility of a contrarian profit (Shefrin, 2002). The reversal of the exaggerated price movements serves as evidence versus both the weak-form and the semi-strong EMH.

2.3 Hypotheses

Hypothesis 1 (H1): Will an investment strategy based on buying losers and selling winners yield statistically significant returns, and is this strategy transferable across the Nordic markets?

We test the possibility of earning significantly abnormal returns by constructing a zero-portfolio consisting of a long position in past loser stocks, and a simultaneous short position in past winner stocks.

$$H_0: AR_{t+j}^{Loser} = AR_{t+j}^{Winner} \quad | \quad H_A: AR_{t+j}^{Loser} > AR_{t+j}^{Winner} \tag{2.2}$$

Identifying overreactions is a natural prerequisite for the strategy to be transferable across the Nordic borders. The alternative hypothesis is based on the assumption that all (i.e. regardless of country of origin) investors are prone to conform to cognitive biases, such as the representativeness heuristic. That is, if overreactions are caused by human foibles in decision making and/or violations of Bayes' theorem, we expect to identify similar evidence in all Nordic markets.

Hypothesis 2 (H2): Does the contrarian investment strategy yield abnormal returns regardless of the sector it is applied to?

Following the logic from hypothesis 1, we expect to find irrational investors, possibly causing an overreaction regardless of the sector we are investigating.

$$H_0: AR_{Sector\ i}^{Loser} = AR_{Sector\ j}^{Winner} \quad | \quad H_A: AR_{Sector\ i}^{Loser} > AR_{Sector\ j}^{Winner} \tag{2.3}$$

Literature Review

In this section, we present and discuss literature we consider to be of utmost importance for this paper. Additionally, we discuss the relevance and contribution of our research in relation to the progressively accepted field of behavioral finance.

3.1 Fundamentals

The OH was first presented by Beaver and Landsman (1981), who observed the possibility to receive abnormal returns by using a "contrarian strategy"[1]. However, De Bondt and Thaler (1985) are known as the first to actually form the hypothesis. They documented the phenomenon of winners and losers in a 36-month period tend to reverse their performance over the next 36-month period. More specifically, they showed that loser portfolios outperformed winner portfolios with 24,6% and interpreted the results as a violation of the weak form efficiency by Fama (1970) which is considered to be one of the theoretical cornerstones in financial theory. The violation of the EMH evolves as the reversal of overshooting stocks should be predictable from past return data alone (De Bondt & Thaler, 1985). These arguments are supported by several other empirical studies; Brown & Warner (1988) Poterba and Summers (1988), Pennegill and Jordan (1990), Chopra (1992) and Antoniou and Galariotis (2006).

3.2 Data Frequency

Naturally, not all empirical research on the OH is identical in design. The major differences among academic papers are primarily related to the length of assumed overreactions. That is, the length of the estimation window used to identify winner and loser stocks. Additionally, the holding period of stocks within the portfolios have been wide-ranging. Furthermore, former research also differs with respect to frequency of observed data. Ammann and Kessler (2009) use daily returns on stocks, Gutierrez and Kelley (2008) and Wang and Power (2006) use weekly returns, while some researchers follow the original study by using monthly

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[1] *Contrarian investing is an investment strategy distinguished by buying and selling against the grain of investor sentiment during a specific time.*

returns, such as Benou and Richie (2003). There has been a rising trend of applying higher frequency data the last couple of years. Regardless, we acknowledge De Bondt and Thaler's (1985) concerns with respect to liquidity noise in high frequency data-sets, whereas lower frequency data-sets have a lower degree of noise. Based on discussions of advantages and disadvantages in former research, we utilize weekly data throughout our study.

3.3 Transferability

We expect to observe evidence of overreactions across both borders and industries, given that the overreaction is a consequence of cognitive biases. This is anchored in the external validity of the representativeness bias coined by Kahneman and Tversky (1974). Specifically, we assume all investors being prone to conform to the cognitive biases, thereby violating the law of Bayes' when predicting future probabilities. Thus, we assume all investors, regardless of market and industry to have the same probability of violating Bayes' law. If the Nordic markets experience irrational investors, statistically significant evidence of overreactions is expected to occur, and ultimately considered to be transferable across markets.

Several studies have been conducted on the OH in several countries, although the U.S market is by far the most researched. However, we have found that the studies differ immensely in terms of applied methodology, time-horizon, underlying assumptions and specifications. These factors affect the identified implications of the OH, and have therefore entailed a variety of findings; both confirmations and contradictions of the presence of overreactions. Consequently, results are rarely comparable across borders.

3.4 Critique

Despite increased acknowledgement, the OH has received a vast amount of critique from several researchers on the field. One of the first to criticize De Bondt and Thaler's findings, was Chan (1988). He argued that the profitability of contrarian investment strategies cannot be regarded as conclusive evidence against the EMH as there is no accounting for change in risk in the profitability calculations. Because risk is not constant, he argued that by not adjusting for changing risk, he found loser portfolios to be less risky than winner portfolios; thereby explaining the abnormal return as a simple compensation for higher risk.

Zarowin (1990), yet another critic, claimed the abnormal returns to origin from the difference in size, rather than overreactions by investors. He suggested that by forming and comparing winners and losers with the same size, all abnormal returns would be exterminated. However, Chopra et.al (1992) reconfirmed the original findings from De Bondt and Thaler after correcting for both market risk and size effect. Yet, they found that the majority of abnormal returns transpire in the month of January, with no immediate satisfactory explanation.

Rozeff and Kinney Jr. (1976) reported the phenomenon of high January returns (the January effect) to be tax-related, as investors seek to realize losses by selling loser stocks before the next tax-year. The incentive to sell establishes a negative price pressure prior to the beginning of the year, before returning to equilibrium levels in January, resulting in abnormally high returns for prior losers (Jones, Pearce, & Wilson, 1987). This theory could help to explain the high abnormal returns in January found in prior research. Zarowin (1990) and Conrad and Kaul (1993) also found supporting evidence for attributing returns to the January effect.

De Bondt and Thaler have also received criticism for the methodology used to calculate abnormal returns. Conrad and Kaul (1993) questioned the use of cumulative returns for portfolio profits. They argued that by adding returns for each period together, the arbitrage portfolio will have an upward drift unrelated to market overreactions; yielding misinterpreted evidence for the OH.

This critique is further supported by Dissanaike (1994) and Loughran and Ritter (1996) who argued that returns calculated in the test period will not equal the realized returns by the investor, and therefore not give any empirical meaning. Consequently, wrong stocks may be ranked as winners and losers, generating incorrect portfolios for the period investigated. To prevent this bias, Dissanaike (1994) suggested to use either the rebalancing method or the buy-and-hold method. These methods are considered to be superior as they involve lower transaction costs and are less exposed to liquidity problems, compared to the cumulative arithmetic method.

Lastly, Fama and French (1996) claimed that the three-factor model can capture the reversal of returns documented by De Bondt and Thaler (1985). This empirical evidence suggests that prior-return-based portfolios should own certain types of characteristics that reflect their prospects. Henceforth, abnormal returns from the contrarian strategy will be explained by the differences in the characteristics between the loser and the winner.

3.5 Contribution

This paper differs from existing literature due to several reasons. Firstly, we apply stocks from Nordic countries, which has not been well explored in the subject of the OH. Secondly, we scrutinize deviations between industries, which has received limited attention in former empirical studies. Additionally, we adjust our methodology to the criticism aimed at the original paper by De Bondt and Thaler (1985). Thus, this paper analyzes return patterns and the characteristics of prior-return-based portfolios in the Nordic stock markets, while considering the January effect, changing risk and the size effect.

Data

4.1 Data Collection

Weekly stock returns are collected from Bloomberg by extracting total company returns adjusted for dividends, in four Nordic stock markets. Thereafter, we collect return series for all stocks that have been listed on the exchange during the time-horizon we are investigating. Consequently, we avoid survivorship bias in our data. The length of the data series in the respective markets is dependent upon the availability of both index- as well as individual stock data. Return series for all stocks are collected from the following stock indexes; Oslo Stock Exchange Benchmark Index, OMX Stockholm, OMX Copenhagen and OMX Helsinki. All sector data is collected from constituents on the MSCI Nordic Index.

4.2 Descriptive Statistics

4.2.1 Nordic Markets

Data for the Norwegian stock market is extracted by selecting all stocks that have been listed on the Oslo Stock Exchange Benchmark Index (OSEBX). The calculations specified in the methodology section are based on return data from 1996 to 2017. Data for the remaining Nordic countries are extracted by identifying all stocks that have been listed on HEX, KFX and OMX. The time-span for the data is adjusted according to the data on OSEBX, in order to ensure consistency.

4.2.2 Nordic Sectors

Data for sector calculations is extracted by identifying constituents from the MSCI Nordic Index[2]. Yet again, time-span is matched with abovementioned indexes to preserve consistency throughout our calculations.

[2] *The MSCI data contained herein is the property of MSCI Inc. (MSCI). MSCI, its affiliates and its information providers make no warranties with respect to any such data. The MSCI data contained herein is used under license and may not be further used, distributed or disseminated without the express written consent of MSCI.*

Methodology

To appropriately investigate the presence of an overreaction effect in the Nordic countries during the period from 1996-2017, we will adapt the methodology first outlined by De Bondt and Thaler (1985). However, we apply certain adjustments that account for criticism and advancements proposed by Dissanaike (1994) and Chopra (1992) which have been discussed in the literature review.

5.1 Model Selection

To calculate abnormal risk-adjusted returns, we subtract expected returns from realized returns. The two most prominent models for estimating expected returns are Brown and Warner's (1985) *market model* and the *constant mean return model*. The market model assumes that a security's expected return can be modelled through a linear relationship with market returns, whereas the constant mean return model assumes expected returns to be constant over time (Campbell & Wesley, 1993). The advantage of using the market model is that the risk is not measured up against single stocks or firm-specific risks, but rather against a diversified portfolio of stocks which is regulated by market risks (MacKinlay, 1997).

The market model has been applied by the majority of prior studies in the field; Brown and Warner (1985) proved that it is not advantageous to apply any other model. It is noteworthy that overreactions do not necessarily appear through a stocks extreme movements relative to the market, but rather through extreme movements relative to the stocks historical volatility adjusted correlation with the market. Thus, we argue the market model to be the most appropriate model for our study.

5.2 Return Calculations

5.2.1 Expected Returns

The Market Model is correctly applied by running an OLS regression on historical weekly returns from single stocks from the respective indexes during the investigated period.

The expected returns are estimated using intercepts and beta-values to generate the expected returns $E[R_{i,t}]$. Returns on stocks are calculated as:

$$E[R_{i,t}] = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \tag{5.1}$$

α_i = Intercept in estimation window (alpha)

β_i = Slope coefficient in estimation window (beta)

$R_{m,t}$ = Market return at time *t*

$\varepsilon_{i,t}$ = Error term with expectation equal to zero

5.2.2 Realized Returns

To calculate returns for markets and stocks, we transform simple returns into logarithmic returns. The reason for applying logarithmic returns is due to their additive nature, which makes them more appropriate for return measures compared to regular arithmetic calculation. Also, the application of logarithmic weekly returns will give a relatively symmetric distribution compared to percentage returns, which is characterized by right-skewed distribution (Fama, 1970). A symmetric distribution is preferable when the aim is to minimize estimation errors. The realized return $R_{i,t}$ is calculated using historical closing prices through the following formula:

$$R_{i,t} = ln \frac{(P_{i,t})}{(P_{i,t-1})} \tag{5.2}$$

$P_{i,t}$= Closing price for stock *i*, at time *t*

$P_{i,t-1}$= Closing price for stock *i*, the day before *t*

The same approach is employed to correctly calculate market return.

5.2.3 Estimation of the Market Model

To calculate predictors for alpha and beta, we have utilized MacKinlay's (1997) approach:

$$\hat{\beta}_i = \frac{\sum_{t=T_0}^{T_1}(R_{i,t} - \hat{\mu}_i)(R_{m,t} - \hat{\mu}_m)}{\sum_{t=T_0+1}^{T_1}\left(R_{m,t} - \hat{\mu}_m\right)^2} \tag{5.3}$$

$$\hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i\hat{\mu}_m \tag{5.4}$$

$$\hat{\sigma}_{\varepsilon i}^2 = \frac{1}{L_1 - 2}\sum_{t=T_0+1}^{T_1}(R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i\hat{\mu}_{m,t})^2 \tag{5.5}$$

Where

$$\hat{\mu}_i = \frac{1}{L_1}\sum_{t=T_0+1}^{T_1} R_{i,t} \quad and \quad \hat{\mu}_m = \frac{1}{L_1}\sum_{t=T_0+1}^{T_1} R_{m,t} \tag{5.6}$$

$R_{i,t}$ = Return in period *t*, for stock *i*

$R_{m,t}$ = Return in period *t*, for market *m*

$L1$ = Length of estimation window

5.2.4 Abnormal Returns

To calculate abnormal returns, we subtract the expected return from the realized return:

$$AR_{i,t} = R_{i,t} - E\left[R_{i,t}\right] = R_{i,t} - \hat{\alpha} - \hat{\beta}_i R_{m,t} \tag{5.7}$$

$AR_{i,t}$= Abnormal return for event *i* in period *t*

$\hat{\alpha}$ = The estimated alpha-value from the market model, for event *i*

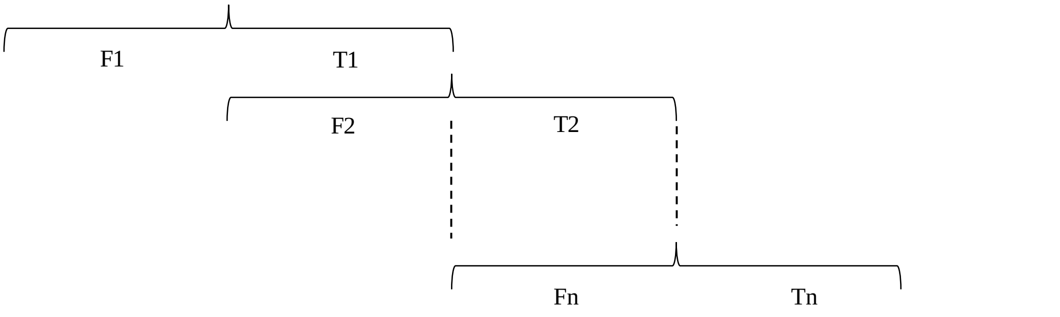
$\hat{\beta}_i$ = The estimated beta value in the market model, for event *i*

5.3 Portfolio Formation

Subsequent to estimating abnormal returns for all stocks, we rank stocks in accordance with their abnormal movements. We divide all stocks in quintiles, where the loser and winner portfolios are constructed contingent upon being top and bottom 20% in their respective markets or sectors, measured by abnormal return during the three-year formation period before *t = 0*. The three mid quintiles (mid-performing portfolios) are not subject to scrutiny, as these are not of particular interest, and certainly not within the scope of this thesis. As such, they will not be discussed further.

Figure 1

Figure 1 illustrates the formative process of each portfolio. F denotes the formation, where stock performances are ranked. T denotes the test period, in which the performance of the formatted portfolios is scrutinized. Ultimately, we have six individual formation- and test periods which our results are contingent upon. The only overlapping occur between test and formation periods.



Portfolio returns are measured as the average return of stocks that are included in winner and loser portfolios. That is, stock returns are equally weighted within each portfolio. In cases with lack of return data (i.e. due to suspended trading), it is set to zero. This supports our critique towards De Bondt and Thaler as we do not ignore the illiquidity by ignoring the trade made on the portfolio selection date. In contrast, we attribute a zero-return position to the average portfolio return. Ultimately, we get the following return measure for the portfolios at time *t*:

$$\pi_{pt} = \frac{1}{N_p} \sum_{i=1}^{N_p} R_{i,t} \tag{5.8}$$

$i =$ Stock

$N =$ Total number of stocks in portfolio p

$p =$ Denotes portfolio

Finally, we derive the aggregated return series for each portfolio:

$$\pi_P = \sum_{t=1}^{T} \pi_{p,t} \tag{5.9}$$

5.4 Testing for Overreaction

When testing for possible overreactions in the respective markets and sectors, we replicate the methodology of De Bondt and Thaler (1985). Our data include 22 years of data, consisting of weekly returns from 1996 throughout 2017. We employ a three-year (156 weeks) formation period and a subsequent three-year test period where we measure abnormal return to identify possible evidence of overreactions. In accordance with De Bondt and Thaler (1985), we derive cumulative market-adjusted return (CAR) by applying the following formula:

$$CAR_{i,t} = \sum_{t=-156}^{t=0} AR_{i,t} \tag{5.10}$$

$AR_{i,t}$ = Abnormal return for event *i*, in period *t*
$R_{i,t}$ = similar to equation (5.2)
$R_{m,t}$ = market return at time *t*

To quantify the performance of the portfolios, we calculate the average CAR of the portfolios 156 weeks forward:

$$CAR_{p,z,T} = \sum_{t=1}^{T} \left(\frac{1}{N} \sum_{i=1}^{N} AR_{i,t} \right) \tag{5.11}$$

p = Denotes portfolio (W for winner; L for loser; L-W for contrarian)
z = Period (1, 2…, 6)
T = Holding period for the portfolio (156 weeks for our chosen strategy)

If the OH holds, implying that stock prices deviate from its fundamental value, the mispricing should be corrected in the long run. The correction of stock prices would then generate negative autocorrelation in returns for our constructed portfolios, measured by the average cumulative abnormal return (ACAR) for all of the six period's CAR:

$$ACAR_{p,T} = \frac{\sum_{z=1}^{Z} CAR_{p,z,T}}{6} \tag{5.12}$$

This price reversal implies that we will observe positive returns for the losers ($ACAR_L > 0$), whilst winners will experience negative returns ($ACAR_W < 0$); yielding a non-zero arbitrage portfolio return, supporting the sanity of the contrarian investment strategy (De Bondt & Thaler, 1985)

To test the statistical significance of portfolio returns, and thereby the theoretical feasibility of exploiting overreactions in the Nordic stock markets, we replicate the methodology suggested by De Bondt and Thaler (1985), which is adopted by the majority of similar research. To assess whether the investment performance is statistically significant, we calculate a pooled estimate of the population variance in the respective CARs:

$$S_t^2 = \frac{\left[\sum_{n=1}^{N}(CAR_{W,n,t} - ACAR_{W,t})^2 + \sum_{n=1}^{N}(CAR_{L,n,t} - ACAR_{L,t})^2\right]}{2(N-1)} \tag{5.13}$$

As all constructed portfolios are equal in sample size *N*, the variance of the difference in sample means is equal to $\frac{2S_t^2}{N}$. Consequently, we apply the following t-statistic:

$$T_t = \frac{\left[ACAR_{L,t} - ACAR_{W,t}\right]}{\sqrt{\frac{2S_t^2}{N}}} \tag{5.14}$$

To validate that returns from the respective test-periods of the portfolios contribute to either $ACAR_W$ or $ACAR_L$, we assess whether the contribution is statistically different from zero. The sample standard deviation of the winner portfolio is expressed as:

$$s_t = \sqrt{\frac{\sum_{n=1}^{N}(AR_{W,n,t} - AR_{W,t})^2}{N-1}} \tag{5.15}$$

Because $\frac{s_t}{\sqrt{N}}$ characterizes the sample estimate of the winner portfolio, the t-statistic equals:

$$T = \frac{AR_{W,t}}{\frac{s_t}{\sqrt{N}}} \tag{5.16}$$

The same methodology is applied for the loser portfolio.

To test the sustainability of our hypotheses, we are most interested in testing the significance of the ACARs, representing the aggregate zero-portfolios. Although the possibility of finding significance for each of the portfolios in the 156 post-formation weeks, this do not enact as independent evidence of sustainability (De Bondt & Thaler, 1985). This is also true for $ACAR_W$ and $ACAR_L$, which need not be statistically significant independently, whereas the combination in a zero-portfolio, $ACAR_{L,156} - ACAR_{W,156}$ (Loser – Winner) may be statistically significant from zero.

Results

As thoroughly discussed in section 5, we have applied the market model for investigative purposes when attempting to identify overreactions in the Nordic markets. This section discusses whether we can identify overreactions through an asset pricing model, and the extent of the possible overreactions. Identification of overreactions is a prerequisite for the feasibility of the strategy to be transferable across markets. Subsequently, we discuss the second hypothesis; whether the strategy yields abnormal returns regardless of the sector the strategy is applied to.

6.1 H1: Overreaction and Transferability Across Markets

To identify the possible presence of overreactions, we use abnormal returns acquired from application of Brown and Warner's market model on returns from each market. As we are investigating the markets in isolation, i.e. whether it is theoretically exploitable for a local investor, stock prices are denoted in local currencies. Consequently, we are not concerned with exchange rate risk. To infer in an adequate manner, we employ a one-tailed T-test formulated in accordance with the alternative hypothesis in equation (2.2).

Table 1

Table 1 illustrates the average cumulative abnormal returns (ACAR) for the winner-, loser- and zero-portfolio. *t*-statistics from a one-sided test, formulated in accord with H_A (equation 2.2) are shown in parentheses. Values with significance at 10%, 5% and 1% are denoted with one, two and three stars, respectively. The rightmost column, Loser-Winner, shows the return from the contrarian strategy ($ACAR_{L,156} - ACAR_{W,156}$).

		ACAR at the End of The Test Period (*t*-statistics, absolute value)		
Market	Average No. of Stocks (Total)	Loser Portfolio	Winner Portfolio	Loser-Winner Portfolio
HEX	35	0.082 (0.63)	- 0.184 (1.64*)	0.266 (11.61***)
KFX	29	0.235 (1.69**)	-0.177 (1.346*)	0.412 (18.9***)
OBX	49	0.278 (1.46*)	-0.401 (3.14***)	0.680 (7.73***)
OMX	40	0.007 (0.08)	-0.314 (2.92***)	0.321 (1.96**)

Table 1 presents separated results from the tests in all markets' ACAR during the portfolio test-periods. The results are consistent with the overreaction hypothesis in all markets for the winner portfolios, albeit of varying magnitude. Specifically, all markets show signs of statistically significant overreactions for the winner portfolios. The OBX index experiences the highest reversal (-40,1%), while the lowest is found on the KFX index (-17,7%). The loser portfolios however, are more ambiguous; only KFX and OBX experience significant reversals. As discussed previously, despite the fact that some single loser portfolios are insignificant, we consistently observe a reversal in returns for the contrarian strategy, aligned with what overreaction literature would predict.

Should investors form a multinational portfolio by selling all winners (26,9%) and buying all losers (15,1%), the expected average return amounts to 42%, disregarding all transaction- and exchange rate costs. The scale of returns, constitute an important aspect of our results. De Bondt and Thaler (1985) observed an average return of 24,63% on the S&P 500, whereas we find the difference in average cumulative abnormal return between the extreme portfolios (Loser-Winner) to exceed this significantly, in all markets. We suspect that the extremity of our results, specifically relative to De Bondt and Thaler's, may be attributed to the differing sample sizes in our research; while our average portfolios consists of 8 stocks, De Bondt and Thaler's portfolios contain an average of 35 stocks. Consequently, their portfolios are more diversified and thus less exposed to extreme fluctuations of single stocks.

Yet another noteworthy aspect of our results is the fact that the overreaction is asymmetric; the extent of reversals is considerably higher for winners than for losers. The asymmetric characteristic in the Nordics is in stark contradiction to De Bondt and Thaler's (1985) findings in the U.S, where losers experienced a larger overreaction than winners.

As our results indicates the presence of overreactions for the isolated winner and loser portfolios in all markets, we are mostly concerned with the characteristics of the zero-portfolio, which ultimately epitomizes the feasibility of the contrarian strategy. These results are rather unambiguous; the zero-portfolios in Finland, Denmark and Norway are all statistically different from zero at the 1% level, and Sweden being significant at the 5% level. The theoretical aspect of these findings suggest that the contrarian strategy generates significant abnormal returns. The highest average return is observed in Norway, a tremendous return of 68%. When reviewing the results in context with our first hypothesis, we have found evidence indicative of the presence of overreactions in all Nordic markets. Thus, our results suggest that the contrarian strategy is transferable across these borders, and not unique to any particular market.

Figure 2

Figure 2 illustrates observed return patterns in each market underlying Table 1, measured by ACAR during the test period. By aggregation, one finds ACAR for the zero-portfolios.

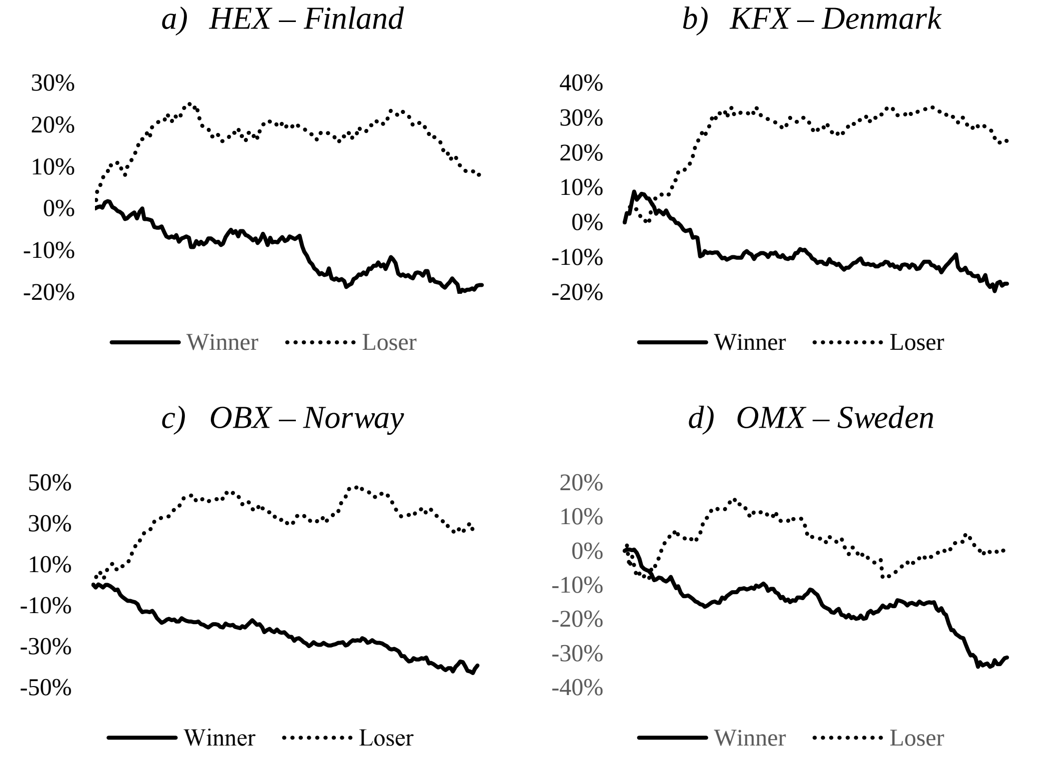


Figure 2 illustrates the underlying average return pattern presented in table 1, and captures the variation across markets. The early separation of the two portfolios is consistent with De Bondt and Thaler's initial research in the U.S market, and is consistent throughout our sample periods. Based on a visual inspection of the return patterns in figure 2, we observe a remarkable resemblance between the abnormal returns on the HEX, KFX and the OBX indexes. Contrarily, the OMX is characterized by larger fluctuations than its peers. We suspect these fluctuations to explain the higher level of variance, which in turn reduces the t-statistic, ultimately reducing the statistical significance.

Figure 3

Figure 3 illustrates relative exposure for all Nordic markets, and thus biases to various sectors, measured by the number of firms in each sector to the total number of firms on that particular stock exchange. Classification is done in accordance with that of Bloomberg, see appendix A.

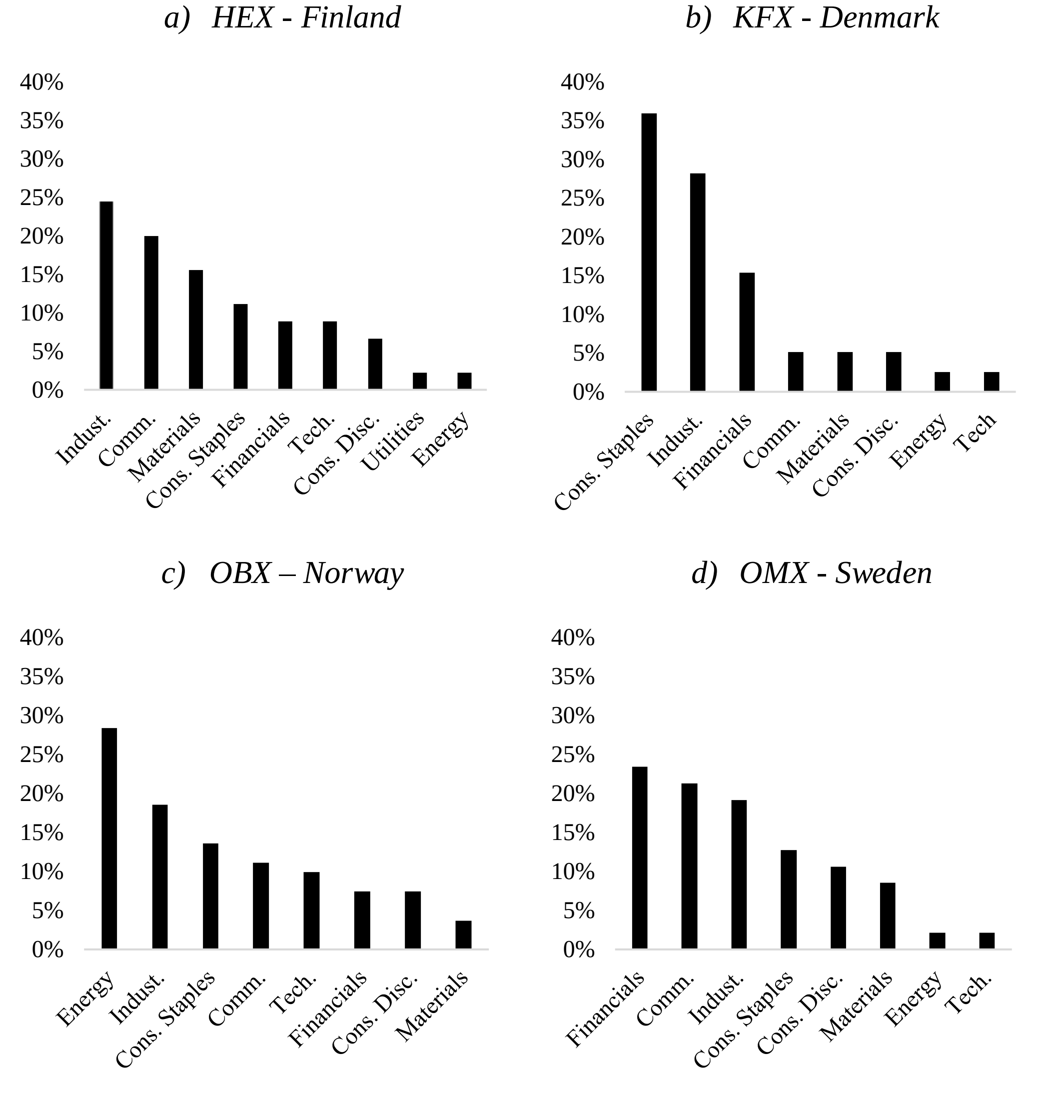


Figure 3 illustrates the market exposure and dispersion amongst relevant sectors in each of the Nordic markets. Noticeably, and quite unsurprisingly, we observe that the OBX is highly exposed to the somewhat volatile energy sector, which may explain some of the extremity in return compared to the other markets. KFX is highly exposed to consumer staples, while both the HEX and OMX are less exposed to individual sectors and can therefore be said to have a higher level of diversification. We believe these exposures to generally influence the magnitude of overreaction, i.e. due to cyclicality and general economic development.

6.2 H2: Transferability Across Sectors

Table 2

Table 2 illustrates the average cumulative abnormal returns (ACAR) for the winner-, loser- and zero-portfolio in each sector. *t*-statistics from a one-sided test formulated in accord with H_A (equation 2.3) are shown in parentheses. Values with significance at 10%, 5% and 1% are marked with one, two and three stars, respectively. The rightmost column, Loser-Winner, shows the return from the contrarian strategy ($ACAR_{L,156} - ACAR_{W,156}$).

		ACAR at the End of The Test Period (*t*-statistics, absolute value)		
Sector	Average No. of Stocks (Total)	Loser Portfolio	Winner Portfolio	Loser-Winner Portfolio
Industrials	35	0.21 (1.8**)	-0.12 (1.00)	0.34 (14.88***)
Financials	28	0.08 (0.57)	-0.19 (1.64**)	0.26 (2.72***)
Consumer (D) [a]	14	0.16 (1.13)	-0.20 (1.58*)	0.36 (23.03***)
Consumer (S) [b]	13	0.14 (0.98)	-0.23 (1.79**)	0.37 (5.4***)
Materials	17	0.13 (0.90)	-0.25 (1.57*)	0.38 (3.89***)
Energy	14	0.16 (0.67)	-0.30 (1.51*)	0.46 (4.08***)

[a] Consumer Discretionary (Cyclical)
[b] Consumer Staples (Non-Cyclical)

Table 2 presents the results of the T-test conducted in accordance with H2. The evidence of overreactions for Loser and Winner portfolios is dependent upon the sector investigated. We find indications of overreactions for winner and loser portfolios, three years' post identification of overreactions. However, we observe some differences with respect to significance of reversals between sectors.

For the Loser portfolios, we observe large differences in the level of significance; for Industrials, we even find the loser portfolio to be more significant than the winner portfolio, which contradicts the findings off all other sectors. For the Winner portfolios, we find the level of significance to be relatively consistent across sectors. Despite these differences, we see that the reversals are statistically significant for Winner portfolios at conventional levels for all sectors, except for Industrials which contradicts the results from all other sectors, for both Loser and Winner portfolios.

Although some of the individual portfolios are insignificant, we still observe positive returns to be followed by negative returns, and vice versa, in similarity to our findings in hypothesis 1. This is in line with what overreaction literature would predict, and somewhat unsurprising after investigating the reversals at market level. Compared to the significance observed at market level, the sectors are consistently lower for the individual portfolios. This may be explained by the limited number of companies represented in each sector, which further affects the variance in each portfolio. The biggest sectors represent a higher differentiated portfolio of companies, thereby decreasing the variance; ultimately affecting the t-statistic and level of significance.

Contrarily, looking at the Loser-Winner portfolio, we find all sector-portfolios to be significant at the 1% level, implying the contrarian strategy to be consistent across sectors. An average return of -21,5% for winners and 14,7% for losers, is somewhat aligned with the returns found at the market level in hypothesis 1. As discussed in section 6.1, figure 3 shows OBX to be particularly exposed to the energy sector, which experiences the highest zero-portfolio return (46%), possibly causing OBX to have the highest (68%) of all market returns.

The variability across sectors can possibly be explained by the nature of the environment in which they operate. Whilst some industries are sensitive to cyclicality and economic development, other sectors are characterized by a more stable demand-outlook regardless of the state of the economy. These findings are supported by Moskowitz and Grinblatt (1999) who found industry momentum to contribute substantially to the profitability of individual stock momentum, and that the industry momentum explains these stocks returns, almost entirely by itself.

6.3 Possible Explanations

As discussed thoroughly in the literature review, some researchers argue that the overreaction effect can in fact be attributed to a variety of factors and anomalies. In this section, we aim to identify whether these anomalies are present in the Nordic stock markets. If we find evidence of such anomalies, it is logical that the same applies for the sectors. Consequently, we address the anomalies at market level.

6.3.1 January Effect

Conrad and Kaul (1993) found that abnormal returns for both winners and losers were diminished after excluding January returns, thus contradicting what De Bondt and Thaler claimed to be explained by the OH. Zarowin (1990) found that losers do not outperform winners after considering the January effect and firm size. Nevertheless, none of these researchers suggested a particular methodology for testing this anomaly, but rather displayed the seasonal pattern through graphs. As such, we have adopted the method proposed in the revised paper by De Bondt and Thaler (1987) to examine the January effect. By isolating the average January returns in each test period, we calculate abnormal returns obtained during these months. Similarly, abnormal returns are calculated for the remaining period February-December, to investigate whether we observe abnormal returns after excluding January from our sample. Results are presented in table 3 below.

Table 3

Table 3 illustrates yearly average return patterns, measured by ACAR in fractions of the year. In panel a) January is isolated as the only single month with the purpose of investigating the presence of the "January Effect". Panel b) represents the average return in the remainder of the year. Values with significance at 10%, 5% and 1% are marked with one, two and three stars, respectively.

		ACAR from isolated periods during post-formation (*t*-statistics, absolute value)		
Period	Market	Loser Portfolio	Winner Portfolio	Loser-Winner Portfolio
Panel a)				
January	HEX	0.128 (2.34***)	0.074 (3.22***)	0.053 (14.76***)
	KFX	0.048 (1.03)	0.072 (1.18)	-0.024 (18.4***)
	OBX	0.110 (1.68**)	0.032 (0.87)	0.078 (11.0***)
	OMX	-0.103 (0.97)	0.025 (1.16)	-0.128 (5.95***)
Panel b)				
February – December	HEX	-0.045 (0.38)	-0.259 (2.41***)	0.214 (1.88**)
	KFX	0.184 (1.40*)	-0.248 (2.13**)	0.432 (6.76***)
	OBX	0.174 (0.95)	-0.424 (3.57***)	0.598 (0.80)
	OMX	0.116 (0.93)	-0.338 (3.21***)	0.454 (8.39***)

Consistent with the findings of Zarowin (1990), we observe significant abnormal returns for the Winner-Loser portfolio in January; albeit of varying degree across markets. For KFX and OMX, we find negative January returns, which is a complete contradiction to the January effect. In other words, the January effect is not present in these markets, and thereby an invalid argument for explaining the overreaction phenomenon. It is noteworthy that despite our findings of positive January for the loser portfolios (also found by Zarowin (1990); Konrad and Kaul (1993)), we also find the January returns to be positive for the Winner portfolios, and thereby suppressing the return of the contrarian investment strategy in January. This contradicts the aforementioned researchers, including the revised paper by De Bondt and Thaler (1987).

In Table 3, we find all markets except for the OBX to yield significantly positive returns in the contrarian portfolio when excluding January returns. The lack of empirical evidence for overreaction in the Norwegian stock market in table 3 may be accredited to several factors. Most prominently, we believe the vast exposure to the highly volatile energy sector can be a plausible explanation for the insignificance. Additionally, Fama (1998) argued that the momentum-anomaly[3] is approximately as frequent as the overreaction. As these two anomalies are contradictory, the consequence is that momentum would offset the effect of overreactions and vice versa; upholding Fama's theory of the efficient market. This may be translated to characterize the Norwegian market, but do by no means seem to be the case for the Nordic market as a whole. However, a continued discussion of this theory is outside the scope of this thesis' hypotheses. Therefore, we acknowledge Fama's argument, but it will not be discussed further.

[3] *The "momentum anomaly" typically refers to patterns in which the best performing stocks over the prior 3 to 12 months continue to outperform weaker performing stocks over the next 12 months.*

Table 4

Table 4 shows the yearly dispersion of return (ACAR) pattern in January throughout the three-year post-formation period. Values significant at 10%, 5% and 1% are marked with one, two and three stars, respectively.

	January-returns, measured by ACAR in respective years post-formation (*t*-statistic, absolute value)					
	Year 1		Year 2		Year 3	
Market	Loser	Winner	Loser	Winner	Loser	Winner
HEX	0.088 (2.04**)	0.017 (1.38*)	0.019 (1.31*)	0.030 (1.54*)	0.020 (0.81)	0.027 (3.19***)
KFX	0.039 (1.24)	0.065 (1.17)	-0.022 (0.80)	0.005 (0.25)	0.032 (1.96**)	0.002 (0.14)
OBX	0.044 (0.75)	0.000 (0.00)	0.040 (1.11)	0.012 (0.57)	0.026 (1.66**)	0.020 (1.42*)
OMX	-0.077 (0.84)	-0.006 (0.55)	0.020 (1.05)	0.012 (1.10)	-0.046 (0.82)	0.019 (1.24)

To further scrutinize whether abnormal January-returns can be attributed to the January effect and tax-loss realizations, we investigate the dispersion of return in January for the winner and loser portfolios during the three-year test period. The results are shown in table 4 above.

If the January effect is a consequence of tax-loss realizations, we expect the excess return in January to be stable during the three-year period, as investors do not merely realize losses during one January, but rather randomly. Table 4 presents the isolated years during the test-period. An interesting aspect of these results is the fact that all Loser portfolios in Year 1 outperform both Year 2 and 3, albeit the majority of results are not on a significant level. This is consistent with Chan's (1988) arguments; if the January effect is due to tax-loss realization, the excess return for the Loser portfolio should be diminished after Year 1.

Ultimately, the evidence presented in table 3 and 4 indicates that the abnormal returns which constitutes the overreaction phenomenon cannot be attributed to the January effect and tax-loss reasons. There may be other explanations than tax-loss related, but this is far beyond the scope of this thesis. We simply conclude that our evidence from January returns are indicative of contradicting the January effect, and thus that the overreaction effect in the Nordic Markets cannot be ascribed to this anomaly.

6.3.2 Other Considerations

As mentioned initially, the overreaction hypothesis has been vastly discussed and debated by various researchers whom have claimed to have found explanations for the mysterious phenomenon. In this section, we confront these considerations and elaborate upon our arranged alterations.

Size effect

Amongst the variety of criticism given to the original paper by De Bondt & Thaler, the size effect has been a prominent explanation for the overreaction hypothesis. There are various studies claiming the abnormal returns to be attributed to the market capitalization of firms in the different portfolios. Yet, Blume and Stambaugh (1983) explain the occurrence of the size effect to be an upward bias resulting from cumulative return calculations. Additionally, they argue that the use of a buy-and-hold method largely avoids this bias. Their findings suggest that the size effect is diminished when the buy-and-hold method is applied, rather than calculating with cumulative returns in the rebalancing method. Hence, by applying the buy-and-hold method, we have attempted to account for the size effect without going beyond the scope of our research.

Changing risk

Amongst others, Chan (1988) criticized De Bondt and Thaler for the lack of appropriate risk-adjustment in their study. Because risk is not constant, he argued that by not adjusting for changing risk, he found loser portfolios to be less risky than winner portfolios; thereby explaining the abnormal return as a simple compensation for higher risk. To adjust for this critique, we applied an asset pricing model with dynamic risk adjustment, through a rolling regression with coherent rolling betas. In contrast to the critique aimed at De Bondt and Thaler, we found evidence that would indicate an overreaction in the Nordic markets. Thus, we also attenuate the critique provided by Ball and Kothari (1989) regarding risk adjustments in overreaction studies. Our results disprove changing risk to justify the abnormal returns presented in this thesis.

Conclusion

7.1 Conclusion

This thesis is a quantitative analysis with the purpose of investigating the presence of the overreaction effect on Nordic stock markets; Finland (HEX), Denmark (KFX), Norway (OBX) and Sweden (OMX) in the period from 1996 throughout 2017. Our results are consistent with the overreaction hypothesis; we find that portfolios of prior losers consistently outperform prior winner portfolios. 156 weeks after portfolio formations, the contrarian investment strategy yields approximately 27%, 41%, 68% and 32% return on the HEX, KFX, OBX and OMX indexes, respectively. The consistency of statistically significant returns implies that the contrarian strategy is transferrable (i.e. applicable) across all Nordic markets. This is also true after addressing various criticism aimed at De Bondt and Thaler's (1985) original proposition of the overreaction hypothesis.

Moreover, the results from investigating sectors are consistent with our findings on market level; loser portfolios outperform winner portfolios in every sector, yielding statistically significant (1%) profits in all industries. We argue the plausibility of sector-exposure to directly impact the extent of returns on a market level, consistent with prior research (i.e. Moskowitz and Grinblatt (1999)).

Even though we find evidence of significant positive January-returns in the majority of investigated markets, these returns are not substantial enough to attribute the abnormal returns from the contrarian strategy exclusively to the January effect, and thus attribute the presence of overreactions solely to the January effect.

To conclude, we deem our results to be robust, as to our adjustment for the most prominent critiques given the original study; the January effect, changing risk and the size effect.

7.2 Critique

To investigate the practical profitability of the contrarian investment strategy, transaction costs must be considered. Despite the fact that our results are statistically significant, this does not imply that they are economically significant; the contrarian strategy and coherent arbitrage possibilities may be diminished by various costs such as commission-, brokerage-fees and exchange rates.

Another critique we would like to highlight is the selected methodology. Conrad and Kaul (1993) and Brown and Warner (1980) pointed out that CAR, like many other financial measures, is not flawless when measuring performance. Although CAR's are independently and identically distributed (IID), they *"like any process which follows a random walk, […] can easily give the appearance of "significant" positive or negative drift, when none is present"* (Brown & Warner, 1980). Despite this criticism, CAR is considered a superior measure, caused by its simplicity when reviewing statistical results.

Thirdly, when testing for overreactions, we have utilized equally weighted portfolios. Thus, the impact of a single stock's performance will affect the portfolio return, independently of the stock's market capitalization. This <u>may</u> lead to a bias, and that the transferability of these results is flawed. A solution to this possible bias would be to make value-weighted portfolios matching the indexes.

Lastly, an application and comparison between multiple models (i.e. CAPM, multi-factor models) could shed light upon the major strengths and weaknesses of different models used to calculate abnormal returns. Thus, providing better insight for concluding arguments.

An important aspect of the results of this thesis is the fact that the direct, practical implications of this study are limited. We do not account for transaction costs, as we are investigating a "perfect market" (i.e. similar to the assumptions underlying CAPM). Although we find statistically significant returns for the contrarian strategy, in contradiction to the EMH, this may not lead to a profitable return if trading on the strategy. Thus, we cannot conclude that the strategy is economically significant and the question of possibly capitalizing on the identified mispricing in the Nordic capital markets remains unanswered.

7.3 Future Research

Looking beyond empirical evidence presented in this thesis, as well as previous studies, we would like to encourage future researchers to consider true, practical and relevant costs in attempting to uncover whether the investment strategy would in fact be economically profitable. Additionally, a comparable study across continents could be interesting in terms of investigating possible deviations in investment behavior and risk aversion. Specifically, a comparison between developed and developing economies. We also encourage future researchers to account for anomalies, to further fortify the increasing foothold of behavioral finance.

Lastly, a qualitative research paper striving to uncover and elaborate on fundamental psychological foibles affecting investor behavior and how these irrationalities affect the dynamics of financial markets in general, would be much welcomed.

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Appendix

A – Classification and Characteristics of Sectors

Industrials (Indust.)

Companies whose businesses are denominated by one of the following activities: manufacture and distribution of capital goods, including aerospace & defense, construction, engineering & building products, electrical equipment and industrial machinery.

Financials

Category of the economy made up of firms that provide financial services to commercial and retail customers. This includes banks, investment funds, insurance companies and real estate.

Materials

Category of stocks for companies involved in the discovery, development and processing of raw materials. The sector includes the mining and refining of metals, chemical products and forestry products. The basic materials sector is sensitive to changes in the business cycle.

Consumer Discretionary, Cyclical (Cons. Disc.)

Goods and services that are considered non-essential by consumers, but desirable if their income is sufficient to purchase them. Consumer discretionary goods include durable goods, apparel, entertainment and leisure, and automobiles.

Consumer Staples, Non-cyclical (Cons. Staples)

Entail companies whose businesses are less sensitive to economic cycles. It includes manufacturers and distributers of food, beverages and tobacco and producers of non-durable household goods and personal products.

Energy

Category of stocks that relate to producing or supplying energy. This sector includes companies involved in the exploration and development of oil or gas reserves, oil and gas drilling and refining, or integrated power utility companies – including renewable energy and coal.

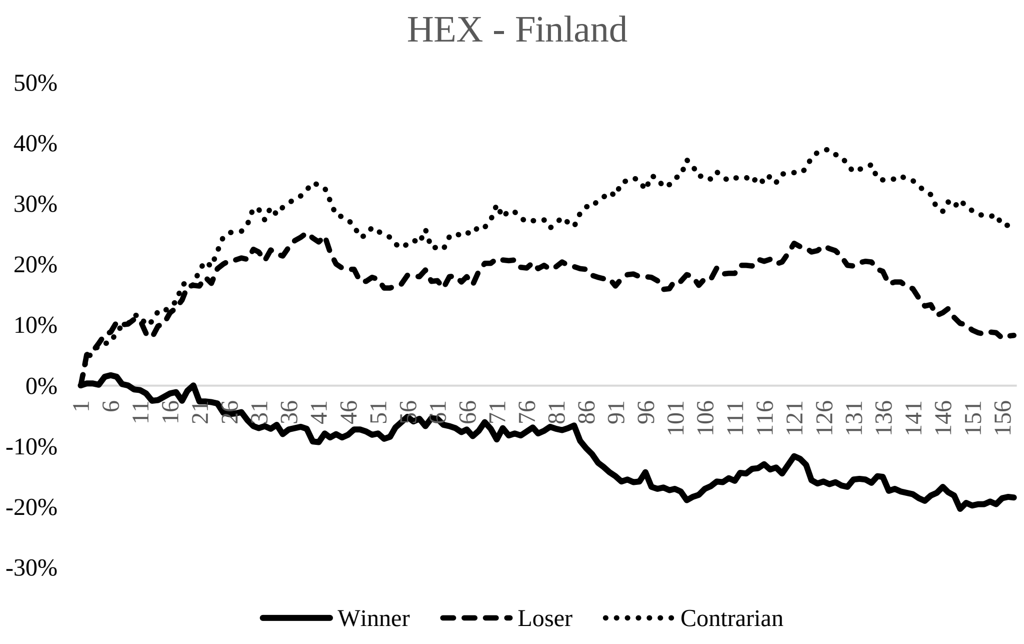
B – Contrarian Strategy Returns: Markets

Finland

CONTRARIAN STRATEGY - HEX

Average Cumulative Abnormal Returns

Period	Loser	Winner	Loser - Winner
1997-1999	-148,71 %	50,29 %	
2000-2002	-10,70 %	-9,28 %	-1,41 %
2000-2002	-68,74 %	51,75 %	
2003-2005	13,36 %	-18,20 %	31,56 %
2003-2005	-26,64 %	53,63 %	
2006-2008	-31,08 %	-32,55 %	1,47 %
2006-2008	-81,30 %	24,75 %	
2009-2011	53,22 %	-16,70 %	69,92 %
2009-2011	-47,60 %	68,38 %	
2012-2014	6,77 %	-20,15 %	26,93 %
2012-2014	-64,41 %	35,21 %	
2015-2017	17,76 %	-13,37 %	31,13 %
Average	8,22 %	-18,38 %	26,60 %
t-stat	*(0,63)*	*(1,64)*	*(11,61)*

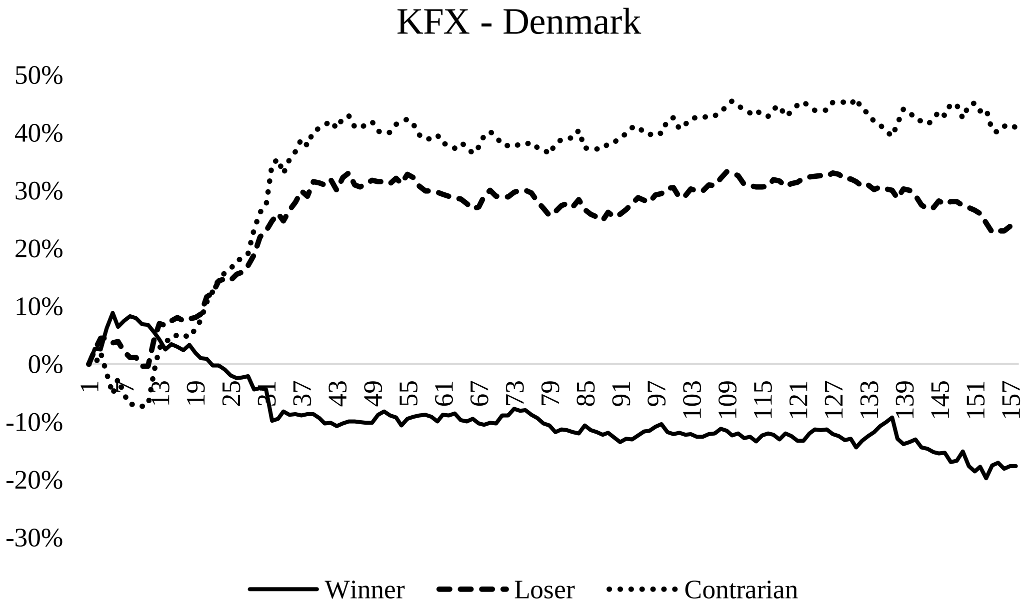


Denmark

CONTRARIAN STRATEGY - KFX

Average Cumulative Abnormal Returns

Period	Loser	Winner	Loser - Winner
1997-1999	-45,00 %	50,76 %	
2000-2002	17,49 %	-40,86 %	58,35 %
2000-2002	-62,64 %	25,57 %	
2003-2005	43,13 %	11,41 %	31,72 %
2003-2005	-24,08 %	55,40 %	
2006-2008	18,16 %	-26,96 %	45,11 %
2006-2008	-66,87 %	28,56 %	
2009-2011	23,73 %	-18,92 %	42,65 %
2009-2011	-88,22 %	38,09 %	
2012-2014	16,62 %	-11,42 %	28,04 %
2012-2014	-19,78 %	33,51 %	
2015-2017	21,85 %	-19,41 %	41,26 %
Average	23,50 %	-17,69 %	41,19 %
t-stat	*(1,69)*	*(1,35)*	*(18,90)*

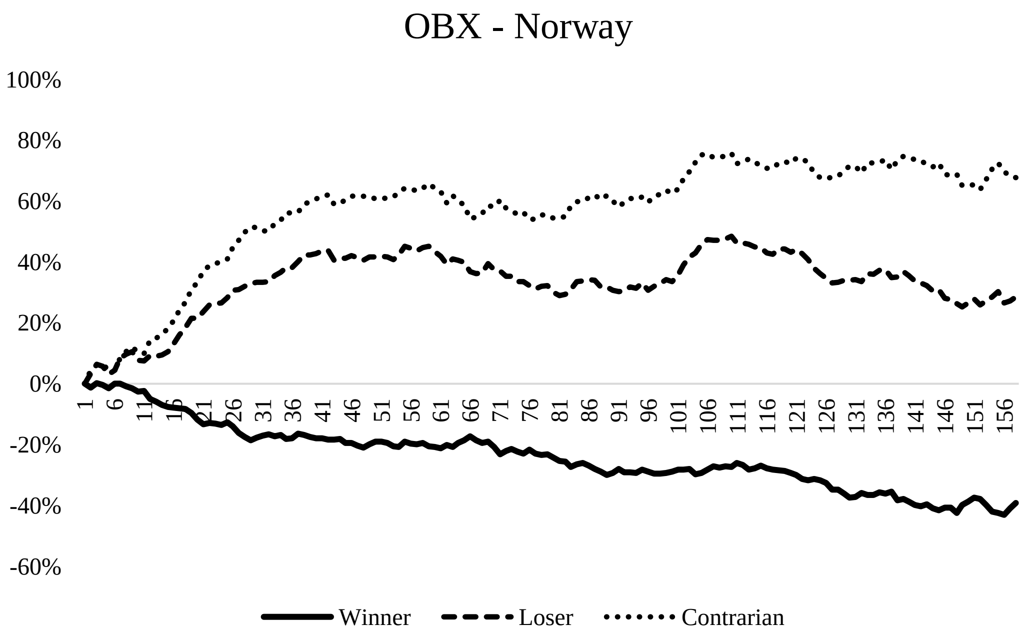


Norway

CONTRARIAN STRATEGY - OBX

Average Cumulative Abnormal Returns

Period	Loser	Winner	Loser - Winner
1997-1999	-65,68 %	120,69 %	
2000-2002	-10,24 %	-91,09 %	80,85 %
2000-2002	-133,91 %	75,12 %	
2003-2005	110,71 %	-13,90 %	124,61 %
2003-2005	-69,53 %	128,44 %	
2006-2008	-25,06 %	-44,52 %	19,46 %
2006-2008	-135,30 %	39,71 %	
2009-2011	16,64 %	-57,36 %	74,00 %
2009-2011	-80,13 %	75,58 %	
2012-2014	44,61 %	-10,26 %	54,87 %
2012-2014	-81,28 %	77,55 %	
2015-2017	30,39 %	-23,51 %	53,90 %
Average	27,84 %	-40,11 %	67,95 %
t-stat	*(1,46)*	*(3,14)*	*(7,73)*

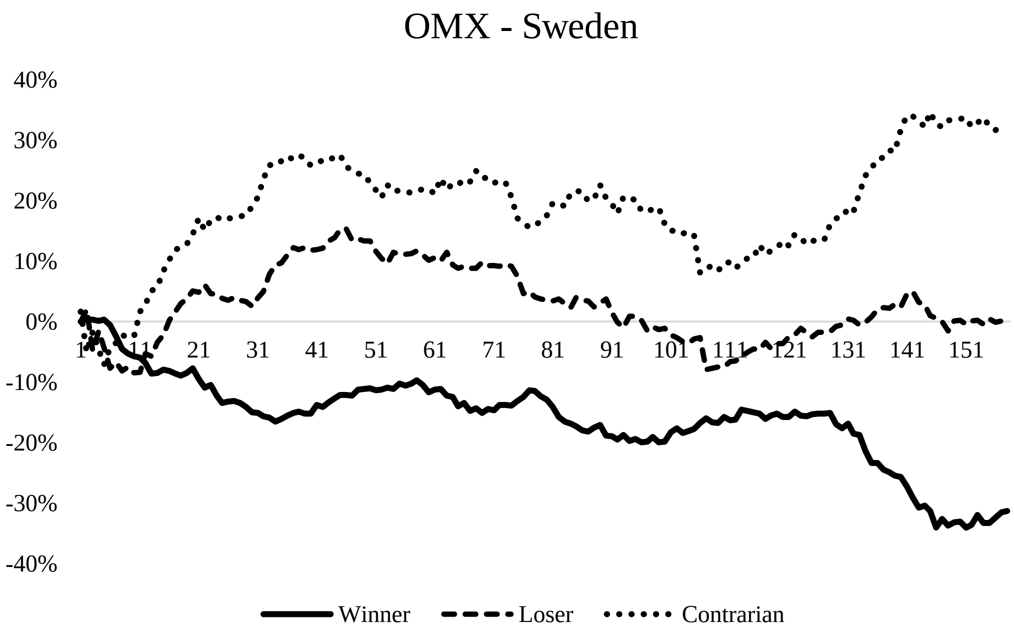


Sweden

CONTRARIAN STRATEGY - OMX

Average Cumulative Abnormal Returns

Period	Loser	Winner	Loser - Winner
1997-1999	-57,20 %	133,28 %	
2000-2002	-16,74 %	-43,71 %	26,97 %
2000-2002	-98,90 %	26,08 %	
2003-2005	18,01 %	-15,56 %	33,57 %
2003-2005	-26,09 %	41,14 %	
2006-2008	-23,34 %	-69,78 %	46,44 %
2006-2008	-104,80 %	20,32 %	
2009-2011	-6,88 %	-19,75 %	12,87 %
2009-2011	-25,21 %	65,66 %	
2012-2014	18,29 %	-32,62 %	50,92 %
2012-2014	-39,56 %	20,90 %	
2015-2017	14,86 %	-6,88 %	21,73 %
Average	0,70 %	-31,38 %	32,08 %
t-stat	*(0,08)*	*(2,92)*	*(1,96)*



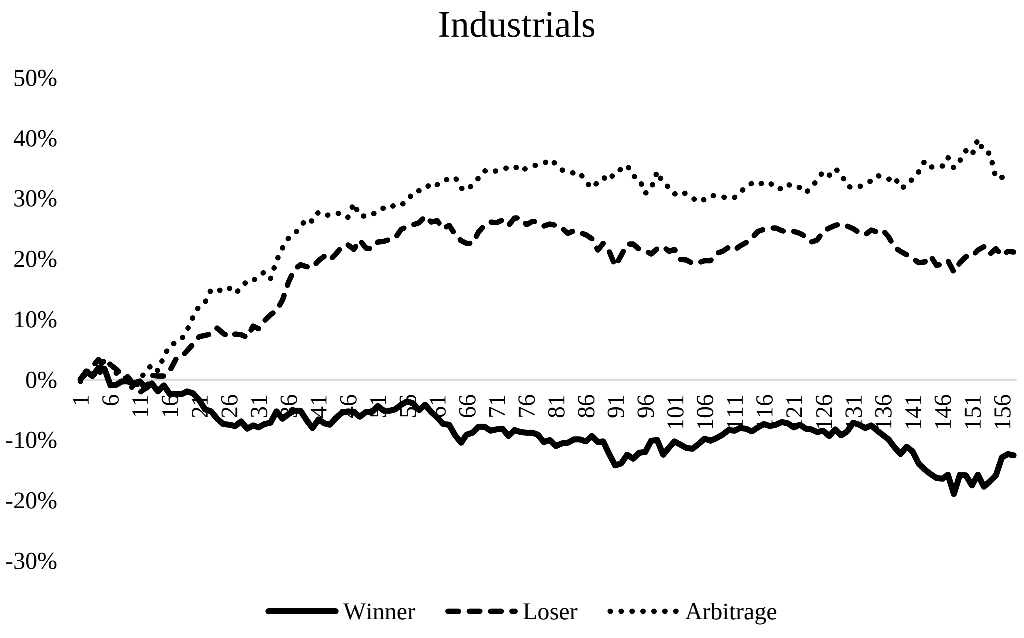
C – Contrarian Strategy Returns: Sectors

Industrials

CONTRARIAN STRATEGY - Industrials

Average Cumulative Abnormal Returns

Period	Loser	Winner	Loser - Winner
1997-1999	-55,92 %	31,57 %	
2000-2002	-1,35 %	-33,35 %	32,00 %
2000-2002	-76,02 %	8,85 %	
2003-2005	45,19 %	7,86 %	37,33 %
2003-2005	-17,25 %	73,05 %	
2006-2008	16,93 %	-5,33 %	22,27 %
2006-2008	-50,22 %	34,79 %	
2009-2011	17,49 %	-35,60 %	53,09 %
2009-2011	-55,45 %	35,58 %	
2012-2014	37,80 %	-0,75 %	38,55 %
2012-2014	-14,33 %	43,05 %	
2015-2017	11,22 %	-7,32 %	18,54 %
Average	21,21 %	-12,41 %	33,63 %
t-stat	*(1,80)*	*-(1,00)*	*(14,88)*

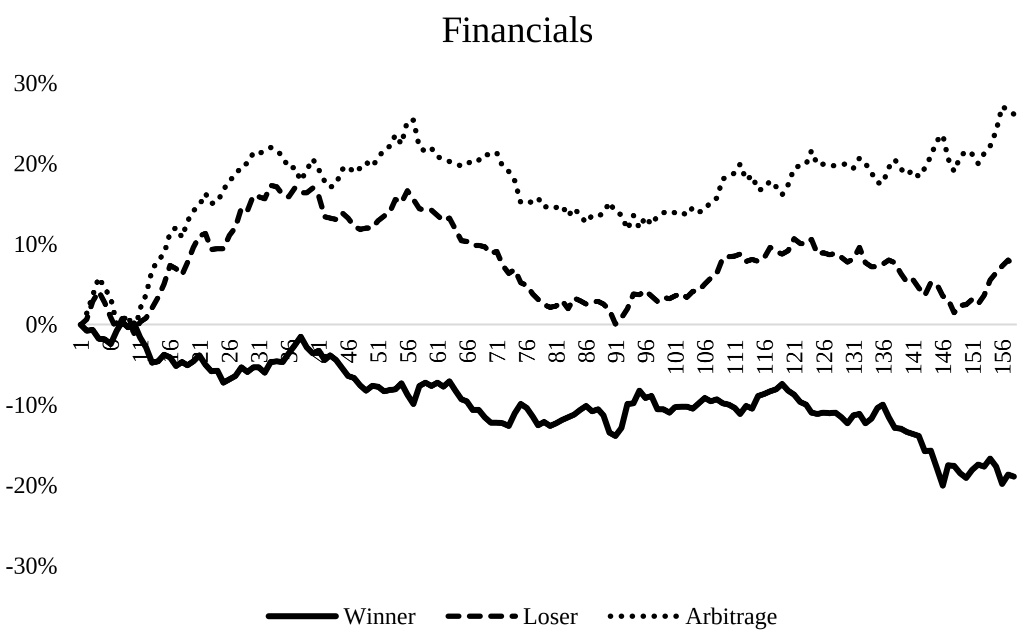


Financials

CONTRARIAN STRATEGY - Financials

Average Cumulative Abnormal Returns

Period	Loser	Winner	Loser - Winner
1997-1999	-63,38 %	32,96 %	
2000-2002	-20,67 %	-18,81 %	-1,86 %
2000-2002	-57,41 %	4,19 %	
2003-2005	19,31 %	-8,51 %	27,82 %
2003-2005	-20,73 %	26,77 %	
2006-2008	21,71 %	-41,52 %	63,23 %
2006-2008	-66,42 %	35,00 %	
2009-2011	7,90 %	-48,79 %	56,69 %
2009-2011	-50,05 %	9,91 %	
2012-2014	8,68 %	23,61 %	-14,93 %
2012-2014	-3,38 %	28,69 %	
2015-2017	8,88 %	-18,60 %	27,48 %
Average	7,63 %	-18,77 %	26,40 %
t-stat	*(0,57)*	*(1,64)*	*(2,72)*

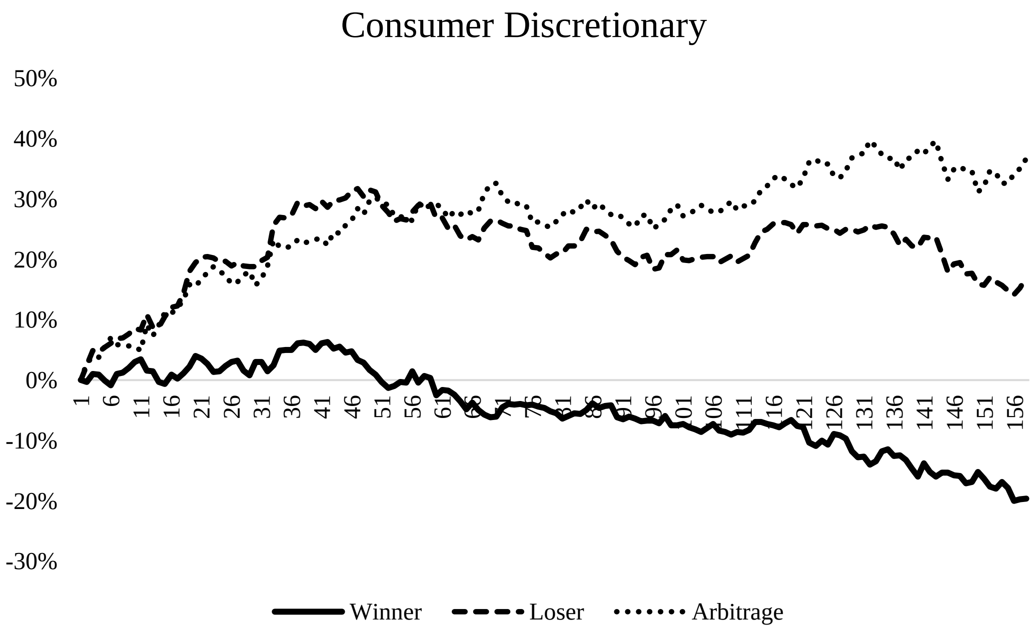


Consumer Discretionary

CONTRARIAN STRATEGY - Consumer Disc.

Average Cumulative Abnormal Returns

Period	Loser	Winner	Loser - Winner
1997-1999	-55,95 %	16,78 %	
2000-2002	-3,94 %	-21,61 %	17,66 %
2000-2002	-55,66 %	35,95 %	
2003-2005	17,26 %	18,47 %	-1,21 %
2003-2005	-17,13 %	31,54 %	
2006-2008	-9,73 %	-57,69 %	47,96 %
2006-2008	-63,08 %	23,73 %	
2009-2011	25,61 %	-11,05 %	36,66 %
2009-2011	-39,83 %	39,74 %	
2012-2014	31,55 %	-19,23 %	50,77 %
2012-2014	-36,67 %	41,46 %	
2015-2017	36,18 %	-27,11 %	63,29 %
Average	16,15 %	-19,70 %	35,86 %
t-stat	*(1,13)*	*(1,58)*	*(23,03)*

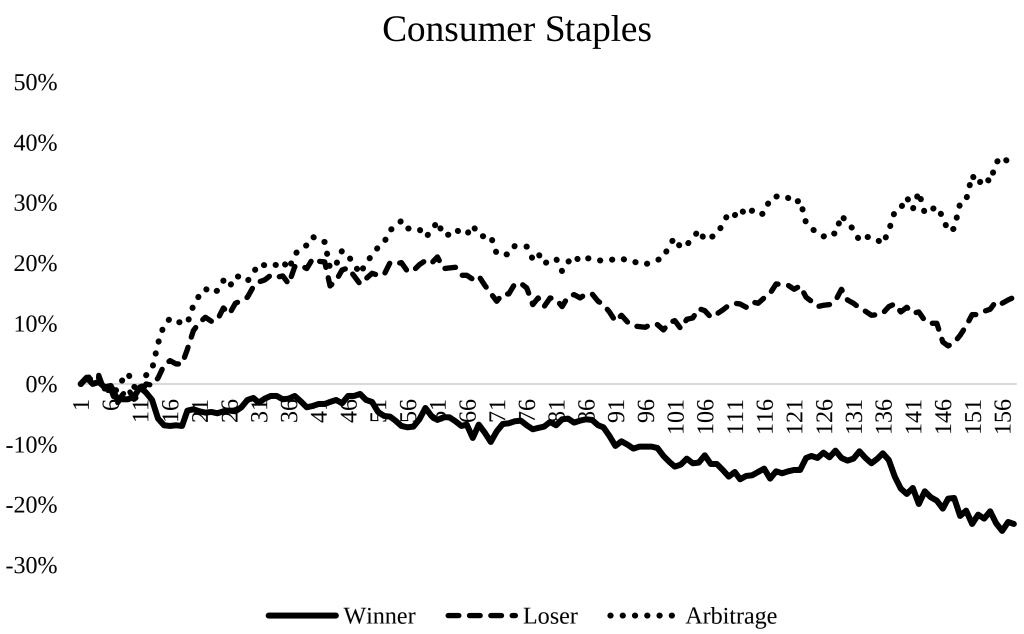


Consumer Staples

CONTRARIAN STRATEGY - Consumer St.

Average Cumulative Abnormal Returns

Period	Loser	Winner	Loser - Winner
1997-1999	-35,45 %	13,51 %	
2000-2002	-13,02 %	-90,64 %	77,62 %
2000-2002	-97,40 %	13,62 %	
2003-2005	85,25 %	0,29 %	84,96 %
2003-2005	-10,80 %	91,77 %	
2006-2008	-8,17 %	-26,69 %	18,52 %
2006-2008	-49,84 %	27,28 %	
2009-2011	7,48 %	-9,26 %	16,74 %
2009-2011	-9,18 %	17,29 %	
2012-2014	3,84 %	18,12 %	-14,28 %
2012-2014	-9,62 %	36,13 %	
2015-2017	9,50 %	-30,01 %	39,51 %
Average	14,15 %	-23,03 %	37,18 %
t-stat	*(0,98)*	*(1,79)*	*(5,40)*

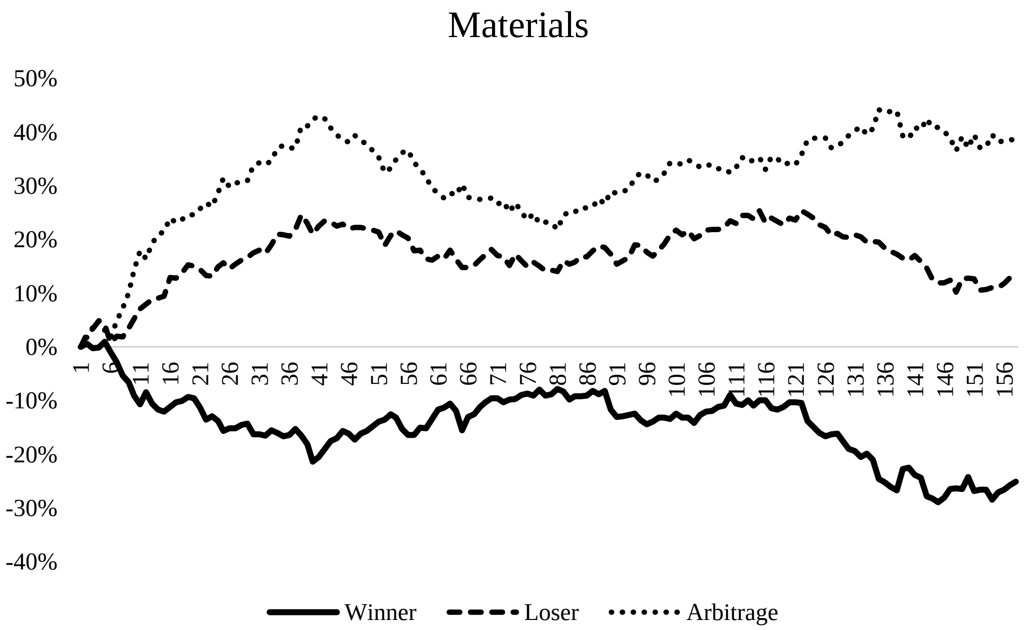


Materials

CONTRARIAN STRATEGY - Materials

Average Cumulative Abnormal Returns

Period	Loser	Winner	Loser - Winner
1997-1999	-26,70 %	36,88 %	
2000-2002	-21,25 %	-62,14 %	40,89 %
2000-2002	-77,67 %	39,90 %	
2003-2005	45,50 %	2,88 %	42,62 %
2003-2005	-14,63 %	66,94 %	
2006-2008	3,98 %	-39,75 %	43,73 %
2006-2008	-47,07 %	26,35 %	
2009-2011	4,26 %	-35,26 %	39,52 %
2009-2011	-40,53 %	31,22 %	
2012-2014	33,70 %	11,47 %	22,24 %
2012-2014	-7,61 %	39,76 %	
2015-2017	12,30 %	-29,63 %	41,92 %
Average	13,08 %	-25,41 %	38,49 %
t-stat	*(0,90)*	*(1,57)*	*(3,89)*



Energy

CONTRARIAN STRATEGY - Energy

Average Cumulative Abnormal Returns

Period	Loser	Winner	Loser - Winner
1997-1999	-66,81 %	83,78 %	
2000-2002	-79,72 %	-40,86 %	-38,86 %
2000-2002	-98,30 %	14,53 %	
2003-2005	144,23 %	-0,17 %	144,40 %
2003-2005	-40,82 %	148,92 %	
2006-2008	-24,39 %	-59,01 %	34,62 %
2006-2008	-97,66 %	2,64 %	
2009-2011	40,51 %	-24,03 %	64,54 %
2009-2011	-82,27 %	61,72 %	
2012-2014	5,12 %	-64,13 %	69,25 %
2012-2014	-79,08 %	35,03 %	
2015-2017	7,91 %	7,36 %	0,55 %
Average	15,61 %	-30,14 %	45,75 %
t-stat	*(0,67)*	*(1,51)*	*(4,08)*