Open your mind. LUT.
Lappeenranta University of Technology
School of Business and Management
Master's Programme in Strategic Finance and Business Analytics

MASTER'S THESIS

Herd Behaviour in the Finnish Stock Market – An Examination of OMXH25 Companies 1998-2017

Eemil Himmelroos, 2019
Examiner: Post-Doctoral Researcher Azzurra Morreale

TIIVISTELMÄ

Tekijä:	Eemil Himmelroos
Otsikko:	Laumakäyttäytyminen Suomen osakemarkkinoilla – OMXH25 yhtiöiden tarkastelu 1998-2017
Lopputyön tyyppi:	Pro Gradu -tutkielma
Vuosi:	2019
Yliopisto:	Lappeenrannan Teknillinen Yliopisto
Tiedekunta:	School of Business and Management
Tutkinto:	Kauppatieteiden maisteri
Maisteriohjelma:	Master's Programme in Strategic Finance and Business Analytics
Sisältö:	97 sivua, 2 kuviota, 12 taulukkoa, 2 liitettä
Tarkastaja:	Azzurra Morreale, tutkijatohtori
Avainsanat:	Laumakäyttäytyminen, Suomen osakemarkkinat, Tuottojen hajonta, Markkinoiden ääriolosuhteet, Markkinoiden tuottojen samankaltainen käyttäytyminen

Tämä Pro Gradu tutkii laumakäyttäytymistä Suomen osakemarkkinoilla 1998-2017. Tätä tarkoitusta varten OMXH25 yhtiöiden kokonaistuottoindekseistä lasketaan päivittäiset logaritmiset tuotot, keskihajonta ja absoluuttinen keskihajonta, mitkä toimivat pääasiallisina muuttujina analyyseissa. Käytettävät tutkimusmenetelmät laumakäyttäytymisen havaitsemiseen nousu- ja laskumarkkinoilla, ääriolosuhteiden vallitessa, yli kansallisrajojen Ruotsin, Norjan, Tanskan, Saksan, Iso-Britannian ja Yhdysvaltojen kanssa, päivittäisten tuottojen, päivittäisen vaihdon sekä volatiliteetin perusteella ovat laajalti tunnettuja ja niitä ovat kehittäneet Christie ja Huang (1995), Chang et al. (2000), Chiang ja Zheng (2010), Economou et al. (2011) ja Mobarek et al. (2014). Tutkielma muodostaa myös kattavan yhteenvedon aikaisemmasta kirjallisuudesta ja yrittää tunnistaa ominaisuuksia, jotka voivat aiheuttaa laumakäyttäytymistä Suomen osakemarkkinoilla. Aikaisemmat tutkimukset ovat keskittyneet enimmäkseen Yhdysvaltoihin tai Aasian markkinoille ja esittäneet ristiriitaisia tuloksia. Harvat tutkimukset ovat käsitelleet Pohjoismaita tai Suomea.

Empiiriset tulokset antavat heikkoa näyttöä laumakäyttäytymisen puolesta Suomen osakemarkkinoilla. Laumakäyttäytymistä ei havaittu erikseen nousu- ja laskumarkkinoilla tai ääriolosuhteiden vallitessa. Tulokset osoittavat, että tuotot Suomen osakemarkkinoilla käyttäytyvät samansuuntaisesti Ruotsin, Norjan, Tanskan, Saksan, Iso-Britannian ja Yhdysvaltojen markkinoiden tuottojen kanssa. Vaihtoon tai volatiliteettiin perustuvaa laumakäyttäytymistä ei havaittu. Päivittäisten tuottojen perusteella havaitaan laumakäyttäytymistä, kun edistyneempiä malleja sovelletaan. Aikaisemman kirjallisuuden ja saatujen empiiristen tulosten perusteella laumakäyttäytyminen Suomen osakemarkkinoilla voi johtua informaation epätäydellisyydestä, yhtiöiden pienestä markkina-arvosta, alhaisesta likviditeettista ja joidenkin yhtiöiden tuottojen korkeasta korrelaatiosta.

ABSTRACT

Author:	Eemil Himmelroos
Title:	Herd Behaviour in the Finnish Stock Market – An Examination of OMXH25 Companies 1998-2017
Type:	Master's Thesis
Year:	2019
University:	Lappeenranta University of Technology
School:	School of Business and Management
Degree:	Master of Science in Economics and Business Administration
Degree programme:	Master's Programme in Strategic Finance and Business Analytics
Contents:	97 pages, 2 figures, 12 tables, 2 appendices
Examiner:	Azzurra Morreale, Post-Doctoral Researcher
Keywords:	Herd behaviour, Finnish stock market, Return dispersion, Extreme market movement, Market co-movement

This thesis examines herd behaviour in the Finnish stock market 1998-2017. For this purpose, daily logarithmic returns for OMXH25 companies are calculated from total return index data and cross-sectional standard deviation and cross-sectional absolute deviation are used as main measures for herd behaviour analysis. Existing and widely recognized methodologies by Christie and Huang (1995), Chang et al. (2000), Chiang and Zheng (2010), Economou et al. (2011) and Mobarek et al. (2014) are applied to detect herd behaviour, up- and down-market herding, extreme market herding, herding with Swedish, Norwegian, Danish, German, UK and US market and daily market return, turnover volume and volatility herding. Furthermore, this thesis builds a comprehensive summary of the earlier academic literature and tries to identify some of the characteristics that could cause herd behaviour in the Finnish stock market. Earlier literature has mostly focused on US or Asian markets and presented mixed results. Very few studies have focused on the Nordic countries or Finland.

Empirical results provide weak evidence in favour of herd behaviour in the Finnish stock market. Herd behaviour is not found for up- or down market in specific or during extreme market conditions. However, results show that Finnish stock market exhibits herd behaviour with Swedish, Norwegian, Danish, German, UK and US markets. There are no signs of turnover volume or volatility herding in the Finnish stock market. Daily market return herding is found when more advanced models are applied, but more simple models do not give supporting evidence. Based on earlier literature and the empirical results of this thesis, herd behaviour in the Finnish stock market could be caused by following characteristics; imperfect information, small market capitalization, low liquidity due to lack of international investors and high correlation of returns between some companies.

ACKNOWLEDGEMENTS

Finishing a Master's degree or another degree of same calibre is a reward for all the sweat and hard work put into learning new things and constantly developing oneself. This Thesis serves as a final benchmark of an unforgettable journey and I'll view my 6 years in LUT with gratitude, thank you!

Few more thanks are worthy of mentioning. First and foremost, I'd like to thank my lovely fiancée Tiina and our two beautiful kids Aatu and Veeti for standing by my side and giving me some extra motivation in the end. I'd also like to thank all the teachers and professors I met at LUT. Especial thanks to Azzurra Morreale for cheerful comments and making this degree a reality. Lastly, I'd like to thank my friends. We had so much fun and I am grateful to have met all the wonderful people during this adventure that has now come to an end.

On to the next adventure ahead!

Eemil Himmelroos 24.6.2019 Järvenpää

Eemil Himmelroos Date & Place

TABLE OF CONTENTS

1 INTRODUCTION

A pack of wolves or a flock is stronger than its number of individuals alone and thanks to recent technological innovations and developments, following the pack has never been easier than it is now. Social media and all kinds of platforms, where people give advice to literally everything are just the tip of the iceberg. We have witnessed Bitcoin price to skyrocket and come down again, Dotcom bubble to burst, financial markets to crash and just recently overwhelming expectations loaded in the stock prices from the likes of Amazon, Apple, Google and Tesla – just to mention a few. These things happen so fast nowadays, that we cannot ignore the power of numbers, and by numbers, I mean real people – who act the same way for a period of time and eventually end up creating these conditions, which would have once been thought as extreme or temporary conditions. Extreme conditions are the new norm for people of today and in the light of these conditions some of the old beliefs and even scientific findings are not accurate anymore.

In the past decades traditional finance theories and its field of research has been challenged by a growing number of behavioural finance scholars. Behavioural finance combines psychology and finance together and with that being said, it is no surprise that the concept was first introduced in the 1980's by a pair of psychologists. Daniel Kahneman and Amos Tversky were the first ones to tailor the concept. Another notable contributor to behavioural finance is economist Richard Thaler. As an evidence about the recognition and importance of the work of these men Kahneman and Thaler have been granted the honour of Nobel Prize in Economic Sciences. Kahneman received his in 2002 and Thaler in 2017. (Nobel Media, 2018)

Behavioural finance presents somewhat opposite view compared to traditional finance theories in a sense how it deals with rationality. Traditional finance theories and concepts have usually ignored non-rational human factors, and whereas efficient markets and many asset pricing models suppose that decision-makers are rational, behavioural finance considers that individual decision-makers are subject to biases and non-rational, even impulsive, decision-making. This non-rational behaviour of human beings creates anomalies and other irregularities in the financial markets. Characteristic to this date, even social media can have a huge impact on the prices of financial instruments. Just think about what happens in the market when the president of the United States tweets anything related to tariffs, custom penalties, public support, public debt or monetary policy.

Nowadays, behavioural finance consists of many different sub-categories and concepts, which are all more or less linked to human behaviour in what we call financial decision-making situations. One could address the question, why do people behave the way they do when facing different dilemmas in decision-making? Phenomena such as market overreaction, underreaction, herd behaviour (or behavior), overconfidence and many more are all connected to behavioural finance and human behaviour. Traditionally empirical studies on behavioural finance have put much emphasis on uncovering new anomalies (Thaler, 1999).

One of the problems, that scholars face, is how to model human behaviour. While it can easily be argued, that human behaviour can explain certain phenomenon, it is much harder to show real evidence or provide parameters for accurate measuring. Another problem is the availability of data on individual investors. Nearly 20 years ago Thaler (1999) called for private firms to share data on individual investors for research purposes, but for most part this obstacle remains to be tackled. During times like these, where data is one of the most valuable assets a firm probably has, it is very unlikely that we will see huge changes in this, at least for low-cost. There are also a lot of privacy issues related to this.

In this thesis we are interested in the concept of herd behaviour in the Finnish stock market. Modelling herd behaviour in Finland is particularly interesting as the Finnish stock market possesses certain characteristics, which would indicate it being a rather inefficient market where herd behaviour could then take place. According to Saastamoinen (2008), Finnish stock market is characterized by small market capitalization of publicly traded companies apart from handful of companies and low liquidity due to lack of international investors or analysts following the stocks. These two reasons are optimal to create room for informational asymmetries that trigger herd behaviour. Another thing that makes studying herd behaviour in the Finnish stock market interesting is that previous research has yielded evidence both against and for the existence of herd behaviour.

Academic literature on herd behaviour in the stock markets is mixed. Although the phenomena is widely recognized, the empirical evidence either supports or contradicts with the existence of herd behaviour. Not so surprisingly, the loudest critics are the ones believing in efficient markets and other traditional finance theories. There are also multiple studies on herd behaviour that show no signs of herd behaviour. At this moment no real consensus exists and people either believe herd behaviour being a factor in decision-making or not.

This study contributes to the existing but scarce literature on herd behaviour in the Finnish context in a variety of ways. It increases general knowledge of the phenomenon, provides detailed literature review on earlier findings on two separate levels, 1. among certain individuals and groups 2. among companies and stock markets, both of which are important to understand from the psychological decision-making point-of-view before conducting any empirical tests. Furthermore, this study applies a number of different models to test whether herd behaviour is present or not, creating not only a comprehensive image on empirical test available but also showing the slightly different results provided by the models. No real practical implications can be directly withdrawn from the study, but investors and analysts in the Finnish stock market should be aware of how company returns behave and effect returns of other companies. For some, this study might also reveal new interesting company and market co-movement scenarios worth noting.

Herd behaviour itself is very natural to humans and we tend to follow the masses in almost everything we do. Think of young children learning new things by observing and mimicking behaviour of their elders or a person searching for most popular travelling destinations and restaurants to go to from social media platforms. An innocent child mimics other people because he is constantly growing and eager to learn new things, and most of all has an example to follow and reflect on. The latter example is strongly influenced by what other people think and say about different considerable travelling destination and restaurant options and arguable this has a major effect on the choice of an individual.

Humans are only humans after all, and this is what we see in the stock market as well. Whether it is about bounded rationality, lack of time or experience or a mix of all these, we tend to follow others. This could be one person listening to his grandfather for an investment advice or following recommendations by analytics on which stocks to buy and sell. What causes us to believe, that someone else is better in predicting future winners or losers? Or is it just coincidence? Bear also in mind, that just recently we have witnessed skyrocketing growth of stock prices in the technology segment, which is at first glance something, that is certainly not explained by the raw fundamentals behind the business.

Definition of herd behaviour is actually pretty simple and quite universal even though many scholars like to say the same thing in a bit different way. Avery and Zemsky (1998) define herd behaviour as occurring when an agent trades against his initial assessment and instead follows the trend in previous trade. Banerjee (1992) describes that herd behaviour means that everyone is doing what everyone else is doing, even though their own information would suggest them to act differently, Bikhchandani and Sharma (2001) define herding behaviour as an obvious intent by investors to ignore their personal beliefs or information and copy the behaviour of other investors. According to Nofsinger and Sias (1999) herding behaviour leads investors to move in the same direction and in and out of markets as a group, or as Grinblatt, Titman and Wermers (1995) would put it "a group of investors transacting in the same way, in a same direction for a given period of time." Christie and Huang (1995) define herd behaviour in a market setting: "herds are characterized by individuals who supress their own beliefs and base their investment decisions solely on the collective actions of the market, even when they disagree with its predictions." By combining all the above definitions, we are able to get a comprehensive overview on what is defined as herd behaviour.

After identifying the concept of herd behaviour, scholars have been able to identify reasons behind it. According to Chang, Cheng and Korana (2000) investor's behaviour is linked to different factors, such as investment horizons, performance measuring, behaviour of other market participants, volatility and presence of fads and speculative trading, and herding can be rational or irrational. Based on previous theoretical studies, Demirer, Kutan and Chen (2010), classify that there are three different explanations on what might trigger herd behaviour; investor psychology, available information and principal-agent relationship. Interestingly, it is also suggested that some markets are culturally more prone to herd-like behaviour (Schmeling, 2009).

Objective of the thesis is to study herd behaviour and its forms in the Finnish stock markets in a detailed way. Motivated by previous findings and existing methodology on herd behaviour in the stock markets (presented more closely in section 2), the main research question of this thesis is:

"Is Finnish stock market subject to herd behaviour?"

To support the main research question, following sub-questions are formed:

"Is herd behaviour found during extreme market conditions or time periods?"

"Does Finnish stock market herd with other stock markets?"

"What are the reasons or characteristics that may cause herd behaviour in the Finnish stock market?"

By answering these research questions through comprehensive analysis of stock market data, a framework for herd behaviour in the Finnish stock market can be build. Apart from empirical work in this thesis one of the goals is to provide a detailed and comprehensive literature review on herd behaviour.

No study is conducted without having any limitations. Limitations of this thesis include, that it mostly deals with herd behaviour in the Finnish stock market, which is not so attractive to foreign investors as a market. This in turn creates illiquidity. Finnish stock market in general is quite centralized and controlled by few big institutional investors such as pension funds, banks and the government. The methods used to detect herd behaviour are also a bit limited and there is no universal consensus on what the best method is. It could be, that the best method to study herd behaviour is yet to be developed.

This thesis is organized as follows: Section 2 summarizes the main findings of the previous empirical papers on herd behaviour in economic context. Section 3 presents all the data and relevant methodology used in this thesis. Section 4 presents the results of the empirical analysis of the data. Finally, section 5 presents the conclusions and implications of this thesis and links the findings of this paper to earlier academic literature of the subject.

2 LITERATURE REVIEW

This section presents the main findings of the earlier academic literature on herd behaviour in the financial market. Most of these studies have been conducted in the past two decades, which highlights that the topic has been recognized by the science community very recently. All in all, herd behaviour in managerial decision-making and financial markets has been examined for roughly 30 years. Schiller and Pound (1986), Scharfstein and Stein (1990), Bikhchandani, Hirshleifer and Welch (1992), Froot, Scharfstein and Stein (1992), Welch (1992), and Christie and Huang (1995) were among the first ones to examine and model herd behaviour. They apply different methodologies and slightly different reasoning in their studies.

Modelling herd behaviour using return dispersions has been the most popular approach among scholars investigating herd behaviour in the financial markets. Pioneers of this approach include Christie and Huang (1995) and Chang et al. (2000). Their work has then been continued by numerous other scholars (see for instance Gleason, Lee and Mathur, 2003; Chiang and Zheng, 2010; Demirer, Kutan and Chen, 2010; Economou, Kostakis and Philippas, 2011; Mobarek, Mollah and Keasey, 2014). Return dispersion, such as cross-sectional standard deviation of returns (later also CSSD), captures the key attribute of herd behaviour as it quantifies the degree to which asset returns tend to rise and fall in relation to market portfolio (Christie and Huang, 1995). As an alternative return dispersion measure for CSSD Chang et al. (2000) used cross-sectional absolute deviations (later also CSAD). CSAD is a more powerful measure to detect herd behaviour and assumes non-linear relationship between returns and dispersions unlike CSSD, which works better if the relationship is linear (Chang et al., 2000). Most of the later studies use CSAD as the dispersion measure and dependent variable in the regression models. Regressions models applied in this thesis are presented in more detail later in section 3.2 of this thesis.

For the purpose of this thesis, previous studies on herd behaviour in the financial market are divided into four different sub-categories, which are: herding inside one market and/or between markets, herding among individuals or certain groups in the market, herding in certain market situations, and other studies on herd behaviour. Each category acts as a chapter of its own for this literature review section of this thesis. It is worth noting that many studies have elements from more than one category and therefore categories presented here are not mutually exclusive. Chapter 2.2, which presents herding among individuals or certain groups in the market differs from the rest of the chapters in a sense that it deals with individuals such as fund managers and decision-makers rather than firm or market level research characterised by rest of the chapters. There are two main reasons why this has been included in the thesis: 1. it is important to understand the psychological aspects that are involved in decision-making and could create herd behaviour 2. one of the goals for this thesis is to present a comprehensive literature review on herd behaviour in the financial markets and it would not be possible if we had excluded this body of research which for instance presents us with informational cascades that are important finding for herd behaviour literature.

2.1 Herding inside one market and/or between markets

Herd behaviour inside one particular stock market or between two or more stock markets has been of major interest for scholars. Most of the studies are based on empirical frameworks presented by Christie and Huang (1995), Chang et al. (2000) or alternatively Hwang and Salmon (2004). Christie and Huang (1995) approach is based on the cross-sectional standard deviation of returns (CSSD), Chang et al. (2000) approach is based on the cross-sectional absolute deviation of returns (CSAD) whereas Hwang and Salmon (2004) method uses the cross-sectional standard deviation of the individual asset betas. Christie and Huang (1995) and Chang et al. (2000) papers act as a core for this thesis and their methods with little adjustments are applied.

Christie and Huang (1995) examine price implications of herding by investigating whether equity returns reveal the presence of herd behaviour. Predictions of herd behaviour were compared to predictions of rational asset pricing models. Christie and Huang (1995) used cross-sectional standard deviation (CSSD) of returns to capture the presence of herd behaviour in the US during periods of extreme price movements and market stress. Data consisted of daily and monthly returns from the Center for Research in Securities Prices (CRSP) at the University of Chicago. Daily data for NYSE and Amex firms was from July 1962 to December 1988, whereas the monthly data for NYSE firms was from December 1925 to December 1988. Portfolio returns were considered equally weighted. Dispersions were calculated for industry portfolios determined by two-digit SIC classification to test herding within industries. Finance and real estate, construction, service, and leisure industry sectors were excluded from monthly portfolios to ensure, that monthly portfolio contained at least 25 securities in any month. Dispersion was found to increase during periods of market stress, which indicates that individual returns do not cluster around the market or around industry returns during periods of extreme price movement. Furthermore, actual dispersion and dispersion predicted by the rational asset pricing models were very similar. These findings suggest no evidence of herd behaviour and according to authors it is possible that herds have a tendency to form around indicators other than the average consensus of all market participants. Even though the model did not test positive for herd behaviour in this setting, it has become widely recognized and used in the science community.

An extension to Christie and Huang (1995) approach is presented by Chang et al. (2000), who propose a new approach, cross-sectional absolute deviations (CSAD), to detect herding using non-linear specification. According to Chang et al. (2000) their approach is more powerful to detect herding based on equity return behaviour. They examine the investment behaviour of market participants in US, Hong Kong, Japan, South Korea and Taiwan. The data for US firms was taken from CRSP, whereas data for other markets was obtained from the Pacific-Basin Capital Markets Research Center (PACAP) records of the University of Rhode Island. They found no evidence of herding in US and Hong Kong, and partial evidence of herding in Japan. In the case of South Korea and Taiwan, however, significant evidence favouring herd behaviour was documented. All of the results are robust across size-based portfolios and over time. Moreover, macroeconomic information seems to have more impact on investor herding behaviour than firm-specific information. This was observed especially in the case of South Korea and Taiwan. Chang et al. (2000) results for US are consistent with earlier work by Christie and Huang (1995).

Work by Chang et al. (2000) is questioned by Bohl, Branger and Trede (2017), who suggest that the true coefficient of Chang et al. (2000) model is positive under the null hypothesis of no herding and not zero as assumed by Chang et al. (2000). They claim, that Chang et al. (2000) test is biased against finding evidence of herd behaviour and after adopting proper testing procedure and definition of the null hypothesis Bohl et al. (2017) observe clear evidence in favour of herding behaviour in the S&P 500 and the EuroStoxx 50 indices.

Gleason et al. (2003) extend research on herding behaviour to contracts traded on European futures markets. They apply Christie and Huang (1995) model to identify existence of herding behaviour in thirteen commodity futures contracts traded on three European exchanges. The daily price series for the thirteen commodity futures contracts was obtained from the Knight-Ridder Database. Analysis indicates, that herding behaviour is not present in the futures markets and individuals trading in futures markets believe in themselves rather than consensus. Furthermore, dispersion increases during extreme market periods which is against assumptions of Christie and Huang (1995).

Hwang and Salmon (2004) separate behavioural herding from common movements in asset returns after changes in fundamentals occur. They propose a state space model based on the cross-sectional dispersion of the factor sensitivity of asset betas rather than returns. This approach is applied to daily data from 1 January 1993 to 30 November 2003 in the US, UK and South Korean stock markets. The results suggest significant herding movement toward the market. Herding movement is persistent from return volatility, the level of mean return and whether the market was rising or falling. Macro factors are found not to explain herding patterns. Furthermore, cycles of herding and adverse herding over time was reported. Herding across markets revealed some patterns (correlation between the US and the UK was 0,435 for instance), but market sentiment does not transfer internationally every time.

Another study applying Hwang and Salmon (2004) methodology was conducted by Wang and Canela (2006). They analyse monthly total returns of 21 financial markets between January 1985 and December 2005 and propose one robust regression technique to calculate the betas of the CAPM and Fama-French three factor model with an intention to diminish the impact of multivariate outliers. Results show that emerging markets have higher level of herding than developed markets. It was also found that correlation of herding between two markets from the same group is higher than between two markets from different groups. Surprisingly, Japan showed negative correlation with all other developed markets included in the analysis. Wang and Canela (2006) call for future research on the possible factors influencing the herd behaviour towards the market along many other interesting questions.

Demirer and Kutan (2006) examine herd behaviour in Chinese markets using both individual firm- and sector-level data. The data set contains daily stock returns for 375 Chinese stocks over a time period from January 1999 to December 2002 and daily sector indices of the Shanghai and Shenzhen Stock Exchanges. The data for Shanghai consists of four sectors for a sample period from 3rd of May 1993 to 16th of November 2001 for a total of 1860 observation, whereas the data for Shenzhen had five sectors from 20th of July 1994 to 16th of November 2001 for a total of 1554 observations. Authors use methodologies by Christie and Huang (1995), Chang et al. (2000) and Gleason et al. (2003, 2004) to analyse return dispersions during periods of large upward or downward changes in the market. Demirer et al. (2006) findings support rational asset pricing models and market efficiency and find no evidence of herd behaviour in the Chinese market. Based on this evidence, investors in Chinese markets tend to make investment decisions rationally.

Another study of Demirer and Kutan, featuring also Chen (Demirer et al., 2010) examined investor herding behaviour in the Taiwanese market using firm level data within different industry portfolios. Their data set contains daily returns for 689 Taiwanese stocks across 18 different sectors traded on the Taiwan Stock Exchange over a period from January 1995 to December 2006. By applying the non-linear model of Chang et al. (2000) they find strong evidence of herd formation in all sectors of the Taiwanese stock market. Also results obtained by model of Hwang and Salmon (2004) leads to similar results. Interestingly, Demirer et al. (2010) found, that linear model based cross-sectional standard deviation testing method proposed by Christie and Huang (1995) yields no significant evidence of herd behaviour. Herding effect was found stronger during periods of market loss.

One of the first papers to use intraday data to test for herd behaviour was Henker, Henker and Mitsios (2006), who use high frequency intraday data to test for market-wide and industry sector herding in the Australian equities market by employing Christie and Huang (1995) and Chang et al. (2000) models. Data comprised from a total of 476 638 intraday observation from 160 frequently traded stocks in the ASX 200 index in 2001 and 2002. Henker et al. (2006) analysis found no evidence of market-wide or industry sector intraday herding in Australian equities market, thus supporting rational asset pricing models.

Standard methodology to detect herd behaviour employs ordinary least squares and dummy variable models. In a study considering 32 companies in the Helsinki Stock Exchange between June 28th 2002 and 31st May 2007, Saastamoinen (2008) employs quantile regression model for the estimation. This approach is suitable for analysing return dispersions in the extreme lower tails of stock return distribution. Saastamoinen (2008) also uses Chang et al. (2000) methodology and interestingly it leads to different results than quantile regression analysis. Chang et al. (2000) model shows no sign of herd behaviour, but with quantile regression, dispersion is found to increase in a less-than proportional rate with the market return at the lower tail of stock return distribution, which according to author, could be an evidence of herding. In the upper tail of stock return distribution rate of increase is found nonlinearly increasing, which implies that stock return dispersion actually increases more than CAPM suggests in the rising markets. Saastamoinen (2008) study is interest in a sense it deals with Finnish stock market data. Furthermore, he mentions, that characteristics of the market in Helsinki suggest that herding could be present. These characteristics include number of small size companies and illiquidity due to lack of international investors.

Goodfellow, Bohl and Gebka (2009) examine individual and institutional investors' trading behaviour in the Polish stock market. They test for the presence of herding behaviour during market up- and downswings by combining methods of Christie and Huang (1995) and Chang et al. (2000) with institutional features of Warsaw Stock Exchange. Daily closing prices for all traded stocks from 9th of July 1996 to 16th of November 2000 were used and individual and institutional trading was distinguished from one and other by analysing two trading platforms separately. The results of the analysis suggest, that individuals engage in herding during market downswings, but not so much during market upswings. Institutions' trading behaviour does not exhibit herd behaviour regardless of the market conditions. Results are interesting in a sense, because they show differences across users of two different trading platforms of one stock exchange.

Chiang and Zheng (2010) extend the analysis of herd behaviour to global stock markets. Applying daily industrial stock return data from 18 countries, they find evidence of herding in what they call advanced stock markets, excluding US markets, and in Asian markets. They found no evidence of herding behaviour in Latin American markets. Except for US and Latin American markets, herding was found in both up and down markets. Results also suggest that crisis trigger herding activity in the crisis country, and this has a triggering effect on the neighbouring countries as well. Interestingly, investors tend to herd with US market in addition to their domestic markets. This could indicate, that excluding foreign markets from herd behaviour testing may produce biased estimates and lead to false conclusions.

Even though numerous studies have been carried out, they rarely analyse herd behaviour in European countries. According to Khan, Hassairi and Viviani (2011), traditionally research has put emphasis on Asian markets and the US markets. Khan et al. (2011) use Hwang et al. (2004) model in a study that focuses on herding in European countries. The scope of the research included data from France, UK, Germany and Italy. Herding behaviour existed in all four countries, when market turmoil and crisis were excluded. This indicates, that herding was present during times of normal market fluctuation.

Economou et al. (2011) study cross-country effects in herd behaviour in the Portuguese, Italian, Spanish and Greek market by analysing daily stock returns for January 1998-December 2008 period using methods by Christie and Huang (1995), Chang et al. (2000) and Chiang and Zheng (2010). Their analysis shows that herding effects are present in the Greek and the Italian market, evidence was mixed for the Portuguese market and no evidence was found for the Spanish market. Evidence also shows, that herding effects present significant asymmetries when considering rising and falling markets, days with high and low trading activity and volatility. Given the results, Economou et al. (2011) conclude that these four markets have great degree of co-movement, which in turn leads to poor portfolio diversification opportunities in these markets. Financial crisis did not trigger more intense herding behaviour in these four markets.

De Almeida, Costa and Da Costa Jr. (2012) provide empirical evidence from the Latin America and examine the presence of herd behaviour in Latin American stock markets using methods by Christie and Huang (1995) and Chang et al. (2000). They analyse daily closing prices and trading volumes from 3.1.2000 to 15.9.2010 in Argentina, Brazil, Chile, Mexico and the United States, with the last one providing a reference for comparison. No evidence of herd behaviour was found using Christie and Huang (1995) method, but Chang et al. (2000) method provided evidence of herd behaviour in the Chilean market for the whole period. Herd behaviour was found asymmetric in Chilean, United States, Argentinean and Mexican markets. For future studies, authors suggest adding additional exogenous variables to regression models and applying additional tests and new models to identify and capture herd behaviour.

Messis and Zapranis (2014) investigate herding behaviour and volatility in the Athens stock exchange over 1995-2010 time period using the state space model introduced by Hwang and Salmon (2004). Different portfolios were formed based on estimated betas and size. Herd behaviour was detected on two time periods, over the 1998-2003 and 2008-2010 period. Herding had positive affect on volatility measures and authors suggest that it should be treated as an additional risk factor in future stock market analysis.

Mobarek et al. (2014) examine country specific herding behaviour in 11 different European countries (Germany, France, Portugal, Italy, Ireland, Greece, Spain, Sweden, Norway, Denmark and Finland). Analysis was conducted to most liquid constituent shares of the main indices by of these countries using methods of Chang et al. (2000), Chiang and Zheng (2010) and Economou et al. (2011). Mobarek et al. (2014) report insignificant results for the whole 2001-2012 analysis period but found significant herding behaviour during crises and asymmetric market conditions. In particular, herding effect is significant during financial crisis for the continental countries and during Eurozone crisis for the Nordic countries. PIIGS (Portugal, Italy, Ireland, Greece and Spain) countries showed evidence of herd behaviour during both crises. Mobarek et al. (2014) reported also evidence that the cross-sectional dispersions of returns can be partly explained by the cross-sectional dispersion of other markets. Especially Germany had greatest influence on others, which is not a surprise as we often consider Germany being the European benchmark economy. This study showed that even developed European countries are prone to herd behaviour when there is turbulence in the market.

Investor herding behaviour in a segmented setting is studied by Tan, Chiang, Mason and Nelling (2008), who examine herding behaviour in Chinese listed A-share and B-share stocks in Shanghai and Shenzhen stock exchange for a period from the 12th of July 1994 to the 31st of December 2003. Tan et al. (2008) report evidence of herding in both, the domestic investor dominant A-share market and the foreign institutional investor dominant B-share market. Herding occurs in both rising and falling markets, but for A-shares, the herding behaviour exhibits asymmetric tendencies, which are not found among B-share investors.

Like Tan et al. (2008), also Yao, Ma and Peng He (2014) examined Chinese A and B stock markets. They used daily and weekly data for firms listed in Shanghai and Shenzhen stock exchange over the period from January 1st 1999 to December 31st 2008. Once again Christie and Huang (1995) and Chang et al. (2000) approach was employed. Yao et al. (2014) report different levels of herding behaviour across A and B markets. Main findings of the study include; strong herding in the B-share market and no evidence of herding in the A-share market, across markets herding being more prevalent at industry level, stronger for the largest and smallest stocks and stronger for growth stocks in comparison to value stocks. During periods of market decline herding behaviour is more pronounced and it diminishes over time despite the market setting. Robustness tests show, that herding behaviour is persistent after controlling for market liquidity. Consistent with earlier findings by Tan et al. (2008), Yao et al. (2014) suggest differences in the level of herding in the different markets. A-share investors in the Shanghai market display asymmetric characteristics.

As numerous scholars before, herding behaviour in the US stock markets is examined by Jlassi and Bensaïda (2014). They modify herding measures developed by Chang et al. (2000) and Christie and Huang (1995) by introducing trading volume component to both of the models. Analysis considers daily data of all DJIA and S&P 100 index firms from 4th of January 2000 to 20th of July 2012. Jlassi and Bensaïda (2014) results indicate, that herding is present and a long-lived phenomenon in the American financial market. Moreover, herding is more pronounced in the S&P 100 index than in the DJIA index and trading volume contributes in increasing asymmetric herding. VAR and Granger causality tests reveal a causal link of herding and trading volume, but interestingly trading volume itself cannot generate herding behaviour, except for liquid market. On the other hand, contemporaneous herding is seen as deterministic factor for increasing trading volume. Examination of herd behaviour during Subprime crisis shows that herding is more intensified during the crisis.

Demirer, Lien and Zhang (2015) study the relation and impact of industry herding on return momentum by analysing 2430 stocks in 50 different industries on the Shanghai and Shenzen stock exchanges from January 1996 to December 2013. After applying methods of Christie and Huang (1995) and Chang et al. (2000) and constructing portfolios for winner and loser companies, Demirer et al. (2015) suggest, that profitability of industry momentum strategies depends on the level of herding. There is an asymmetric relationship between herding and momentum returns. Winner industries outperform loser industries and loser industries with low level of herding yield higher returns than loser industries with high level of herding in following months. There is no significant difference among winner industries.

Javaira and Hassan (2015) examine herd behaviour in the Pakistani stock market by assigning methodologies of Christie and Huang (1995), Chang et al. (2000) and Gleason et al. (2004). They use daily and monthly stock data of Karachi Stock Exchange KSE-100 index for the 2002-2007 period. No evidence of herding behaviour was found in general, but March 2005 liquidity crisis exhibited some characteristics of herd behaviour. During periods of extreme price movements, equity dispersions tended to increase rather than decrease.

Guo and Shih (2008) examine herd behaviour in the Taiwanese stock market. Guo and Shih (2008) study focuses on high-tech stocks, which in fact can be thought to be more sensitive to herd behaviour-like movement. They found high-tech industries to have more significant evidence of return dispersion, volatility dispersion and higher degree of directional co-movement than traditional industries. Return and volatility dispersions were found to be associated with extreme market movements for high-tech stocks. As in many other studies, the analysis was conducted by using Christie and Huang (1995) methodology, but also model by Lakonishok et al. (1992) was used in order to detect directional co-movement of stock prices.

Like Guo and Shih (2008), also Huang, Lin and Yang (2015) study the impact of idiosyncratic volatility on investment behaviour of market participants in Taiwan equity market. Their empirical analysis following methods by Christie and Huang (1995) as well as Chang et al. (2000) shows evidence in favour of herd behaviour in Taiwan equity market and herding shows distinct patterns under various portfolios according to idiosyncratic volatility. Investment behaviour was reported to be different during the financial crisis.

Motivated by earlier findings on the Indian market, which imply no evidence of severe herding behaviour Dutta, Gahan and Panda (2016) revisit the theme and examine herding behaviour in the Indian stock market by using methodology developed by Christie and Huang (1995). Their analysis on daily tick data of 50 stocks of various capitalizations and the Index from 2006 to 2016 shows that some periodic herding exists in the Indian stock market. In particular, herding was observed when returns enter lower tail and markets are showing signs of panic. Dutta et al. (2016) suggest that Indian market is of semi-strong form based on the study.

Shah, Shah and Khan (2017) examine herding behaviour in the Pakistan stock market. Their examination is multidimensional as it investigates herding of firms towards market, herding of firms towards industry portfolios, herding of industry portfolios towards market, herding in mostly traded stocks, large and small stocks, and herding under the crisis. They use the model of Christie and Huang (1995) on daily closing prices of 609 firms in the Pakistani stock market from January 2004 to December 2013. Results indicate that individual firms do not herd towards market index unless the Pakistani market has a negative return of 5 % or more percent. Other results include, that large firms are found suspect to herd behaviour during extreme market movements and firms in several industries herd towards their industry portfolios. However, evidence for industry portfolios to herd toward the market is reported to be weak.

2.2 Herding among individuals or certain groups in the market

Most of the studies concerning herding among individuals or certain groups in the market are concentrated around institutional investors or mutual fund managers. One of the first recognized papers on this kind of herd behaviour is the one Schiller and Pound wrote in 1986 with a headline; "Survey Evidence on Diffusion of Interest Among Institutional Investors". By the time the survey was conducted, no real models to detect herd behaviour had been developed. By analysing the survey material of 71 completed questionnaires, Schiller and Pound (1986) found supporting evidence on the existence of herd behaviour among professional institutional investors. Some of the investors were found to exhibit unsystematic behaviour allowing word-of-mouth or other stimuli to affect their decision-making.

Scharfstein and Stein (1990) examine the forces leading to herd behaviour in an investment decision-making situation. They introduce a "learning" model, which includes corporate investment decision and managers who are in charge of the investment. The model applies better to a corporate investment than to the stock market. There are two firms involved, firm A and firm B, which are run by managers A and B respectively. Manager A makes the decision first at date 1 and this is followed by the decision of manager B at date 2. It is assumed, that there are two types of managers: "smart" ones, who receive information about the value of an investment, and "dumb" ones, who receive only noisy signals. The value of the investment will realize in the future and each manager receives a signal. There are two possible signals, good and bad and two possible outcomes for the investment, high and low state. Ex ante distribution of signals is the same for both manager types, but managers themselves don't know whether they are smart or dumb. If one manager is smart and the other is dumb, their signals are drawn independently. Same goes, if both of the managers are dumb. If both managers are smart, they are assumed to draw the same signal. Based on the analysis Scharfstein and Stein (1990) propose, that reputational concerns, "sharing-the-blame" effect and the state of managerial labour market have influence on herding. "Sharing-the-blame" effect is a result of correlated prediction errors that lead managers to herd. Furthermore, it was found, that under certain circumstances managers simply mimic investment decisions of other managers and ignore their own private information.

Bikhchandani et al. (1992) study behaviour of individuals using informational cascades. They model the dynamics of imitative decision processes as informational cascades. An informational cascade occurs, when an individual, having observed the actions of those ahead of him, follows the actions of other preceding individuals without considering his own information. It is assumed, that individuals observe only the actions of previous individuals. Based on thorough analysis of informational cascades they argue that localized conformity of behaviour and fragility of mass behaviours are explained by the cascades. Cascades can also explain the process by which society switched from one equilibrium to another. Bikhchandani et al. (1992) indicate that informational cascades are particularly common in politics, zoology, medical practice and scientific theory, finance, peer influence, fashion and design.

Like Bikhchandani et al. (1992), Welch (1992) studied informational cascades on another paper as well. However, this time Welch focused on IPOs. Welch's model does four predictions: 1) offerings succeed or fail rapidly, 2) demand can be so elastic that even risk-neutral issuers under-price to completely avoid failure, 3) issuers with good inside information can price their shares so high that they sometimes fail and 4) an underwriter may want to reduce the communication among investors by spreading the selling effort over a more segmented market. Based on empirical test on his model, Welch argues, that pricing decisions of issuers can reflect informational cascades, where investors rely completely on the purchasing decisions of earlier investors and ignore their own information. In other words, investors start to herd.

Froot et al. (1992) argue that there are informational inefficiencies in the market because of short-term speculation. Authors use a model, which considers a trade in a market for a single asset which is in fixed supply. This asset has one pay-out, its liquidating dividend *v*, which in turn is a sum of two normally distributed random variables *α* and *b,* which have means of zero and variances of σ_{α}^{2} and σ_{b}^{2}. After analysing types of traders, timing of trades, market-maker pricing rules and speculators demands the equilibrium of the model is solved. If speculators were rational, trading horizons should not have an effect on asset prices, but this study shows, that speculators with short horizons may herd on the same information creating inefficiencies in pricing. Generally, two models were found leading to short trading horizon inefficiencies, fads and noise trading, and rational bubbles. Sometimes this herding leads to speculators studying information that has nothing to do with fundamentals. This kind of behaviour and the model used by Froot et al. (1992) suggest, that prices will follow a random walk.

Banerjee (1992) analyses sequential decision model, where people make decisions on the basis of their own signalling and history of previous choices made by other participants. Basically, one person chooses first based on intuition or his own signalling and after that the next one chooses, but he is now allowed to observe the choice of the first one. Then the third participant chooses and is again allowed to observe the decisions made by the first two participants. However, participants are not allowed to find out whether the person before him got a signal or not. The game continues this way and each decision maker makes the decision based on history and their own signal if there is one. Some extensive herd behaviour was reported among the participants. It was found that, if the first two choose the same option, the third one will follow, and eventually all decision makers choose the same option. Furthermore, herding was found even when the first and second decision are different. This is because after enough different options have been chosen, a decision maker without a signal tend to choose the option with the highest number of choices. Banerjee (1992) states, that observing decisions made by others does not guarantee herd behaviour. Furthermore, the model has few assumptions that create deficiencies; signals to the participants are free and cannot be traded, there are only two types of decision-makers – ones that have signals and ones that do not, all options other than right one get the same return, whereas in reality options close to true option are often better than other options.

Schiller (1995) discusses how the informational cascade models of Banerjee (1992) and Bikhchandani et al. (1992) may be limited since they assert that differences across groups in herd behaviour can be attributed to the random decisions of the first movers. Schiller (1995) suggests that differences across groups in herd behaviour might be explained more often in terms of different modes of interpersonal information transmission.

Smith and Sørensen (2000) describe that there is a clear difference between informational cascade and herd behaviour. They define an informational cascade occurring when an infinite sequence of individuals ignore their private information when making a decision, whereas herd behaviour occurs when an infinite sequence of individuals make an identical decision and not necessarily ignore their private information. Celen and Kariv (2004) distinguish informational cascades from herd behaviour in a laboratory set-up. They continue the path of social learning literature highlighted by Bikhchandani et al. (1992), Banerjee (1992), and Smith and Sørensen (2000). Laboratory set-up in Celen and Kariv (2004) showed herd behaviour in 36 percent of the cases and informational cascades in 34,7 percent of the cases. Laboratory subjects were found to give excessive weight to their private information relative to the public information revealed by the behaviour of others.

Lakonishik, Shleifer and Vishny (1992) use data on the holdings of 769 pension funds to measure the potential effect of their trading on stock prices. Institutional money managers are found subject to herding and trend-chasing behaviour. What it comes to smaller stocks, weak evidence of herding and positive-feedback herding was detected. On the other hand, herding and positive-feedback trading was almost non-existent among the largest stocks. Institutions were found to apply a wide range of different styles and strategies with offsetting trades without having much impact on the prices. Grinblatt et al. (1995) analyse mutual funds' stock purchases and their tendency to exhibit herding behaviour. 77 percent of mutual funds analysed were found to be momentum investors. Mutual funds showing tendency to buy stocks based on their past returns, can itself be regarded as a weak evidence of herd behaviour. Furthermore, following methodology by Lakonishok et al. (1992), Grinnblatt et al. (1995) show weak evidence in favour of herd behaviour, but after controlling for the fund's tendency to buy past winners, it largely disappeared. Total sample consisted of quarterly holdings of 155 mutual funds in the US over the 1975-1984 period.

Avery and Zemsky (1998) study the relationship between rational herd behaviour and asset prices. They argue that when traders have an informational advantage on a single dimension (new asset value), price adjustments by a competitive market maker prevent any herd behaviour. However, if the market maker is additionally uncertain as to whether the underlying asset value has changed, Avery and Zemsky (1998) show that herd behaviour is possible. Furthermore, if the market is uncertain about whether the asset value has changed and whether traders are well or poorly informed on the new asset value, herd behaviour can lead to significant, short-run price movements that have nothing to do with the true value of the asset. Avery and Zemsky (1998) modify the Bikhchandani et al. (1992) model in the analysis and conclude that more complex information structures can lead to herd behaviour and ultimately make price bubbles possible.

One of the most cited papers on herd behaviour is written by Nofsinger and Sias (1999). They studied herding and feedback trading among institutional and individual investors. Their key finding was, that there is strong positive correlation between changes in institutional ownership and returns measured over the same period. They think, that the results are an indication of the two outcomes; either institutional investors positive-feedback trade more than individual investors or institutional herding impacts prices more than herding by individual investors. Both factors are found to explain herding. Furthermore, institutional herding is positively correlated with lag returns and by so appears to be related to stock return momentum.

Study on mutual fund herding and the impact on stock prices by Wermers (1999) has received even more citations than paper by Nofsinger and Sias (1999). By analysing mutual fund trading activity and performance from 1975 to 1994, high levels of herding is found in trades of small stocks and in funds trading growth-oriented, whereas very little herding was found by mutual funds in the average stock. Herding by growth-oriented funds is a result of positive-feedback trading strategies. Stocks herding buy outperform stocks that herd sell, and the effect is bigger among small stocks. Wermers (1999) applied herding measure developed by Lakonishok et al. (1992) to capture herding behaviour in this study.

Sias (2004) studied quarterly institutional ownership data from March 1983 to December 1997 in the US and tested for institutional herding by examining the cross-sectional temporal dependence in institutional demand over adjacent quarters. He found that institutional investors follow each other into and out of same securities and follow their own lag trades. Furthermore, herding effect declined over time and differed across capitalizations and different investor types. Institutional investors are seen as momentum traders, but yet herding itself does not often result from momentum trading.

Security analysts are an interesting group what it comes to herding. Welch (2000) study this group of professionals and shows, that buy or sell recommendations of security analysts for individual stocks have a significant positive influence on the recommendations of the next two analysts. This is due to analysts exploiting fundamental and short-lived information when reviewing recent revisions. Also, prevailing consensus has an influence on the analysts' choices. Consensus has a stronger influence when conditions in the market are favourable. Welch's (2000) data was large in a sense, that it included an overall of 302 458 recommendations from 226 brokers between 1989 and 1994.

Graham (1999) conducted a particularly interesting research on herding among investment newsletters. Based on the model developed in the study, newsletter analysts possessing certain characteristics were found likely to herd. If an analyst has high reputation or low ability or if there is some strong public information inconsistent with the analyst's private information, herding was likely. Herding was also common when analyst's private signals were positively correlated with other analysts. Another rather interesting study was conducted by Hirschey, Richardson and Scholz (2000), who studied stock-price effects of Internet buy-sell recommendations. They analysed recommendations by the Motley Fool company and found that on average buy recommendations generated 1,62 % rise in stock prices on the announcement day (*t = 0*) and 2,40 % returns over the announcement period (*t = -1,+1*). Sell recommendations caused -1,49 % return on the announcement day and -3,33 % return over the announcement period. Hirschey et al. (2000) state that these findings can be viewed as herd-like behaviour among Internet investors. Studies like these would be extremely interesting nowadays as the importance of Internet as a source of information is at whole new level compared to late 90's and early 2000's.

Choi and Sias (2009) examine whether or not institutional investors follow each other into and out of the same industries in the United States by analysing quarterly holdings and changes in holdings of institutional investors from 1983-2005. They follow earlier paper by Sias (2004) to test for institutional herding by calculating the cross-sectional correlation between institutional investors' industry demand in this quarter and their demand last quarter. The Empirical evidence is strong for institutional industry herding. According to authors, institutional investors' herding results from managers' decisions rather than underlying investors' flows. Furthermore, institutional industry herding can be regarded as one cause for industry prices differentiate from fundamental values.

Economou, Gavriilidis, Kallinterakis and Yordanov (2015) investigate fund manager herd behaviour in two frontier markets, Bulgaria and Montenegro, by using quarterly portfolio holdings from the January 2015-December 2012 period. Unlike many other studies of the same type, which use Lakonishok et al. 1992) approach, this study uses the methodology presented by Sias (2004). Results of Economou et al. (2015) show that fund manager herd significantly in Bulgarian and Montenegrin stock markets and the effect is stronger during periods of positive market performance and high volume. In Montenegro herd behaviour is significant also during periods of low volatility. Authors state that the results are show fund managers herding intentionally and in anticipation of either informational or professional payoffs. It is worth noting that sample for Bulgaria included 25 funds and only 6 funds were included from Montenegro.

Zhang, Li and Zhu (2015) examine how institutional herding affects future excess stock returns in China's stock market by employing herding measure created following Lakonishok et al. (1992). Both short-term and long-term future excess stock returns were found positively correlated with the herding measure. Herding effect is found most significant on the buy side and herding was more significant during crisis period. Interestingly herding effect lasted longer when institutional investors herd on smaller, growth or illiquid stocks. Results also indicate, that amateur and other individual investors tend to follow large institutional investors.

Foreign institutional investor herding in emerging markets is explored by Garg, Mitra and Kumar (2016), who do this for Indian stock market. They apply method developed by Lakonishok (1992) to detect buy-side and sell-side herding and method by Sias (2004) to find out intertemporal trading pattern of foreign institutional investors. The analysis of daily data from June 2003 to July 2004 suggests, that both buy-side and sell-side herding of foreign institutional investors are present in the Indian stock market. Herding is greater on sell-side. Based on panel regression, foreign institutional investors have a destabilizing effect in the Indian stock market returns. It is worth noting, that Garg et al. (2016) study concerned only large cap stocks.

2.3 Herding in certain market situations

Herd behaviour is particularly interesting, when markets are experiencing turmoil such as extreme volatility or price movement right before bubbles burst or crashes occur. These so-called extreme market conditions are characteristic to crisis situations and speculative markets. Many of the papers presented in section 2.1 could have been introduced also here.

Lux (1995) examines herd behaviour in speculative markets, such as bubbles and crashes. He uses a contagion model to capture market dynamics. Some microeconomic explanations for herd behaviour of speculative traders include; acting irrationally, attempting to draw information on what others do and reputational concerns.

Financial market contagion during late 90’s Asian crisis was studied by Baig and Goldfajn (1999). Data from Thailand, Malaysia, Indonesia, Korea and the Philippines showed, that correlation in currency and sovereign spreads increased significantly during the crisis period, whereas the evidence was mixed for equity market correlations. To test for biases, Baig and Goldfajn (1999) constructed a set of dummy variables to capture the impact of own-country and cross-border news on the market. After controlling for own-country news, evidence of cross-border contagion in the currency and equity markets was profound. This evidence suggests, that during financial crises market participants move in the same direction together across countries making diversification hard with these markets.

Kaminsky and Schmukler (1999) analysis of financial environment of Asia in 1997-1998 reveals that market movements were triggered by local and neighbour-country news, with news about agreements with international organizations and credit rating agencies having the most weight. Some of the movements cannot be explained by news and are likely a result of herd instincts of the Asian market itself. Kaminsky and Schmukler (1999) analysed twenty largest one-day swings in stock prices in nine Asian countries.

Chiang, Jeon and Li (2007) also studied financial market contagion in the Asian market. They apply a dynamic conditional-correlation model and dynamic multivariate GARCH model to eight Asian daily stock-return data series (Thailand, Malaysia, Indonesia, the Philippines, South Korea, Taiwan, Hong Kong and Singapore) from 1990 to 2003. Japan and the US are also added for further and more comprehensive analysis. Contagion effect is found present and by analysing correlation-coefficient series authors are able to identify two phases of the Asian crisis. First phase shows increase in correlation and second phase shows continued high correlation. One explanation for this is that the contagion effect takes place early in the crisis and that herding behaviour dominates the latter stages of the crisis. Furthermore, correlation coefficients are significantly influenced by news about changes in foreign-currency sovereign credit ratings in its own and foreign markets. There is also a shift in variance during the crisis period.

Gleason et al. (2004) use intraday data to examine if traders herd during periods of extreme market movements using sector ETFs. They apply methods of Christie and Huang (1995) and Chang et al. (2000) to analyse the data. Results indicate, that sector ETF investors do not herd during periods of extreme market movements.

Boyer, Kumagai and Yuan (2006) performed a study on how stock market crises spread globally through asset holdings of international investors. After separating stocks into two categories – those that are eligible for purchase by foreigners (accessible) and those that are not (inaccessible) – Boyer et al. (2006) estimate and compare the degree to which stock index returns co-move with crisis country index returns in the case of 1997 Asian crisis. Both emerging and developed markets were analysed. Results show greater co-movement during high volatility periods, in particular for accessible stock index returns, which would suggest that crises spread through asset holdings of international investors rather than as a result of changes in fundamentals. A difference was found in how the Asian crisis spread to emerging markets and developed markets. Spread to emerging markets happened through asymmetric market frictions such as wealth constraints, whereas for developed markets portfolio rebalancing acts as a channel through which the crises spread.

Ahmed, Abbass and Abbasi (2012) explore how financial crises effected the herding behaviour in Spanish financial market. They do ex-ante and ex-post analysis of the 2008 financial crises using daily returns of Spanish stock market index over a ten-year period from 2002 to 2011 tallying 2549 observations. By applying methods of Christie and Huang (1995) and Chang et al. (2000), Ahmed et al. (2012) results indicate that either before or after the crises the investors do not form a herd, hence making rational investment decisions.

Balcilar, Demirer and Hammoudeh (2013) study herd behaviour and market regime-switches in the Gulf Arab stock markets, which include Abu Dhabi, Dubai, Kuwait, Qatar and Saudi Arabia. There are three market regimes (low, high and extreme volatility) present in those markets with transition order being from low to extreme, and then from extreme to high volatility. According to authors, this indicates that these markets have different structure than developed markets. Results showed evidence of herd behaviour during extreme volatility regime for all but Qatar, which showed signs of herd behaviour under the high volatility regime. Unlike traditional testing methodology, the three-state Markov switching model of the cross-sectional return dispersions was used to test herding behaviour under regime-switches. Simultaneous herding co-movements were found, which indicates, that diversification and speculation using these countries is very risky.

Herd behaviour in the French stock market is studied by Litimi (2017), who also examines its effect on the idiosyncratic conditional volatility at sector level. He uses the cross-sectional absolute deviation model used originally in this context by Chang et al. (2000) and modifies it by including trading volume and investor sentiment as herding triggers. Modified GARCH model is used to examine the effect of herding on conditional volatility. Based on the analysis of all listed companies in the French stock market over four major crisis periods, Litimi (2017) suggest that herding behaviour is present during crises and for some sectors (5 out of 11) herding is present over the entire sample period from 2000 to 2016. Moreover, he suggests, that herding behaviour has a preventive effect on market conditional volatility

2.4 Other relevant studies

Other relevant studies for the purpose of this thesis have also been conducted in the past and this chapter consists of those papers included, but not qualified for previous sections of the literature review. These mainly consist of summary papers or thoughts from scholars as well as few earlier Master’s Thesis made in the Nordics and published in the last 10 years.

In a summary paper on rational herding in financial economics by Devenow and Welch (1996), the authors expressed a need for more rigorous empirical evidence in herding literature. Most of the empirical studies concentrate on price patterns, but good tests on herding also require data on how investors communicate with each other. As authors point out, this data is often difficult if not impossible to get.

Bikhchandani and Sharma (2001) did an extensive review for IMF on herd behaviour in financial markets. They categorized causes of herding into three main categories: 1. Information-based herding and cascades (see Banerjee (1992), Bikhchandani et al. (1992) and Welch (1992)), 2. Reputation-based herding (see Scharfstein and Stein (1990) and Graham (1999) and 3. Compensation-based herding. The also gave some criticism to models developed by Lakonishok et al. (1992) and Christie and Huang (1995). Review by Bikhchandani and Sharma (2001) pointed out the need to do more empirical work on emerging markets, where the tendency to herd is more profound based on previous evidence. They also expressed the need to develop more adequate models and measures for herd behaviour as it is hard to distinguish what is truly herd behaviour. One challenge that scholars face is also the availability of data.

Hirshleifer and Teoh (2003) review herd behaviour and cascading in capital markets. They discuss about theory and evidence related to herd behaviour, payoff and reputational interactions, social learning, and informational cascades in capital markets. Moreover, they discuss how earlier literature on these can be applied to a number of investments, financing, reporting and pricing contexts. Hirshleifer and Teoh (2003) conclude that herding in capital markets is likely to involve a mixture of reputational effects, informational effects, direct payoff interactions, preference effects, and imperfect rationality. It is then a different thing, how one can model all these together to be able to make a thorough analysis in a financial market setting. Further Hirshleifer and Teoh (2003) rightly describe, that Christie and Huang (1995) use an indirect measure of the tendency for some group of investors to react in a common way more at the time of extreme shocks than at other times, rather than measuring herd behaviour and its social influence as such, which is of greater interest for many social psychology scholars.

A completely new measure for expected degree of herd behaviour or co-movement between stock prices is developed by Dhaene, Linders, Schoutens and Vycnke (2012). The Herd Behaviour Index (HIX) introduces easy-to-calculate and forward-looking model-independent measure that is based on observed option data. The measure compares the currently observed market situation with an estimate of the worst-case or extreme theoretical situation under which the whole system is driven by a single factor. The index can get values between 0 and 1, with higher values indicating higher degree of herd behaviour. Authors believe, that this new measure combined with an alternative measure for herd behaviour, called the implied Comonotonicity Index (CIX) can be used in future research to forecast realized degree of herd behaviour between assets in the underlying index. Another paper that has presented a new model is Cont and Bouchaud (2000). They presented a model of a stock market where a random communication structure between agents generally gives rise to heavy tails in the distributions of stock price variations in the form of an exponentially truncated power-law. Based on the model, their study suggests a relation between the excess kurtosis observed in asset returns, the market order flow and the tendency of market participants to imitate each other.

Investment behaviour in the Finnish financial markets have been studied by Grinblatt and Keloharju (2000), Ekholm and Pasternack (2008), and Grinblatt, Keloharju and Linnainmaa (2012). Grinblatt and Keloharju (2000) separate sophisticated players from the less sophisticated investors in the Finnish stock market, with first ones being the foreign investors and latter ones representing Finnish investors. Contrarian behaviour is reported as foreign investors pursue momentum strategies – buying past winners and selling past losers – but Finnish investors and households in particular buy losers and sell winners. Ekholm and Pasternack (2008) study show that Finnish individual investors are more overconfident than institutions. Goodfellow et al. (2009) argue that the higher the degree of overconfidence is, the less likely investors are to rely on others' behaviour rather than their own beliefs. Thus, this would conclude, that Finnish individuals are less prone to herding than institutions. Grinblatt et al. (2012) combine two decades of scores from IQ tests by nearly every Finnish male of draft age with trading behaviour and stock market performance. They found that IQ-grouped investors herd more with investors of similar IQ, overall the low-IQ investors have greater tendency to herd with other individual investors and large levels of coefficients for herding indicate that all investors tend to herd with current and lagged trades of all investors in the market.

A few Master's Thesis studying herd behaviour have been published in the Nordics. Ohlson (2010) was interested in the Stockholm stock exchange, Lindhe (2012) studied all four Nordic countries (Denmark, Finland, Norway and Sweden) and Sulasalmi (2014) analysed Finnish stock market data. Ohlson (2010) applied methods by Christie and Huang (1995) and Chang et al. (2000), Lindhe (2012) used Chiang and Zheng (2010) and Sulasalmi (2014) employed Christie and Huang (1995) as well as Chiang and Zheng (2010) to detect herd behaviour. Ohlson (2010) found market-wide herd behaviour in the Stockholm stock exchange and in particular in the bullish market between 2005 and 2007. Overall increasing level of herd behaviour was observed over the 1998 to 2009 time period, which could be a result of increased influence of institutional ownership. According to Ohlson (2010), thinly traded stocks might be a negative bias on the herd measure.

Lindhe (2012) found significant of market-wide herding in Finland during both up and down-market days. Unlike in Finland, the 2001-2011 data showed no evidence of market-wide herding in Denmark, Norway and Sweden. Evidence from Sweden contradicts with earlier findings of Ohlson (2010), who did not apply Chiang and Zheng (2010) model. Herding in Finland was most prominent in the bear market of 2001 and the bull market of 2004. Results suggest, that Finland and Sweden herd around the US market, all four countries herd around the European market and all four countries herd around each other. This indicates that markets move to same direction together, thus suggesting that geographical distance could be an important factor when examining herd behaviour. However, based on the study it's not clear what data was used as a benchmark for Europe.

Sulasalmi (2014) examined market-wide herding, up and down-market herding, extreme price movement herding and turnover volume herding for Finnish stock market for a time period from 2004 to 2013, including 2516 market days in total. Turnover volume herding is examined following Mobarek et al (2014). No signs of herding behaviour were found for the whole period or any of the individual calendar years. Herding was not found in positive market days, negative market days showed some signs of herding behaviour, but without any real statistical significance. Extreme market movements did not seem to cause any herd behaviour and neither did the trading volume, despite it being low or high.

2.5 Summary of the papers included in the literature review

By looking at the summary in table 1, earlier literature on herd behaviour in different market settings and among different market participants either supports the existence of herd behaviour or shows evidence against the existence of herd behaviour. Many times, it is not clear whether or not the findings actually result from herd behaviour or are evidence of something else happening in the market. Different forms of herd behaviour have been studied for a roughly over 30 years. A lot of studies have been conducted using models created by Christie and Huang (1995), Chang et al. (2000), Hwang and Salmon (2004) or alternatively following methodologies in Lakonishok et al. (1992) or Sias (2004) for institutional investor or managerial herd behaviour. Newer studies have applied methodologies of Chiang and Zheng (2010), Economou et al. (2011) and Mobarek et al. (2014).

In recent years scholars have put more emphasis on developing new and more accurate models. Interestingly, even these models, which are many times just modifications to the existing models, show different results depending on the market and timeframe of the study. This raises some questions about the validity of the existing models and at the same time it is also a clear indication, that there is still a need for better and even more accurate models to detect herd behaviour. The object of this thesis is not to develop a new model, but rather examine herd behaviour in the Finnish stock market by using existing models and framework. Data and methodology of this thesis will be presented in the next chapter.

Table 1. Summary of earlier literature

Author(s)	Country	Level of data	Type of herding?	Model/method	Main findings
Ahmed et al. (2012)	Spain	Daily returns for 145 stocks between 2002 and 2011	Stock market	CH/CCK	No evidence of herd behavior in the Spanish market
Avery & Zemsky (1998)	-	Probabilities & rules	Relationship between herd behaviour and asset prices	General Model	Complex information structures can lead to herd behaviour and price bubbles
Baig & Goldfajn (1999)	Thailand, Malaysia, Indonesia, Korea & Philippines	Three and half years of daily data from 1995 to 1998	Stock market	Correlation and VAR analysis	Correlations in currency and sovereign spreads increase significantly during the Asian crisis period
Balcilar et al. (2013)	Gulf Arab stock markets (Abu Dhabi, Dubai, Kuwait, Qatar & Saudi Arabia)	Daily closing prices for individual stocks from 9.7.2006 to 28.9.2018	Stock market	Three-state Markov switching model of the cross-sectional return dispersions	Three different market regimes (low, high and extreme or crash volatility regimes) are present in the GCC stock markets. Some of the regimes display more evidence of herd behaviour.
Banerjee (1992)	-	Probabilities & rules	Individuals	Sequental decision model	Herd behaviour exists with certain strong assumptions
Bikchandani & Sharma (2001)	-	-	-	Summary paper of different methodologies	-
Bikchandani et al. (1992)	-	Probabilities & rules	Individuals	Informational cascades	Herd behaviour exists with certain strong assumptions
Bohl et al. (2017)	S&P500 and EuroStoxx 50	Daily returns for constituents of S&P500 and EuroStoxx 50 index between 2008-2013	Stock market	Modified CCK	Supporting evidence in favour of herd behaviour in S&P500 and EuroStoxx50 stocks
Boyer et al. (2006)	Multiple emerging and developed markets	Weekly data of returns and yearly data on other variables 1989-2002.	Stock market co-movements	Regime-switching correlation model	Stock market crises spread globally through asset holdings of international investors. Greater co-movement is observed during high volatility periods.
Celen & Kariv (2004)	US	-	Herding in laboratory conditions	Experiment of 40 people and analysis	Herd behavior develops frequently in laboratory setup and it's likely to be correct

Author(s)	Country	Level of data	Type of herding?	Model/method	Main findings
Chang et al. (2000)	US, Hong Kong, Japan, South Korea and Taiwan	Daily stock prices (1963-1997 US, 1981-1995 Hong Kong, 1976-1995 Japan and Taiwan, 1978-1995 South Korea) & year-end market capitalization	Stock market	CCK (original)	No evidence of herd behaviour in US and Hong Kong, partial evidence in Japan and significant evidence in South Korea and Taiwan
Chiang et al. (2007)	Nine Asian countries/markets	Nine Asian daily stock-return data series from 1990 to 2003	Stock market	Dynamic conditional-correlation model, dynamic multivariate GARCH	Contagion effect is present in Asian markets, two phases of the Asian crisis can be identified and there is a shift in variance during crisis period
Chiang & Zheng (2010)	18 countries	Daily industry and market prices 1988-2009	Stock market	CH/CCK/CZ (original)	Evidence of herd behaviour in advanced stock markets (except US) and in Asian markets. No evidence in Latin American markets
Choi & Sias (2009)	US	Quarterly industry data for 92 quarters 1983-2005	Institutional investors	Sias & LSV	Strong evidence of insitutional industry herding. Industry market values may differ greatly from fundamental values.
Christie & Huang (1995)	US	Daily & monthly data for NYSE and Amex firms between 1962-1988 with monthly data for NYSE extending from 1925 to 1988.	Stock market	CH (original)	No evidence of herd behaviour in US
Cont & Bouchaud (2000)	-	Rules and equations	Stock market	Simple stock market model	There is a relation between the excess kurtosis observed in asset returns, the market order flow and the tendency of market participants to imitate each other.
De Almeida et al. (2012)	Argentina, Brazil, Chile, Mexico & the US	Daily closing prices and trading volumes from 3rd of January 2000 to September 15th 2010	Stock market	CH/CCK	CH found no evidence of herd behavior, but CCK detected herd behavior in Chilean market
Demirer & Kutan (2006)	China	Daily stock returns for 375 Chinese stocks between 1999 and 2002	Stock market	CH/CCK and Gleason	No evidence of herd behaviour in Chinese stock market
Demirer et al. (2010)	Taiwan	Daily stock returns of 689 stocks between 1995 and 2006	Stock market	CH/CCK, Hwang & Salmon	No evidence of herd behaviour with CH. Strong evidence with CCK and Hwang & Salmon
Demirer et al. (2015)	China	Daily returns of 50 industries and 942 stocks between 1996 and 2013	Industry herding on return momentum	CH/CCK	Relationship between herding and return momentum is asymmetric in Chinese stock market

Author(s)	Country	Level of data	Type of herding?	Model/method	Main findings
Devenow & Welch (1996)	-	-	-	Summary paper	-
Dhaene et al. (2012)	US	Numerical illustration with daily closing bid and ask prices for Dow Jones options	Stock market	Own approach	The Herd Behavior Index (HIX) is introduced
Dutta et al. (2016)	India	Daily data of 50 stocks from 2006 to 2016	Stock market	CH	Periodic herding is present in Indian stock market
Economou et al. (2011)	Portugal, Italy, Spain and Greece	Daily logaritmic returns from 1.1.1998 to 31.12.2008	Stock market	CH/CCK/CZ	Herding is present in the Greek and the Italian market. No evidence in the Spanish market and mixed evidence in the Portugese market. There is a great degree of Co-movement in the cross-sectional returns' dispersion across these four markets.
Economou et al. (2015)	Bulgaria and Montenegro	Quartely fund holdings for the January 2005-December 2012 period.	Institutional investors	Sias	Fund managers herd significantly in both markets and herding is stronger during periods od positive market performance and high volume, and in Montenegro herding is also significant during periods of low volatility
Froot et al. (1992)	-	Probabilities & rules	Individual speculators	Informed trading models	Speculators herd on some informational spillovers
Garg et al. (2016)	India	Daily data of 50 stocks from 2003 to mid 2014	Foreign institutional investors	LSV and Sias	Evidence in favour of herding behaviour among foreign institutional investors in Indian stock market
Gleason et al. (2003)	European futures market	Daily price series of thirteen commodity futures contracts with different sample periods	Futures market	CH	No evidence of herding behaviour in the European futures market
Gleason et al. (2004)	US	Daily tick by tick data for nine sector ETFs including 5 561 890 trades	ETF trader herding during periods of extreme market movements	CH/CCK and Gleason	No evidence of herding behaviour in ETFs during up or down market
Goodfellow et al. (2009)	Poland	Daily closing price for all traded stocks in Warsaw Stock Exchance from 9 July 1996 to 16 November 2000	Stock market (up and downswing herding)	CH/CCK	Individuals exhibit herd behaviour during market downswings, less evidence during rising markets. Institutions' trading behaviour is not subject to herd behaviour

Author(s)	Country	Level of data	Type of herding?	Model/method	Main findings
Graham (1999)	US	Probabilities & rules, analyst recommendations	Investment newsletters/analyst reputation herding	Reputational Herding Model	Newsletter analysts are likely to herd if her reputation is high, if her ability is low or if signal correlation is high
Grinblatt et al. (1995)	US	Quarterly holdings of 155 mutual funds over the 1975-1984	Mutual funds	Momentum measures and LSV	77 percent of mutual funds were momentum investors and averaged better performance than other funds. Weak evidence of herd behaviour
Guo & Shih (2008)	Taiwan	Daily equity returns of 443 stock from January 1996 to December 2000	Stock market	CH & LSV	High-tech industries exhibit more significant evidence of return dispersion, volatility dispersion and higher degree of directional co-movement than traditional industries
Henker et al. (2006)	Australia	High frequency intraday data of 160 stocks	Stock market	CH/CCK	No market-wide or industry sector herding was detected, thus supporting rational asset pricing and market efficiency
Hirschey et al. (2000)	US	The Motley fool portfolio holdings and buy-sell recommendations	Buy-Sell recommendations among Internet investors - Case	Abnormal returns and test statistics	Motley Fool buy recommendations generate 1,62% (0) rise on announcement day and 2,40 % over the announcement period (-1,+1). Sell recommendations cause -1,49 % return on announcement date and -3,33 % over the announcement period. Results suggest herd-like behaviour.
Hirshleifer & Teoh (2003)	-	-	-	Summary paper & review of existing literature	-
Huang et al. (2015)	Taiwan	Daily stock prices from 2004 to mid 2013	Impact of idiosyncratic volatility on investment behaviour	Idiosyncratic volatility, CH/CCK and Gleason	Herd behaviour exists in Taiwan equity market
Hwang & Salmon (2004)	US, UK and South Korea	Daily market returns for constituents of the S&P500, FTSE350 and 657 stocks included in the KOSPI index between 1993 and 2003	Stock market	Hwang & Salmon (original)	Herding toward the market shows significant movements and persistence independently from and given market conditions
Javaira & Hassan (2015)	Pakistan	Daily and monthly closing prices and trading volumes of KSE-100 index constituents 2002-2007	Stock market	CH/CCK and Gleason	No evidence of herding behaviour in general, but March 2005 liquidity crisis had herd behaviour characteristics.
Jlassi & Bensaida (2014)	US	Daily market stock prices, volumes, market capitalizations and share prices for all DJIA and S&P 100 index from January 4th 2000 to July 20th 2012.	Stock market	CH/CCK	Herding is present in the American financial market. Herding is stronger in the S&P 100 index than in the DJIA index. Trading volume contributes in increasing asymmetric herding.

Author(s)	Country	Level of data	Type of herding?	Model/method	Main findings
Kaminsky & Schmukler (1999)	Nine Asian countries	20 largest one-day swings in stock prices 1997-1998	Stock market	Regressions	Market movements were triggered by local and neighbour-country news, with news about agreements with international organizations and credit rating agencies having the most weight
Khan et al. (2011)	France, UK, Germany and Italy	Daily market returns from 2003 to 2008	Stock market	Hwang & Salmon	Herding behaviour is present in all countries, excluding periods of market turmoil and crises
Lakonishok et al (1992)	US	Quarterly share holdings of 769 tax-etemp equity funds between 1985 and 1989	Money managers/pension funds	LSV (original)	Evidence on herding and trend-chasing behaviour of institutional money managers
Lindhe (2010)	Four Nordic countries (Denmark, Finland, Norway and Sweden)	Daily total return data from 2001 to 2011	Stock market	CZ	Significant evidence of market-wide herding in Finland during both up and down market days. No evidence in Denmark, Norway and Sweden. Finland and Sweden herd around the US market, all four countries herd with European markets and with each other.
Litimi (2017)	France	Daily data of 232 companies 2000-2016	Stock market and idiosycratic conditional volatility at sectoral level	Modified CH/CCK and GARCH	Herding is present during crisis periods. Also present the whole period for 5 ouf of 11 industries.
Lux (1995)	-	Assumptions, equations and propositions	Herd behaviour in speculative markets	Contagion model	Contagion of opinions and behaviour on stock market is made explicit by the model
Messis & Zapranis (2014)	Greece	Monthly returns of 41 stock from February 1995 to April 2010	Stock market and volatility	Hwang & Salmon, four volatility measures	Herding is present during two periods, 1998-2003 and 2008-2010
Mobarek et al. (2014)	Portugal, Italy, Ireland, Greece, Spain, Germany, France, Sweden, Norway, Denmark and Finland	Daily logaritmic returns from 1.1.2001 to 16.2.2012	Stock market	CCK/CZ & Economou	Herding forces exist among similar markets, especially during extreme market conditions. Herding exist also in developed European countries.
Nofsinger & Sias (1999)	US	Monthly stock returns, annual market capitalizations and the annual fraction of shares held by institutional investors for all NYSE firms for 1977-1996	Institutional investors	Sorting and portfolio analysis	There is strong positive relation between annual changes in institutional ownership and returns over the herding interval
Ohlson (2010)	Sweden	Daily closing prices of all listed companies in the Stockholm stock exchange from 1998 to 2009.	Stock market	CH/CCK	Herd behaviour is present and particularly in the bullish market between 2005 and 2007. Increasing level of herd behaviour was observed during the time frame of the study.

Author(s)	Country	Level of data	Type of herding?	Model/method	Main findings
Saastamoinen (2008)	Finland	Daily closing prices for 32 companies from 28.6.2002 until 31.5.2007	Stock market	CCK and Quantile regression analysis	Dispersion does not decrease, indicating that pricing is rational and investors do not herd. However, testing market stress with quantile regression yields results that contradict with CAPM and might be weak evidence of herd behaviour
Scharfstein & Stein (1990)	-	Probabilities & rules	Managerial herding in decision-making	Learning model	Herding is caused by variety of reasons, including reputation, "sharing-the-blame" and managerial labour market
Schiller (1995)	-	-	-	Discussion paper	-
Schiller & Pound (1986)	US	Survey data	Institutional investors	Survey	Theory on market efficiency needs to be modified
Shah et al. (2017)	Pakistan	Daily closing prices of 609 firms listen on the PSX from January 2004 to December 2013	Stock market	CH	Individual firms do not herd towards the market unless market has negative return of 5 %. Large firms show herding in extreme market movements.
Sias (2004)	US	Quarterly Institutional ownersip data from March 1983 to December 1997	Institutional investors	Evaluation & Analysis across capitalizations	Institutional investors follow each other into and out of same securities and follow their own lag trades. Institutional herding declines over time and differs across capitalizations and investor types.
Sulasalmi (2014)	Finland	Daily total return data from 2004 to 2013	Stock market	CH/CZ	No signs of herd behaviour. Market-wide herding, up or down market herding, extreme price movement herding, or turnover volume herding was not present in the Finnish stock market.
Tan et al. (2008)	China	Daily, weekly and monthly data on stock prices, trading volume, EPS for A and B shares in Shanghai and Shenzen stock exchange from July 1994 to December 2003	Stock market	CH/CCK	Evidence of herding behaviour within Shanghai and Shenzen markets. Herding occurs in both rising and falling market conditions
Wang & Canela (2006)	21 financial markets	Monthly total returns from January 1985 to December 2005	Stock market	Hwang & Salmon	There is higher level of herding in emerging markets than in developed markets. Correlation of herding between two markets from the same group is higher than that between two markets from different groups
Welch (1992)	-	Probabilities & rules	IPO herding	Informational cascades	Pricing decisions of issuers can reflect informational cascades, where later investors rely on purchasing deicison of earlier investors and ignore their own information

Author(s)	Country	Level of data	Type of herding?	Model/method	Main findings
Welch (2000)	US	302 thousand individual buy/sell recommendations issued by 226 brokers during the 1989-1994 period	Security analysts	Own approach	An analyst's recommendation revision has positive influence on next analysts' revisions and prevailing consensus has a positive influence on the recommendation revisions
Wermers (1999)	US	Monthly returns and end of month prices and portfolio holdings for mutual funds in US between December 31, 1974 and December 31, 1994.	Mutual fund manager herding and impact on stock prices	LSV	Little herding on average stock, higher levels in trades of small stocks and in trading by growth-oriented funds. Stock that herd buy outperform stock that sell by 4 percent during following six months.
Yao et al. (2014)	China	Daily and weekly returns of all listed firms in Shanghai and Shenzen stock exchange 1999-2008 and monthly data on different variables	Stock market	CH/modified CCK/CZ	A and B market investors exhibit different levels of herd behaviour. Herding behaviour is more pronounced under declining markets
Zheng et al. (2015)	China	Daily stock returns of al common stocks in Shanghai and Shenzen stock exchange 2003-2012 and other variables at monthly and quarterly level	Institutional investors	LSV	Herding effect is most significant on buy side and affects excess stock returns more significantly during crisis period

Abbreviations:

* CH = Christie and Huang (1995) methodology
* CCK = Chang et al. (2000) methodology
* CZ = Chiang et al. (2010) methodology
* Hwang & Salmon = Hwang & Salmon (2004) methodology
* Sias = Sias (2004) methodology

Other studies included:

Ekholm & Pasternack (2008): Overconfidence and Investor Size - Finnish Study

Grinblatt & Keloharju (2000): The investment behavior and performance of various investor types: a study of Finland's unique data set

Grinblatt et al. (2012): IQ, Trading Behavior and Performance

Schmeling (2009): Investor sentiment and Stock returns. "Culturally more prone to herd-like behaviour"

Smith & Sørensen (2000): Pathological Outcomes of Observational learning

Thaler (1999): End of behavioral finance

3 DATA AND METHODOLOGY

In this section, the data and methodology of this thesis are presented. Results obtained and presented in section 4 are based on the data and methodology presented in sections 3.1 and 3.2 respectively. Section 3.1 describes the data used in the analysis along with its defining descriptive statistics. Section 3.2 presents main methodologies used in the analysis. These include methods used by Christie and Huang (1995), Chang et al. (2000), Chiang and Zheng (2010), Economou et al. (2011) and Mobarek et al. (2014).

3.1 Data

The main data set of the thesis consists of daily total return indices of the OMXH25 companies listed as of 1.8.2018. In general, the list for OMXH25 companies is updated twice a year to represent 25 most traded stocks in the Helsinki Stock Exchange, but as the Helsinki Stock Exchange is pretty centralized and new companies are listed seldomly, we consider OMXH25 company status 1.8.2018 for this study. As for the OMXH25 index itself, the weight of the individual companies is restricted to a maximum of 10 % per company. For companies like Cargotec, Kesko, Metsä Board, Orion and Stora Enso, who possess multiple stock series, only B series or R series in the case of Stora Enso, are considered. In the case of Sampo, only A series stocks are considered.

The data sample covers a 20-year period from 1st of January 1998 to 31st of December 2017. The reasoning behind, why only 25 largest companies are involved in the data sample of this thesis is, that Finnish stock market is rather illiquid, and these 25 companies make up most of the market capitalization and trading volume. Other data series used is daily trading volume for each of the 25 companies. The number of observations varies between companies, and 16 of the 25 companies have been listed for the whole 20-year period.

The calculation of the daily stock return for a particular company stock *i* is presented in equation 1.

$$R_t = 100\ x\ (log(P_{it}) - log(P_{it-1})) \quad (1)$$

Where P_{it} denotes the value of total return index of company *i* at time *t* and P_{it-1} is the value of total return index of company *i* at time *t-1*. Logarithmic returns are used as they are more convenient in finance and fit the purposes of this paper better than simple returns. All the data are taken from Thomson Reuters Datastream 5,1. and processed in Microsoft Excel. Table 2 presents the summary statistics for the returns of the 25 sample companies. Graphical illustrations of the logarithmic returns for individual companies are presented in appendix 1.

Table 2. Summary statistics for the returns of OMX Helsinki 25 companies.

Company	Mean	Std dev	Kurtosis	Skewness	Min	Max	N
Amer Sports	0,0181	0,9256	7,2753	-0,1396	-8,0173	6,4587	5216
Cargotec B	0,0128	1,0928	3,7845	-0,0577	-6,4961	6,0370	3282
DNA	0,0747	0,5056	1,3083	0,5600	-1,3149	2,0571	282
Elisa	0,0128	0,9940	8,2367	-0,1247	-9,3443	6,4644	4826
Fortum	0,0212	0,7470	6,2280	-0,0944	-6,1593	5,9189	4965
Huhtamaki	0,0167	0,8076	9,5353	-0,3348	-9,9643	5,2609	5216
Kesko B	0,0199	0,8055	7,7848	-0,0159	-6,0759	6,4740	5216
Kone B	0,0371	0,8252	4,8226	-0,0419	-6,6035	4,9657	5216
Konecranes	0,0195	1,0299	6,3006	0,3257	-6,9393	8,7209	5216
Metsä Board B	0,0077	1,1696	10,8663	0,1741	-11,9725	10,7217	5216
Metso	0,0166	1,0681	4,4139	-0,1671	-8,4342	7,7102	5216
Neste	0,0215	0,9619	5,5401	0,0891	-5,7179	9,2330	3314
Nokia	0,0045	1,2538	8,5735	-0,3729	-11,2859	12,6913	5216
Nokian Renkaat	0,0262	1,0723	11,0435	-0,2268	-10,6099	9,5563	5216
Nordea Bank	0,0147	0,9246	6,5278	0,3380	-5,7988	7,8892	4674
Orion B	0,0209	0,7581	14,8168	-0,8318	-10,8501	6,1873	5216
Outokumpu A	-0,0047	1,2755	5,9581	-0,0372	-12,1639	8,5936	5216
Outotec	0,0155	1,2816	6,3637	-0,3777	-12,1867	7,8649	2928
Sampo A	0,0270	0,8326	6,8950	0,1404	-7,9182	5,9370	5216
Stora Enso R	0,0119	0,9977	3,0859	0,0861	-7,1951	6,3374	5216
Telia	0,0095	0,7161	5,6275	-0,0751	-5,0335	4,5021	3929
UPM-Kymmene	0,0164	0,9273	3,6839	-0,0759	-5,7011	5,3695	5216
Valmet	0,0422	0,8128	2,2448	0,0790	-3,7609	3,6533	1041
Wartsilä	0,0274	0,9631	10,2804	-0,1730	-10,0056	8,9863	5216
YIT	0,0169	0,9698	6,7579	-0,2417	-10,6953	6,5975	5216

The average logarithmic return among the sample companies is 0,0203, with Outokumpu being the only one with a negative average return. Standard deviations vary between 0,5056 of Telia and 1,2816 of Outotec. Kurtosis varies a lot from company to company, but in general high kurtosis values are an indication of leptokurtic distribution. Skewness measures between -0,5 and 0,5 for almost all the companies, which means that the data is fairly symmetrical. When looking at both of these measures, we must not forget that a rather large sample size is considered. Min and Max present the greatest negative and greatest positive returns and N is the number of observations.

Additionally, data from a few selected indices are used in this study in order to investigate whether Finnish stocks present cross-country herding effects. Total return indices for the constituents of OMX Stockholm 30, OMX Copenhagen 20, OMX Oslo 20, DAX 30, FTSE 100 and S&P 100 are included. Descriptive statistics for the average returns of the index constituents are shown in table 3. Graphical illustrations of the logarithmic returns for the indices are presented in appendix 2.

Table 3. Summary statistics for the average returns of the selected indices.

Index	Mean	Std dev	Kurtosis	Skewness	Min	Max	N
OMXH25	0,0176	0,5829	4,6567	-0,1898	-4,0522	3,9560	5216
OMXS30	0,0163	0,6016	5,4419	0,0020	-3,8251	4,2278	5216
OMXC20	0,0212	0,5027	7,2590	-0,5396	-4,5449	4,0378	5216
OMXO20	0,0161	0,6138	4,4998	-0,4745	-4,2105	3,2704	5216
DAX 30	0,0119	0,5713	5,5788	-0,2908	-3,7293	5,0859	5216
FTSE 100	0,0163	0,4745	5,5845	-0,3527	-3,5659	3,2113	5216
S&P 100	0,0177	0,5160	9,5821	-0,2031	-4,2289	4,9746	5216

Average returns vary between 0,0119 of DAX 30 and 0,0213 of Copenhagen. FTSE 100 presents the lowest standard deviation, whereas highest standard deviation is observed in average returns of Oslo. Returns of S&P 100 and Copenhagen differ from the rest in terms of kurtosis, but there is not much difference in skewness, minimum or maximum returns of the indices.

3.2 Methodology

The main methodology of the study follows that of previous studies on herd behaviour in the stock market by Christie and Huang (1995), Chang et al. (2000), Chiang and Zheng (2010), Economou et al. (2011) and Mobarek et al. (2014). Methods of all these authors are quite similar and based on same theoretical grounds. Some modifications to these models have been made throughout the years by other scholars. Before analysing results obtained with these methods, correlations and return direction signs are analysed.

Christie and Huang (1995) approach to measure return dispersion with cross-sectional standard deviation (CSSD) method is used. This value is first calculated for the whole data sample and then for yearly based sub-periods. Equation 2 presents this calculation for CSSD in more detail.

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{it}-R_{mt})^2}{(N-1)}} \tag{2}$$

where R_{it} is the return of company *i* at time *t*, and R_{mt} is the cross-sectional average of the *N* returns in the aggregate market portfolio at time *t*. Here the market portfolio is considered to be equally weighted. According to Christie and Huang (1995) this measure captures the key attribute of herd behaviour as it quantifies the degree to which asset returns tend to rise and fall in relation to market portfolio. Dispersions should be low if herd behaviour is present, but low dispersions themselves do not guarantee the presence of herding (Christie and Huang, 1995).

As an alternative to CSSD, Chang et al. (2000) method of using cross-sectional absolute deviation, CSAD, to capture return dispersion, is applied to see if the results are any different from previously calculated CSSD value. Different results between CSSD and CSAD has been argued by Demirer et al. (2010). Calculation of cross-sectional absolute deviation following Chang et al. (2000) is presented in equation 3.

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{it} - R_{mt}| \tag{3}$$

All the parameters are same as in equation 2.

To test the presence of herd behaviour during periods of extreme market movements, we estimate the following linear regression suggested by Christie and Huang (1995) and presented by equation 4.

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \tag{4}$$

Where α coefficient denotes the average dispersion for the sample excluding the regions covered by the dummy variables and ε_t is the error term. D_t^L = 1, if the return of the portfolio on day *t* lies in the extreme lower tail of the return distribution; 0 otherwise, and D_t^U = 1, if the return of the portfolio on day *t* lies in the upper extreme tail of the return distribution: 0 otherwise. In the literature an extreme return is defined as return that lies in the one percent lower or upper tail of return distribution (Demirer et al. 2010), and this is also one definition for lower and upper tail in this thesis. In addition to this strict definition, also five percent criterion is tested as in Christie and Huang (1995). Dummies D_t^L and D_t^U are used in order to capture differences in return dispersion during times of extreme market movement. By definition, negative and statistically significant β_1 and β_2 coefficients would indicate aspects of herd formation by market participants in extreme down and up markets respectively. In contrast, positive coefficients for β_1 and β_2 are predicted by rational asset pricing models.

Equation 4 tested for herd behaviour during extreme market movements using CSSD. In equation 5 we replace CSSD with CSAD to see if results are any different. Definitions for all other parameters stay the same.

$$CSAD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \tag{5}$$

Chang et al. (2000) also considered quadratic relationship between $CSAD_t$ and R_{mt} for all positive R_{mt} values. In equations 6 and 7, the presence of negative γ_2 parameter is an indication of herd behaviour. The only difference in equations 6 and 7 is, that equation 7 applies absolute value of R_{mt}, whereas equation 6 allows R_{mt} to be negative.

$$CSAD_t = \alpha + \gamma_1 R_{mt} + \gamma_2 R_{mt}^2 + \varepsilon_t \tag{6}$$

$$CSAD_t = \alpha + \gamma_1 |R_{mt}| + \gamma_2 R_{mt}^2 + \varepsilon_t \tag{7}$$

Empirical specification presented in equations 8 and 9 is run to allow for the possibility that the degree of herding may be asymmetric in the up- and down-market. (Chang et al., 2000)

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP}|R_{mt}^{UP}| + \gamma_2^{UP}(R_{mt}^{UP})^2 + \varepsilon_t \qquad \text{if } R_{mt} > 0 \quad (8)$$

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}|R_{mt}^{DOWN}| + \gamma_2^{DOWN}(R_{mt}^{DOWN})^2 + \varepsilon_t \quad \text{if } R_{mt} < 0 \quad (9)$$

The next model used is a modification to Chang et al. (2000), proposed by Chiang and Zheng (2010). In this model cross-sectional absolute deviation is obtained using equation 10.

$$CSAD_t = \alpha + \gamma_1 R_{mt} + \gamma_2 |R_{mt}| + \gamma_3 R_{mt}^2 + \varepsilon_t \qquad (10)$$

If herding is present, the non-linear γ_3 coefficient will be negative and statistically significant (Demirer et al., 2010). Chiang and Zheng (2010) included the effect of US markets to the analysis as it is generally believed to have an impact on other stock markets as well. We use this same equation 11 to test the role and impact of the US market and other selected markets to the Finnish stock market.

$$CSAD_t = \alpha + \gamma_1 R_{mt} + \gamma_2 |R_{mt}| + \gamma_3 R_{mt}^2 + \gamma_4 CSAD_{ft} + \gamma_5 R_{fmt}^2 + \varepsilon_t \qquad (11)$$

Where $CSAD_{ft}$ is the CSAD value for a foreign stock exchange or index and R_{fmt}^2 is the market return for the foreign market power to two.

To test herding under different market conditions the following equations 12 and 13 by Chiang and Zheng (2010) are used. They also tested for crisis market effect by adding two more crisis country variables to equation 11, but this approach has not been applied in this thesis.

$$CSAD_t = \alpha + \gamma_1(1-D)R_{mt} + \gamma_2 DR_{mt} + \gamma_3(1-D)R_{mt}^2 + \gamma_4 DR_{mt}^2 + \varepsilon_t \qquad (12)$$

$$CSAD_t = \alpha + \gamma_1(1-D)R_{mt} + \gamma_2 DR_{mt} + \gamma_3(1-D)R_{mt}^2 + \gamma_4 DR_{mt}^2$$
$$+\gamma_5 CSAD_{ft} + \gamma_6 R_{fmt}^2 + \varepsilon_t \qquad (13)$$

The dummy variable *D* in equations 12 and 13 equals one when return is negative and zero if positive. As in equation 11, also here $CSAD_{ft}$ is the CSAD value for a foreign stock exchange or index and R_{fmt}^2 is the market return for the foreign market power to two.

Finally, equations 14, 15 and 16 by Economou et al. (2011) and Mobarek et al. (2014) are used to detect whether daily market return, turnover or volatility have an effect on herding.

$$CSAD_t = \alpha + \gamma_1 D^{up}|R_{mt}| + \gamma_2(1 - D^{up})|R_{mt}| + \gamma_3 D^{up}(R_{mt})^2 + \gamma_4(1 - D^{up})(R_{mt})^2 + \varepsilon_t \tag{14}$$

Where D^{up} equals 1 for days with positive market return and 0 for days with negative market return. In the absence of herding effects $\gamma_1 > 0$ and $\gamma_2 > 0$ is assumed. Herding effects are present if $\gamma_3 < 0$ and $\gamma_4 < 0$, with $\gamma_4 < \gamma_3$ if effects are more pronounced during days with negative market returns.

$$CSAD_t = \alpha + \gamma_1 D^{Vol-High}|R_{mt}| + \gamma_2\left(1 - D^{Vol-High}\right)|R_{mt}| + \gamma_3 D^{Vol-High}(R_{mt})^2 + \gamma_4(1 - D^{Vol-High})(R_{mt})^2 + \varepsilon_t \tag{15}$$

Where $D^{Vol-High}$ is 1 if the trading volume of the market portfolio is greater than the previous 30-day moving average and 0 if the trading volume is lower than the previous 30-day moving average. In the absence of herding effects $\gamma_1 > 0$ and $\gamma_2 > 0$ is assumed. Herding effects are present if $\gamma_3 < 0$ and $\gamma_4 < 0$, with $\gamma_3 < \gamma_4$ if effects are more pronounced during days with high trading volume.

$$CSAD_t = \alpha + \gamma_1 D^{\sigma^2-High}|R_{mt}| + \gamma_2\left(1 - D^{\sigma^2-High}\right)|R_{mt}| + \gamma_3 D^{\sigma^2-High}(R_{mt})^2 + \gamma_4(1 - D^{\sigma^2-High})(R_{mt})^2 + \varepsilon_t \tag{16}$$

Where D^{σ^2-High} is 1 if the volatility of the market portfolio is greater than the previous 30-day moving average and 0 if the volatility is lower than the previous 30-day moving average. In the absence of herding effects $\gamma_1 > 0$ and $\gamma_2 > 0$ is assumed. Herding effects are present if $\gamma_3 < 0$ and $\gamma_4 < 0$, with $\gamma_3 < \gamma_4$ if effects are more pronounced during days with high volatility.

4 RESULTS

Results of the empirical analysis are presented in this section. First correlations of the returns are and return direction sign similarity are analysed. Then CSSD and CSAD are analysed before examining whether extreme market movements have an effect on herding. After this, Chang et al. (2000), Chiang and Zheng (2010), Economou et al. (2011) and Mobarek et al. (2014) approaches are applied. Through this thorough analysis we thrive to build comprehensive view of herd behaviour in the Finnish stock market.

4.1 Correlation analysis

Before conducting any further analysis, we first take a look at the correlation matrix in table 4, where the correlation for the returns of OMXH25 companies are mapped. No company A has a negative correlation with company B if we exclude DNA from the sample. Low and negative correlation is explained by DNA being a listed company for a very short time in comparison to other companies in this study. Positive and high correlations are a positive sign when trying to identify aspects of herd formation.

In most cases correlations are positive and between 0,20 and 0,40 (in 195 of possible 300 correlation pairs). Relatively moderate correlations (> 0,40 in 77 of possible 300) are observed for Cargotec with most of the companies, and Konecranes, Metso, Neste, Nordea, Outotec, Sampo, Stora Enso, UPM-Kymmene and Wärtsilä with many of the companies. The highest correlation is over 0,75 between Stora Enso and UPM-Kymmene, which comes as no surprise considering the nature of the businesses of these two companies. Even though equally-weighted market portfolio is used in later analysis, it is worth noting, that the correlation of Nokia’s return is not over 0,40 with any of the companies considered. At first, one might have thought that the returns and development of the stock price of other companies would have been closely dependent on Nokia’s success, but in the light of this observation this has not been the case in the past for OMXH25 companies.

Table 4. Correlation matrix of the returns for OMXH25 companies.

	AMER SPORTS	CARGOTEC B	DNA	ELISA	FORTUM	HUHTAMAKI	KESKO B	KONE B	KONECRANES	METSA BOARD B	METSO	NESTE	NOKIA	NOKIAN RENKAAT	NORDEA BANK	ORION B	OUTOKUMPU A	OUTOTEC	SAMPO A	STORA ENSO R	TELIA	UPM-KYMMENE	VALMET	WARTSILA	YIT
AMER SPORTS	1,000																								
CARGOTEC B	0,418	1,000																							
DNA	0,216	0,001	1,000																						
ELISA	0,188	0,390	0,188	1,000																					
FORTUM	0,250	0,420	0,079	0,211	1,000																				
HUHTAMAKI	0,296	0,425	0,109	0,207	0,249	1,000																			
KESKO B	0,231	0,454	0,021	0,206	0,242	0,244	1,000																		
KONE B	0,253	0,521	0,089	0,207	0,269	0,288	0,297	1,000																	
KONECRANES	0,269	0,600	0,066	0,254	0,300	0,305	0,307	0,383	1,000																
METSA BOARD B	0,309	0,445	0,049	0,218	0,261	0,316	0,295	0,283	0,334	1,000															
METSO	0,292	0,590	0,083	0,232	0,337	0,320	0,344	0,384	0,457	0,374	1,000														
NESTE	0,325	0,432	-0,096	0,299	0,397	0,345	0,368	0,417	0,433	0,361	0,473	1,000													
NOKIA	0,221	0,377	0,120	0,372	0,233	0,228	0,235	0,251	0,279	0,284	0,292	0,320	1,000												
NOKIAN RENKAAT	0,290	0,503	0,084	0,202	0,291	0,275	0,255	0,314	0,367	0,311	0,371	0,369	0,255	1,000											
NORDEA BANK	0,296	0,509	-0,087	0,302	0,327	0,362	0,325	0,380	0,415	0,378	0,444	0,423	0,397	0,370	1,000										
ORION B	0,213	0,338	0,071	0,178	0,243	0,244	0,239	0,212	0,247	0,191	0,263	0,273	0,190	0,225	0,236	1,000									
OUTOKUMPU A	0,247	0,440	0,047	0,185	0,278	0,277	0,287	0,330	0,366	0,347	0,433	0,393	0,265	0,311	0,356	0,211	1,000								
OUTOTEC	0,322	0,526	0,003	0,342	0,420	0,376	0,392	0,508	0,552	0,391	0,656	0,430	0,333	0,517	0,488	0,330	0,497	1,000							
SAMPO A	0,270	0,500	0,045	0,266	0,322	0,321	0,303	0,311	0,331	0,335	0,383	0,425	0,355	0,315	0,506	0,246	0,312	0,472	1,000						
STORA ENSO R	0,293	0,518	0,019	0,269	0,320	0,370	0,315	0,340	0,396	0,529	0,437	0,444	0,349	0,337	0,504	0,250	0,406	0,465	0,404	1,000					
TELIA	0,277	0,430	0,017	0,398	0,356	0,328	0,318	0,390	0,390	0,324	0,421	0,374	0,368	0,359	0,575	0,257	0,325	0,411	0,437	0,437	1,000				
UPM-KYMMENE	0,286	0,498	0,045	0,259	0,309	0,359	0,316	0,343	0,395	0,520	0,424	0,435	0,335	0,337	0,480	0,237	0,405	0,473	0,392	0,755	0,417	1,000			
VALMET	0,284	0,411	0,071	0,295	0,335	0,299	0,225	0,428	0,383	0,353	0,417	0,213	0,279	0,326	0,353	0,323	0,254	0,359	0,416	0,425	0,339	0,378	1,000		
WARTSILA	0,311	0,575	0,195	0,276	0,365	0,310	0,347	0,398	0,447	0,351	0,478	0,457	0,289	0,367	0,434	0,276	0,391	0,554	0,360	0,411	0,415	0,414	0,414	1,000	
YIT	0,288	0,527	0,102	0,225	0,301	0,317	0,292	0,343	0,415	0,338	0,429	0,396	0,259	0,379	0,416	0,241	0,382	0,524	0,347	0,387	0,392	0,387	0,373	0,421	1,000

Looking at return correlations on a yearly basis, it was observed that correlations had been at their highest in 2011 (correlation > 0,4 in 248 of possible 300 pairs) and 2016 (205/300). By contrast return correlations were at their lowest in 1999 (2/300), 2000 (2/300), 2001 (3/300), 2004 (1/300) and 2005 (3/300). Interestingly 2016 (205/300) was followed by relatively low correlations in 2017 (15/300). In general correlations are much lower in the first 10-year period from 1998 to 2007, than in the latter 10-year period from 2008 to 2017. It remains questionable whether this is some sort of side effect of globalisation or digitalisation or both together. There is also a clear jump from 2007 (98/300) to 2008 (184/300), which was most likely triggered by the financial crisis.

Correlation matrix for average logarithmic returns of OMXH25, OMXS30, OMXC20, OMXO20, DAX 30, FTSE 100 and S&P 100 constituents in table 5, reveals that there are high correlations between European stock indices in the sample period 1998-2017.

Table 5. Correlation matrix for returns of the selected indices

	OMXH25	*OMXS30*	*OMXC20*	*OMXO20*	*DAX 30*	*FTSE 100*	*S&P 100*
OMXH25	1,000						
OMXS30	0,822	1,000					
OMXC20	0,719	0,704	1,000				
OMXO20	0,692	0,680	0,640	1,000			
DAX 30	0,748	0,792	0,670	0,616	1,000		
FTSE 100	0,787	0,818	0,704	0,671	0,795	1,000	
S&P 100	0,465	0,506	0,400	0,394	0,598	0,514	1,000

Part of the earlier literature would have expected US market to have a great effect on returns of other stock markets. Here it is observed that US market has the lowest correlations with each of the market. This could partly be explained by demographics and on the other hand data reveals that in the late 1990s and early 2000s correlations in general are much smaller than in latter period of 2008-2017. This could be consequence of globalisation, where our world is getting smaller and effects in one market are easily transferred to other markets as well, which in turn is reflected by greater correlations.

Findings of correlation analysis give very little direct support to herd behaviour in the Finnish stock exchange, but it revealed some aspects which we can take notice. Return correlations have increased in recent times compared to earlier times. There was a significant jump from 2007 to 2008, which can be interpreted as some sort of herd formation during extreme time periods. Finnish stock market had high correlations with some of the selected foreign markets, but not with US market. This is an indication that Finnish stock market is very likely to herd with other stock markets.

4.2 Return sign analysis

After checking correlations for the OMXH25 companies' returns we examine the sign, negative or positive, of the returns. For herd behaviour to occur, returns first need to be of same direction and after that the dispersion of returns need to be as little as possible. Table 6 presents return direction (positive, negative or zero) for the aggregate market portfolio and for individual companies.

Only three of the 25 companies, Metsä Board, Outukumpu and Telia have more negative return days than positive return days. In general, the amount of positive and negative return days is almost parallel and there is no obvious domination of positive return days over negative return days in any particular company. Same holds for the amount of negative return days not dominating positive return days for Metsä Board, Outokumpu or Telia. These findings support market efficiency in a sense stock returns seem to go up and down randomly. This is also an aspect of random walk theory. Slightly more positive days are present, and this can actually be considered as necessary condition for a market to function, as who would be investing if one could get nothing in return? Or even worse, lose money?

Return direction is compared to aggregate market portfolio return direction to see, if individual stock return direction is the same as the direction of the market return. On average when individual stock return is positive, the aggregate market return is positive in 74,91 % of the cases and negative or zero in 25,09 % of the cases. On the other hand, when individual stock return is negative, the aggregate market return is negative on average in 68,26 % of the cases and positive or zero in 31,74 % of the cases.

In the light of this observation, positive returns are more likely to generate herd behaviour as returns are of same direction more often than when negative returns are considered. However, above analysis does not rule out the possibility that it could be the other way around as is does not take into account the magnitude of positive or negative returns and like rest of the thesis, it considers market portfolio to be equally-weighted. Furthermore, correlation analysis revealed somewhat opposite finding as return correlations were higher than average when the financial crisis started, and returns were negative. This was then countered by high correlations in 2011 when returns were largely positive.

Table 6. Direction of the returns.

	N (R>0)		N (R<0)		N (R=0)		N (Ri & Rm >0)		N (Ri>0, Rm ≤0)		N (Ri & Rm <0)		N (Ri<0, Rm ≥0)		N (Ri & Rm = 0)		N (Ri=0, Rm ≠0)		N
MARKET PORTFOLIO	2700	51,76 %	2324	44,56 %	192	3,68 %													5216
AMER SPORTS	2394	45,90 %	2363	45,30 %	459	8,80 %	1735	72,47 %	659	27,53 %	1534	64,92 %	829	35,08 %	192	41,83 %	267	58,17 %	5216
CARGOTEC B	1583	48,23 %	1552	47,29 %	147	4,48 %	1259	79,53 %	324	20,47 %	1130	72,81 %	422	27,19 %	118	80,27 %	29	19,73 %	3282
DNA	141	50,00 %	118	41,84 %	23	8,16 %	92	65,25 %	49	34,75 %	70	59,32 %	48	40,68 %	11	47,83 %	12	52,17 %	282
ELISA	2352	48,74 %	2183	45,23 %	291	6,03 %	1706	72,53 %	646	27,47 %	1454	66,61 %	729	33,39 %	178	61,17 %	113	38,83 %	4826
FORTUM	2363	47,59 %	2234	44,99 %	368	7,41 %	1663	70,38 %	700	29,62 %	1427	63,88 %	807	36,12 %	188	51,09 %	180	48,91 %	4965
HUHTAMAKI	2424	46,47 %	2304	44,17 %	488	9,36 %	1747	72,07 %	677	27,93 %	1506	65,36 %	798	34,64 %	192	39,34 %	296	60,66 %	5216
KESKO B	2476	47,47 %	2332	44,71 %	408	7,82 %	1785	72,09 %	691	27,91 %	1532	65,69 %	800	34,31 %	192	47,06 %	216	52,94 %	5216
KONE B	2489	47,72 %	2267	43,46 %	460	8,82 %	1833	73,64 %	656	26,36 %	1536	67,75 %	731	32,25 %	192	41,74 %	268	58,26 %	5216
KONECRANES	2429	46,57 %	2335	44,77 %	452	8,67 %	1869	76,95 %	560	23,05 %	1625	69,59 %	710	30,41 %	192	42,48 %	260	57,52 %	5216
METSA BOARD B	2259	43,31 %	2358	45,21 %	599	11,48 %	1724	76,32 %	535	23,68 %	1608	68,19 %	750	31,81 %	192	32,05 %	407	67,95 %	5216
METSO	2493	47,80 %	2381	45,65 %	342	6,56 %	1949	78,18 %	544	21,82 %	1716	72,07 %	665	27,93 %	192	56,14 %	150	43,86 %	5216
NESTE	1628	49,12 %	1522	45,93 %	164	4,95 %	1224	75,18 %	404	24,82 %	1050	68,99 %	472	31,01 %	119	72,56 %	45	27,44 %	3314
NOKIA	2512	48,16 %	2431	46,61 %	273	5,23 %	1920	76,43 %	592	23,57 %	1691	69,56 %	740	30,44 %	192	70,33 %	81	29,67 %	5216
NOKIAN RENKAAT	2439	46,76 %	2309	44,27 %	468	8,97 %	1818	74,54 %	621	25,46 %	1562	67,65 %	747	32,35 %	192	41,03 %	276	58,97 %	5216
NORDEA BANK FDR	2216	47,41 %	2125	45,46 %	333	7,12 %	1683	75,95 %	533	24,05 %	1489	70,07 %	636	29,93 %	174	52,25 %	159	47,75 %	4674
ORION B	2508	48,08 %	2300	44,10 %	408	7,82 %	1766	70,41 %	742	29,59 %	1474	64,09 %	826	35,91 %	192	47,06 %	216	52,94 %	5216
OUTOKUMPU A	2398	45,97 %	2445	46,88 %	373	7,15 %	1796	74,90 %	602	25,10 %	1648	67,40 %	797	32,60 %	192	51,47 %	181	48,53 %	5216
OUTOTEC	1398	47,75 %	1386	47,34 %	144	4,92 %	1107	79,18 %	291	20,82 %	1017	73,38 %	369	26,62 %	109	75,69 %	35	24,31 %	2928
SAMPO A	2531	48,52 %	2357	45,19 %	328	6,29 %	1911	75,50 %	620	24,50 %	1640	69,58 %	717	30,42 %	192	58,54 %	136	41,46 %	5216
STORA ENSO R	2499	47,91 %	2364	45,32 %	353	6,77 %	1964	78,59 %	535	21,41 %	1716	72,59 %	648	27,41 %	192	54,39 %	161	45,61 %	5216
TELIA COMPANY	1802	45,86 %	1803	45,89 %	324	8,25 %	1369	75,97 %	433	24,03 %	1207	66,94 %	596	33,06 %	146	45,06 %	178	54,94 %	3929
UPM-KYMMENE	2503	47,99 %	2393	45,88 %	320	6,13 %	1948	77,83 %	555	22,17 %	1717	71,75 %	676	28,25 %	192	60,00 %	128	40,00 %	5216
VALMET	507	48,70 %	475	45,63 %	59	5,67 %	384	75,74 %	123	24,26 %	325	68,42 %	150	31,58 %	37	62,71 %	22	37,29 %	1041
WARTSILA	2486	47,66 %	2325	44,57 %	405	7,76 %	1909	76,79 %	577	23,21 %	1648	70,88 %	677	29,12 %	192	47,41 %	213	52,59 %	5216
YIT	2342	44,90 %	2311	44,31 %	563	10,79 %	1786	76,26 %	556	23,74 %	1596	69,06 %	715	30,94 %	192	34,10 %	371	65,90 %	5216

4.3 Simple analysis of CSSD and CSAD

Table 7 provides the summary statistics for CSSD and CSAD, calculated with equations 2 and 3 respectively. Both values are also calculated for yearly sub-periods to see the yearly fluctuations and changes in the average return dispersions and standard deviations of dispersions. When considering the whole sample from 1998 to 2017 the average return dispersion for CSSD is at 0,7266, whereas as expected the CSAD value is lower at 0,5306. The standard deviation of dispersion is 0,3700 for CSSD and 0,2545 for CSAD.

When CSSD and CSAD are analysed on yearly basis it can be observed, that both of them receive their highest values in 2000. The second highest values are observed in 2008. As we all know, in spring 2000 the Dotcom bubble started to burst and 2008 was the year dominated by the global financial crisis started in the United States. Also considering this particular data set, Nokia was at its highest in spring 2000 and many OMXH25 companies broke records just before the financial crises hit Finland.

Table 7. Summary statistics for CSSD and CSAD.

Data	Mean	Std dev	Kurtosis	Skewness	Min	Max	N
CSSD OMXH25	0,7266	0,3700	3,2562	1,1975	0	3,1690	5216
1998	0,8844	0,4437	4,6794	1,4926	0	3,1690	260
1999	0,9323	0,3385	1,4286	-0,0899	0	2,0183	261
2000	1,0686	0,3975	1,7838	0,2422	0	2,4151	260
2001	0,9792	0,3886	2,1997	0,2339	0	2,5622	261
2002	0,8099	0,3382	1,8058	0,4101	0	1,9945	261
2003	0,7115	0,3092	5,4569	1,0627	0	2,5509	261
2004	0,5717	0,2464	5,9242	1,3840	0	1,9807	262
2005	0,5830	0,2487	15,3723	2,4838	0	2,4183	260
2006	0,5955	0,2189	3,1666	0,4793	0	1,6115	260
2007	0,6398	0,2687	2,7951	0,7594	0	1,6901	261
2008	1,0362	0,4688	2,4717	0,9648	0	2,9962	262
2009	0,8955	0,4225	1,6335	0,7654	0	2,6857	261
2010	0,5739	0,2631	4,2108	1,3399	0	1,8847	261
2011	0,6532	0,3165	4,0012	1,4182	0	2,2683	260
2012	0,6710	0,3046	3,0660	0,9816	0	1,8798	261
2013	0,5835	0,2963	10,4230	1,9752	0	2,6366	261
2014	0,5975	0,2604	1,8646	0,6843	0	1,5781	261
2015	0,6450	0,3148	3,9230	1,2803	0	2,3501	261
2016	0,6099	0,3100	3,5466	1,4125	0	2,0137	261
2017	0,4896	0,2575	11,9900	2,4603	0	2,2696	260
CSAD OMXH25	0,5306	0,2545	2,2517	0,9367	0	2,0914	5216
1998	0,6567	0,2994	1,8986	0,8386	0	1,8167	260
1999	0,6935	0,2412	1,8536	-0,2774	0	1,5120	261
2000	0,7802	0,2745	1,4532	-0,1540	0	1,7666	260
2001	0,7179	0,2669	1,5084	-0,2157	0	1,5792	261
2002	0,5980	0,2405	1,3797	0,1529	0	1,3756	261
2003	0,5279	0,2068	1,5847	0,1898	0	1,2266	261
2004	0,4196	0,1511	2,0590	0,1251	0	1,0546	262
2005	0,4212	0,1366	3,1933	0,2214	0	1,0023	260
2006	0,4439	0,1486	2,2109	-0,1522	0	0,8954	260
2007	0,4704	0,1772	2,1964	0,1964	0	1,1416	261
2008	0,7782	0,3326	1,7354	0,7083	0	2,0914	262
2009	0,6691	0,3021	0,9008	0,5214	0	1,6729	261
2010	0,4222	0,1622	1,5055	0,3290	0	0,9230	261
2011	0,4847	0,2054	1,6580	0,7355	0	1,2656	260
2012	0,4732	0,1819	1,4114	0,0610	0	1,1119	261
2013	0,4064	0,1666	2,4091	0,4496	0	1,1072	261
2014	0,4173	0,1571	2,3709	0,2050	0	1,0508	261
2015	0,4564	0,1855	2,0617	0,4698	0	1,3074	261
2016	0,4284	0,1935	2,3642	0,9806	0	1,1835	261
2017	0,3449	0,1584	11,0571	2,0861	0	1,4165	260

The theory predicts dispersion to be low when herd behaviour is present. Yearly average return dispersions are lower than the sample average in two different time periods from 2003 to 2007 and from 2010 to 2017. It is arguable, what is considered as low dispersion as for example Christie and Huang (1995) state, that 1,60 % dispersion for utilities industry is low, but in our sample the average dispersion never goes over 1,10 %. Also, Chang et al. (2000) do not report average CSAD values lower than any average CSAD value in this study. Part of this can surely be explained by the different sample time period and it might also be, that the Finnish stock market is rather conservative in its movements compared to other stock markets.

Higher CSSD and CSAD values in table 7 for 2000 and 2008 suggest, that the most traded stocks in Helsinki Stock Exchange are not prone to herd behaviour during times of extreme market movements like the ones experienced in late 90s and early 2000s as well as years of financial crises. The observation is consistent with Christie and Huang (1995), who also report increasing dispersions during periods of large average price changes.

Following Chang et al. (2000), dispersion measures and the corresponding equally-weighted market returns are plotted for each day. Figures 1 and 2 present the relationship between the daily cross-sectional standard and absolute deviation and the corresponding equally-weighted market return. Both figures illustrate the magnitude of the non-linearity in the CSSD-market and CSAD-market relation respectively. As no linear relationship can be observed from the figures, it can quite comfortable be said, that models requiring linear relationship for these variables are not suitable for analysis.

Figure 1. Relationship between the daily cross-sectional standard deviation and the corresponding equally-weighted market return.

Figure 2. Relationship between the daily cross-sectional absolute deviation and the corresponding equally-weighted market return.

Descriptive statistics for CSAD of the indices are presented in table 8. Average CSAD ranges from 0,4665 of Stockholm to 0,6275 of Oslo. There is not much difference in standard deviations, but Copenhagen has a kurtosis of 22,9982 which differs massively from the rest of the indices. This is due to few big extreme values in the data set and for instance maximum value of CSAD for Copenhagen is much higher than maximum value of CSAD of other indices.

Table 8. Descriptive statistics for CSAD

Index	Mean	Std dev	Kurtosis	Skewness	Min	Max	N
CSAD OMXH25	0,5306	0,2545	2,2517	0,9367	0	2,0914	5216
CSAD OMXS30	0,4665	0,2451	4,2544	1,2867	0	2,8817	5216
CSAD OMXC20	0,5351	0,2796	22,9982	2,4145	0	4,8140	5216
CSAD OMXO20	0,6275	0,3508	5,1755	1,6593	0	3,1216	5216
CSAD DAX 30	0,4990	0,2605	4,0788	1,4585	0	2,6444	5216
CSAD FTSE 100	0,5110	0,2432	6,9589	1,6726	0	2,9849	5216
CSAD S&P 100	0,4886	0,2772	4,1230	1,4810	0	2,7984	5216

Analysis of the CSSD and CSAD in this section does not support herd behaviour during extreme market conditions, but it does not rule out that herding do not exist. Especially later years have smaller values of CSSD and CSAD, which is consistent with rising correlations observed in section 4.1. However, results for 2017 contradict with general findings as it had the lowest CSSD and CSAD values, but correlations were also small. This is something, which we are unable to explain.

4.4 Extreme market movements analysis

It has been argued, that herding would be most prevalent during periods of market stress. Christie and Huang (1995) state, that during periods of abnormally large price movements, the differences in predictions of asset pricing models and herd behaviour are most pronounced. When extreme market movements are usual and there is lot of uncertainty in the market, market participants are more likely to dismiss their own beliefs and follow others in fear of losing money or in fear of missing out on an opportunity. For herding behaviour to be present, we should find reduced levels of dispersion. However, many studies find no signs of reduced dispersions and herd behaviour during periods of market stress.

To analyse, whether extreme market movements could cause herd behaviour we use regressions in equations 4 and 5. Table 9 shows the regression coefficients for the daily dispersions during periods of market stress. Coefficients for both one percent and five percent criterion are presented. By following one percent criterion only 52 D_t^L and D_t^U parameters receive value 1 and rest of the parameters are valued 0. For five percent criterion the amount of D_t^L and D_t^U parameters receiving value 1 increases to 260 observations. The α coefficient is the intercept and denotes the average dispersion of the sample excluding the regions covered by the two dummy variables. Negative β coefficients would favour herd behaviour and positive β coefficients support rational asset pricing models. (Christie and Huang, 1995)

Table 9. Regression coefficients for the daily dispersions during periods of market stress.

	1 Percent Criterion			5 Percent Criterion		
Variable	α	β_1	β_2	α	β_1	β_2
CSSD OMXH25	0,716***	0,511***	0,584***	0,692***	0,317***	0,374***
		(10,12)	(11,58)		(14,03)	(16,52)
CSAD OMXH25	0,522***	0,405***	0,455***	0,503***	0,251***	0,295***
		(11,73)	(13,20)		(16,32)	(19,20)

*** = Statistical significance at 1 % confidence level.

Values in parentheses present the t-statistics for the coefficients.

All the α and β coefficients are found positive and statistically significant at 1 % confidence level regardless of the model and regression. Dispersions are significantly higher during extreme market movements for both the 1 percent and 5 percent than for sample average dispersions. 5 percent criterion produces smaller estimates, which is an indication that dispersions are higher when extreme market movements are considered at upper and lower 1 percent of market returns. This observation is consistent with rational asset pricing model, as the more there is uncertainty the higher the dispersions are. For herd behaviour to be present the dispersions for 1 and 5 percent criterion should have first been smaller than the average dispersions and then the 1 percent criterion should have had smaller dispersion than the 5 percent criterion.

Findings are of similar kind for CSSD and CSAD models. Also, the differences between the β_1 and β_2 coefficients of all the models are similar. The β_1 coefficients are smaller than the corresponding β_2 coefficients, which is an indication, that the increase in dispersion during large market downturns is smaller than the increase in dispersion during large market upswings. In the light of these findings, we can quite comfortably answer our first sub-question and state that herd behaviour is not found among OMXH25 companies during extreme market conditions or time periods. This is also supported by findings in previous sections. Results from the models are consistent with Christie and Huang (1995) for US market and Chang et al. (2000) for US, Hong Kong and Japan.

4.5 Further analysis of CSAD

Next, we focus on the relationship of CSAD and market return by following Chang et al. (2000). They argue that this approach is more powerful to detect herding based on equity return behaviour than the previously applied dummy method. Here the empirical model is based on assumption that there is a non-linear relation between return dispersion and market return. Table 10 presents the results for regressions in equations 6, 7, 8 and 9. Negative and statistically significant coefficients are interpreted as an indication of herd behaviour.

Table 10. Coefficients for the daily CSAD under Chang et al. (2000) equations.

Equation	α	γ_1	γ_2	Adj. R^2
$CSAD_t = \alpha + \gamma_1 R_{mt} + \gamma_2 R_{mt}^2 + \varepsilon_t$	0,494***	0,017***	0,106***	0,132
		(3,09)	(28,16)	
$CSAD_t = \alpha + \gamma_1 \lvert R_{mt} \rvert + \gamma_2 R_{mt}^2 + \varepsilon_t$	0,413***	0,312***	-0,026***	0,192
		(19,95)	(-3,45)	
$CSAD_t^{UP} = \alpha + \gamma_1^{UP} \lvert R_{mt}^{UP} \rvert + \gamma_2^{UP} (R_{mt}^{UP})^2 + \varepsilon_t$	0,453***	0,229***	0,013	0,182
		(11,07)	(1,36)	
$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN} \lvert R_{mt}^{DOWN} \rvert + \gamma_2^{DOWN} (R_{mt}^{DOWN})^2 + \varepsilon_t$	0,469***	0,180***	0,011	0,142
		(7,94)	(1,02)	

*** = Statistical significance at 1 % confidence level.

Values in parentheses present the t-statistics for the coefficients.

The average level of equity dispersions in a market where R_{mt} equals zero ranges from 0,413 to 0,494 among all models. It is observed that all linear term coefficients γ_1 (for R_{mt}, $\lvert R_{mt} \rvert$, $\lvert R_{mt}^{UP} \rvert$, $\lvert R_{mt}^{DOWN} \rvert$) are positive and statistically significant. This means that $CSAD_t$ increases with linear term. Rate of increase is higher for up-market (0,229) than for the down-market (0,180). This finding is consistent with Chang et al. (2000) who also report higher rate of increase for up-market.

The γ_2 estimates are statistically insignificant for $(R_{mt}^{UP})^2$ and $(R_{mt}^{DOWN})^2$, which supports capital asset pricing model. Even though γ_2 estimate is statistically significant for equation 6, it is positive, which in turn does not support herd behaviour either. Only negative coefficient is observed for γ_2 in equation 7. Negative value for the coefficient is small at -0,026, but statistically significant. Negative and statistically significant coefficient value indicates that linear relationship between $CSAD_t$ and R_{mt} does not hold across all the observations and when the average market return becomes large in absolute terms, the $CSAD_t$ increases at a decreasing rate. The non-linearity can also be observed from graphical illustration in figure 2. This finding indicates that herd behaviour could have been present at times in the Finnish stock market from 1998 to 2017. Findings for equations 8 and 9 are similar to Chang et al. (2000) findings for US and show no signs of herd behaviour.

4.6 Herding with foreign markets

Chiang and Zheng (2010) continue on the empirical path guided by earlier theoretical framework and findings by Christie and Huang (1995) and Chang et al. (2000). By including more variables than previous authors, Chiang and Zheng (2010) are able to provide more comprehensive tools for herd behaviour analysis. Now foreign market variables are included in the analysis. Table 11 presents the results obtained by using equations 10, 11, 12 and 13.

Equation 10 estimates whether OMXH25 companies exhibit herd behaviour. Negative and statistically significant γ_3 coefficient for R_{mt}^2 would be an indication of market-wide herding. In this data γ_3 coefficient is negative at -0,025 and statistically significant at 1 % confidence level. Results are consistent with findings of Chiang and Zheng (2010) in a sense that they also reported signs of herd behaviour using same approach in what are considered to be advanced markets. Results similar to this thesis were reported by Lindhe (2012) in her thesis as well. She found Finnish market to have negative and statistically significant γ_3 coefficient by using same methodology and equation. However, yearly examination then revealed that there are fluctuations in the values of γ_3 coefficient and its sign.

Chiang and Zheng (2010) suggest that foreign markets could have significant impact to herd behaviour. Equation 11 adds two foreign market variables to equation 10 to test these effects and to determine whether investor behaviour is driven by market developments of OMXS30, OMXC20, OMXO20, DAX 30, FTSE 100 or S&P 100. Positive and statistically significant values for γ_4 coefficients suggest that foreign return dispersion has a significant influence on the dependent variable whereas negative and statistically significant γ_5 coefficient values suggest herding with the foreign market.

Positive and statistically significant values at 1 % confidence level are observed for γ_4 coefficients across all foreign markets, which means that return dispersions of Sweden, Denmark, Norway, Germany, UK and US all have influence in return dispersion here in Finland. Not so surprisingly Sweden as a neighbouring country has the highest γ_4 coefficient value, but on the other hand lowest γ_4 coefficient value comes from Norway. There might be a rational explanation to this, the biggest companies in Oslo stock exchange are oil, gas and energy companies so the market is basically driven by the success of these companies. In Finland only Neste falls into this industry category, which makes OMXH25 more decentralized than OMXO20.

Table 11. Coefficients for the daily CSAD under Chiang and Zheng (2010) equations.

	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	*Adj.* R^2
Eq. (10)	0,413***	0,018***	0,312***	-0,025***				0,194
		(3,33)	(19,99)	(-3,39)				
Eq. (11) OMXS30	0,154***	0,008**	0,174***	-0,009	0,676***	-0,018***		0,552
		(2,05)	(14,67)	(-1,37)	(62,62)	(-4,53)		
Eq. (11) OMXC20	0,240***	0,015***	0,232***	-0,012	0,387***	-0,025***		0,343
		(2,99)	(16,15)	(-1,61)	(33,53)	(-4,68)		
Eq. (11) OMXO20	0,253***	0,011**	0,254***	-0,020***	0,301***	-0,021***		0,335
		(2,21)	(17,80)	(-2,74)	(32,13)	(-4,99)		
Eq. (11) DAX 30	0,178***	0,013***	0,206***	-0,024***	0,567***	-0,015***		0,477
		(3,04)	(16,14)	(-3,64)	(51,83)	(-3,91)		
Eq. (11) FTSE 100	0,151***	0,019***	0,188***	0,001	0,626***	-0,074***		0,460
		(4,26)	(14,40)	(-0,09)	(50,22)	(-11,19)		
Eq. (11) S&P 100	0,197***	0,021***	0,250***	-0,035***	0,505***	-0,010***		0,463
		(4,83)	(19,47)	(-5,57)	(48,43)	(-2,80)		
Eq. (12)	0,413***	0,321***	-0,306***	-0,018*	-0,034***			0,194
		(17,70)	(-16,07)	(-1,93)	(-3,37)			
Eq. (13) OMXS30	0,154***	0,174***	-0,176***	0,003	-0,016**	0,676***	-0,018***	0,552
		(12,69)	(-12,27)	(-0,34)	(-1,98)	(62,63)	(-4,58)	
Eq. (13) OMXC20	0,240***	0,243***	-0,222***	-0,010	-0,015	0,387***	-0,025***	0,343
		(14,66)	(-12,73)	(-1,06)	(-1,57)	(33,50)	(-4,66)	
Eq. (13) OMXO20	0,253***	0,259***	-0,251***	-0,015*	-0,026***	0,301***	-0,021***	0,335
		(15,63)	(-14,47)	(-1,71)	(-2,69)	(32,08)	(-4,88)	
Eq. (13) DAX 30	0,178***	0,213***	-0,201***	-0,019**	-0,030***	0,567***	-0,016***	0,477
		(14,34)	(-12,98)	(-2,28)	(-3,53)	(51,84)	(-4,01)	
Eq. (13) FTSE 100	0,151***	0,202***	-0,174***	0,003	-0,005	0,626***	-0,074***	0,460
		(13,46)	(-11,01)	(0,30)	(-0,51)	(50,20)	(-11,18)	
Eq. (13) S&P 100	0,197***	0,278***	-0,220***	-0,041***	-0,029***	0,506***	-0,009***	0,463
		(18,66)	(-14,06)	(-5,11)	(-3,52)	(48,44)	(-2,73)	

*** = Statistical significance at 1 % confidence level.

** = Statistical significance at 5 % confidence level.

* = Statistical significance at 10 % confidence level.

Values in parentheses present the t-statistics for the coefficients.

All the observed γ_5 coefficients are negative and statistically significant at 1 % confidence level. Although, negative values are small it can be interpreted that Finnish stock exchange and OMXH25 companies in particular herd around Swedish, Danish, Norwegian, German, British and US companies. Results are consistent with Chiang and Zheng (2010), who recognized the influence of US market to herd formation in other markets. Earlier we found that correlation between OMXH25 and S&P 100 was not that great, but it seems to have very little influence on results obtained with equation 11. One of the findings is, that the explanatory power nominated by adjusted R^2 is much higher than in any of the equations that had previously been applied in this thesis. This also indicates that foreign market variables have similarities with the dependent variable. Same observation was also noted by Lindhe (2012).

By applying equation 12 we separate up- and down-market movements from each other. Negative and statistically significant γ_3 coefficient values indicate herding during up-markets, whereas negative and statistically significant γ_4 coefficient values indicate herding during down-markets. Results for OMXH25 companies suggest that both γ_3 and γ_4 coefficients are negative and statistically significant at 10 % and 1 % confidence level, respectively. Difference in statistical significance might be an indication of different investor behaviour in up-market compared to down-markets. Results are consistent with Lindhe (2012), but inconsistent with Sulasalmi (2014), who observe no herd behaviour in Finnish stock exchange using the same equation.

Equation 13 is a similar extension to equation 11 as was equation 12 to equation 10. We examine whether the market exhibits different behaviour in up- and down-market days when foreign market variables are included. Interestingly, when foreign market variables are included, the results for coefficients γ_3 and γ_4 are a bit different from results of equation 12. Even though both of the coefficients are negative in all setups, except slightly positive γ_3 coefficient when UK was involved, the statistical significance of the coefficients varies a lot. Only statistically significant results at 1 % confidence level were observed when US market variables were used as foreign market variables. When Germany was included, γ_3 was significant at 5 % confidence level and γ_4 at 1 % confidence level. When UK and Denmark were considered, γ_3 and γ_4 coefficient showed no statistical significance even at 10 % confidence level. Coefficients for γ_5 and γ_6 are as expected based on results from equation 11 and confirm foreign market influence on herd behaviour. Based on the results presented in this section we can comfortably confirm that Finnish stock market herds with other stock markets.

4.7 Daily market return, turnover volume and volatility herding

Economou et al. (2011) and Mobarek et al. (2014) tested whether daily market return, turnover volume or volatility have an effect on herd behaviour. Similar approach is applied to the data of this thesis and equations 14, 15 and 16 are used to obtain the results. As in theory we focus on analysing γ_3 and γ_4 coefficients. For OMXH25 companies to exhibit herd behaviour both coefficients should be negative and statistically significant. Table 12 presents the results under Economou et al. (2011) and Mobarek et al. (2014) equations.

Table 12. Coefficients for the daily CSAD under equations 14, 15 and 16.

	α	γ_1	γ_2	γ_3	γ_4	$Adj.\ R^2$
Eq. (14)	0,413***	0,321***	0,306***	-0,018*	-0,034***	0,194
		(17,70)	(16,07)	(-1,93)	(-3,37)	
Eq. (15)	0,417***	0,366***	0,233***	-0,051***	0,011	0,199
		(20,79)	(11,72)	(-5,77)	(1,02)	
Eq. (16)	0,431***	0,486***	0,002	-0,087***	0,078***	0,305
		(30,88)	(0,09)	(-11,79)	(4,95)	

*** = Statistical significance at 1 % confidence level.

** = Statistical significance at 5 % confidence level.

* = Statistical significance at 10 % confidence level.

Values in parentheses present the t-statistics for the coefficients.

Results indicate that γ_3 and γ_4 coefficients are negative at -0,018 and -0,034 respectively for equation 14, which represents equation for daily market return. The γ_3 value is statistically significant at 10 % confidence level, whereas γ_4 is statistically significant at 1 % confidence level. This observation is an indication that there might be some herd behavioural aspects in the daily market returns for OMXH25 companies. Another finding is that $\gamma_4 < \gamma_3$ holds for equation 14, which according to Economou et al. (2011) and Mobarek et al. (2014) is an indication, that herding effects are more pronounced during days with negative market returns.

Despite negative and statistically significant γ_3 coefficients for equations 15 and 16, results show positive γ_4 coefficients meaning that turnover volume or volatility do not play a role in herding for OMXH25 companies. If γ_4 coefficient was negative and statistically significant, we would have concluded that effects are more pronounced during days with high trading volume and high market volatility as $\gamma_3 < \gamma_4$ holds for equations 15 and 16.

Results presented here differ a bit from results Mobarek et al. (2014) presented for Finland. They also found γ_3 and γ_4 coefficients negative for equation 14, but value for γ_3 coefficient was without any statistical significance. Interestingly Mobarek et al. (2014) presented negative γ_3 and γ_4 coefficient for equations 15 and 16, whereas this study founds γ_3 negative and γ_4 positive. Mobarek et al. (2014) conducted additional Wald test of Chi-square to check whether the coefficients are equal under asymmetric conditions in each case. After running the test and judging by the statistical significance of the regression coefficients γ_3 and γ_4 for Finnish data, Mobarek et al. (2014) come to conclusion, that Finland does not exhibit market return, turnover volume or volatility herd behaviour. This finding is similar to the finding of this thesis, although equation 14 reveals, that there might be some small herd formation effects in market return for OMXH25 companies. This thesis examined OMXH25 companies from 1998 to 2017, whereas Mobarek et al. (2014) analysed OMXH25 companies from 1.1.2001 to 16.2.2012. It is 100 % sure that constituent companies were a bit different, because this thesis defines them as OMXH25 companies in 1.8.2018, not to mention the difference in timeframe.

4.8 Discussion of the results

As we can see results are mixed and, in my opinion, should be interpreted cautiously. Analysis and results are dependent not only from the data, but the models and point of analysis. This is highlighted by the fact that same data yielded different results with different models. Latter models, which could also be named as more sophisticated models, were the ones showing signs of herd behaviour. On the opposite, earlier models were simpler to apply, but showed no signs of herd behaviour. All the models used in this thesis are widely recognized by the science community and used by numerous scholars with different research set-ups.

One can always argue against some of the choices made in the data, analysis and their effect regarding results. For instance, it can be questioned if average from the aggregate OMXH25 constituent company returns was appropriate market portfolio for this sort of analysis. However, judging by earlier literature this kind of market portfolio construction has been applied in most cases.

Next, we answer the research questions of this thesis starting from the sub-questions. Following sub-questions were constructed to support the main research question.

“Is herd behaviour found during extreme market conditions or time periods?”

Christie and Huang (1995) provided main methodology for examination of herd behaviour during extreme conditions. After analysing both CSSD and CSAD, we found no evidence in favour of herd behaviour during extreme market conditions or time periods in the Finnish stock market. Earlier correlation analysis revealed increase in correlation from 2007 to 2008, but as we see from analysis of CSSD and CSAD in chapter 4.3., dispersions are higher than average during the Dotcom bubble and start of the financial crisis, thus indicating evidence against herd behaviour during extreme market conditions or time periods.

“Does Finnish stock market herd with other stock markets?”

In order to investigate herding across borders and with other stock markets, we included data from selected indices. Correlation analysis revealed relatively high correlations between Finnish stock market and other stock markets. More specific analysis was conducted in section 4.6. following Chiang and Zheng (2010) methodology. Results revealed statistically significant evidence in favour of herd behaviour for Finnish stock market with Swedish, Danish, Norwegian, German, British and US markets. It is then a different question whether markets move to same direction because they herd or is there something more to it, which could then eventually be just simultaneous adjustments to new market information for instance.

“What are the reasons or characteristics that may cause herd behaviour in the Finnish stock market?”

This sub-question is probably the hardest one to provide an answer for as reasons or characteristics that may cause herd behaviour in the Finnish stock market could basically be anything. Results are contradicting with each other and no real consensus is found. Based on the correlation analysis, there are some companies with higher correlations with companies within the same industry. Return sign analysis reveals that companies are more likely to have same direction in returns in particular market day if these returns are positive. This could mean that rising markets are more likely to generate herding, but yet there was no other evidence from regressions supporting this. In fact, results from Economou et al. (2011) and Mobarek et al. (2014) methodology in previous section suggests that herding effects for Finnish stock market are more pronounced during days with negative market returns. Based on similar approach, turnover volume or volatility are found not to play a role in herd behaviour in the Finnish stock market. Analysis of CSSD and CSAD showed yearly fluctuations and the general trend seems to be that dispersions are getting smaller as years go by. Bikhchandani and Sharma (2001) list imperfect information as one of the most important causes of herd behaviour and it is not that far-fetched that this applies to Finnish stock market as well.

Sub-questions help to form our answer to the main research question of this thesis:

“Is Finnish stock market subject to herd behaviour?”

As contradicting as the subject itself is, so is our answer to the main research question. Finnish stock market is subject to herd behaviour in a sense, that empirical evidence provides some weak support for herding inside the market and some strong evidence for herding with other markets. However, at times and with most of the models, which did not include foreign market variables, no herd behaviour was found. It also remains questionable, which market developments and reactions are actually caused by herd behaviour and what not. Analysis reveals the weakness of current methodologies. Methods are easy to apply, but results are at general level and one cannot really say, what is actually caused by herd behaviour.

One thing, that is less arguable than the methodologies to detect herd behaviour or the results of this study and other papers dealing with herd behaviour, is the effects of the phenomenon. Herd behaviour in the stock market has many profound effects. It imposes a serious threat to national and international diversification, fools investors when it gains momentum and can lead to serious misinterpretations about how markets adjust to new information. These are just some of the effects, that come to mind and there are definitely many more. The more complex our markets and available financial instruments evolve, the more likely we are to witness and explore new anomalies and phenomena.

By definition herd behaviour sounds simple (for different definitions see Avery and Zemsky, 1998; Banerjee, 1992; Bikhchandani and Sharma, 2001; Nofsinger and Sias, 1999; Grinblatt et al., 1995; Christie and Huang, 1995), but in reality, the phenomena is hard to identify and explain. Current approaches developed by Lakonishok et al. (1992), Christie and Huang (1995), Chang et al. (2000), Hwang and Salmon (2004), Sias (2004), Chiang and Zheng (2010) Economou et al. (2011) and Mobarek et al. (2014) only capture certain type of herding. As for approach of this thesis, it can fairly easily be stated, that herd behaviour is something much more abstract and cannot be recognized just by analysing returns dispersions.

5 SUMMARY AND CONCLUSIONS

Throughout the history of behavioural finance, empirical research has focused on revealing new anomalies to challenge traditional finance theories. Herd behaviour is one area of behavioural finance, which has gained considerable attention from the scholars in recent decades. Herd behaviour studies have focused on finding herd behaviour inside particular market, between markets, among individuals or groups and in certain market situations such as during times of financial turmoil. Different approaches have been developed over the years, but most of them are based on the empirical grounds of either Christie and Huang (1995), Lakonishok et al. (1992) or Hwang and Salmon (2004).

This thesis examined herd behaviour in the Finnish stock market by applying methods developed by Christie and Huang (1995), Chang et al. (2000), Chiang and Zheng (2010) and Mobarek et al. (2014) to daily return data of OMXH25 companies from 1st of January 1998 to 29th of December 2017. These methodologies are based on the cross-sectional standard deviations (CSSD) and absolute standard deviations (CSAD) of returns, also known as dispersions. For herd behaviour to be present, dispersions should be low. After analysing for market-wide herding in Finland, foreign market data from Sweden, Denmark, Norway, Germany, UK and US was added to analyse if Finnish stock market herds with other foreign markets or across the borders.

Earlier literature has presented mixed and even contradicting results. Christie and Huang (1995) found no evidence of herd behaviour in the US. Chang et al. (2000) found evidence of herding in South Korea and Taiwan, partial evidence in Japan and no evidence in US and Hong Kong. Using different approach, Hwang and Salmon (2004) report herd behaviour in US, UK and South Korea. Wang and Canela (2006) show that emerging markets have higher level of herding than developed markets. Still Demirer and Kutan (2006) find no signs of herding in Chinese market. On the opposite, Tan et al. (2008) report herding in Chinese market and Demirer et al. (2010) report herd behaviour from Taiwanese market. Chiang and Zheng (2010) found evidence of herding in advanced stock markets. Khan et al. (2011) found herd behaviour in France, UK, Germany and Italy. Economou et al. (2011) show herding in Greece and Italy, partial herding in Portugal and no herding in Spain. Mobarek et al. (2014) found that herding effects are significant during financial crisis for continental European countries and during Eurozone crisis for the Nordic countries.

Very few past studies had focused on herd behaviour in the Finnish context. Saastamoinen (2008) reported no herd behaviour when Chang et al. (2000) model was applied, but contradicting observation was made by employing quantile regression model. Quantile regression model revealed, that herd behaviour could be present in the Finnish stock market and author himself mentions, that there are also some characteristics supporting presence of herd behaviour in Helsinki stock exchange. Lindhe (2012) found significant market-wide herding in Finland. She also reported Finland to herd around the US market, European market and with Swedish, Danish and Norwegian markets. Sulasalmi (2014) reported no herd behaviour at all. Mobarek et al. (2014) reported some signs of herd behaviour in Finland during crises and in regimes of different extreme market conditions, but their analysis of market return, turnover volume or volatility herd behaviour was negative.

Results of this thesis indicate that there are some aspects of market-wide herd behaviour present in the Finnish stock market. Some of the OMXH25 companies have relatively high correlations in stock returns. Return sign analysis reveals, that company returns are more likely to follow market portfolio returns than deviate from them. CSSD and CSAD showed yearly fluctuations and have decreased in recent times compared to earlier times and some of the regressions had negative and statistically significant coefficients, which are interpreted as signs of herd behaviour. Interestingly Chiang and Zheng (2010) models were more sensitive to show signs of herd behaviour compared to previous models by Christie and Huang (1995) and Chang et al. (2000). Herd behaviour was not found during periods of market stress. Furthermore, turnover volume or volatility do not play a role in herding for Finnish stock market. Overall, findings could be described as weak evidence of market-wide herd behaviour as not all the regressions models showed signs herd behaviour.

Evidence for herding with foreign markets is more evident and a great degree of co-movement can be observed. Index returns of OMXH25 correlate greatly with most of the indices and other indices correlate greatly with each other as well with one exception, the US market represented by the S&P 100 index. Chiang and Zheng (2010) models with foreign markets confirmed our assumptions as returns of OMXH25 herd significantly with returns of OMXS30, OMXC20, OMXO20, DAX 30, FTSE 100 and S&P 100. However, based on earlier literature we would have expected the US market to show a more significant impact.

It is important to bear in mind, that this analysis on herd behaviour in the Finnish stock market is based on observations from daily logarithmic stock returns. Although, the methodology to detect herd behaviour is widely recognized and used by the science community, it has some serious deficiencies. It is very hard to identify what is actually caused by herd behaviour and what is caused by something else. Moreover, models are quite simple to use, but they do not give conclusive evidence and results are always subject to interpretation. For instance, some other methodology could yield positive results for extreme market herding, but with our study set-up supportive evidence was not found. Bikhchandani and Sharma (2001) and Hwang and Salmon (2004) criticize existing statistical approaches to measure herd behaviour and there is clearly a need to develop more powerful methodologies to analyse herd behaviour.

This study contributes to existing literature in a variety of ways. First of all, it increases knowledge on herd behaviour in the Finnish stock market. Secondly, by applying wide range of existing methodologies this study continues on the empirical path guided by previous literature. Thirdly, literature review section puts together a comprehensive summary of the existing literature in case someone wants to work with a similar subject in the future.

Future research on herd behaviour could include studies related to analyst recommendations. Especially during periods when stock prices are rising, and people are more interested in increasing their wealth through trading stocks and making capital investments. It would also be interesting to see if analyst recommendations and goal price indications have short-term and/or long-term effect on stock price movements and direction of the movement. This is already partially witnessed by the so called Inderes –effect, which highlights that private investors are extremely prone to following recommendations by the professionals. Same kind of behaviour is very common in video games, if there is some form of virtual currency and possibility to trade within the game. Some famous Youtubers are already using this as a tool and many followers are seen to mimic setups seen in videos. More traditionally future research could be made using alternative approach, for example Hwang and Salmon (2004) or Choi and Sias (2009), to see if results are any different. Also, different sub-samples such as small cap versus large cap stocks would be interesting to compare. Greater herding for small cap stocks due to lack of publicly available information was first argued by Lakonishok et al. (1992).

LIST OF REFERENCES

Ahmed, M., Abbass, M. Y. & Abbasi, S. (2012) Herd Behaviour in Extreme Conditions. An Evidence from Spanish Market. *Abasyn Journal of Social Science*, Vol. 8, No. 1, pp. 74-97.

Avery C. & Zemsky, P. (1998) Multi-Dimensional Uncertainty and Herd Behavior in Financial Markets. *The American Economic Review*, Vol. 88, No. 4, pp. 724-748.

Baig, T. & Goldfajn, I. (1999) Financial Market Contagion in the Asian Crises. *IMF Staff Papers*, Vol. 46, No. 2, pp. 167-195.

Balcilar, M., Demirer, R. & Hammoudeh, S. (2013) Investor Herds and Regime-Switching: Evidence from Gulf Arab Stock Market. *Journal of International Financial Markets, Institutions & Money*, Vol. 23, No. 1, pp. 295-321.

Banerjee, A. V. (1992) A Simple Model of Herd Behaviour. *The Quarterly Journal of Economics*, Vol. 107, No. 3, pp. 797-817.

Bikhchandani, S., Hirshleifer, D. & Welch, I. (1992) A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy*, Vol. 100, No. 5, pp. 992-1026.

Bikhchandani, S. & Sharma, S. (2001) Herd Behaviour in Financial Markets. *IMF Staff Papers*, Vol. 47, No.3, pp. 279-310.

Bohl, M. T., Branger, N. & Trede, M. (2017) The Case for Herding Is Stronger than You Think. *Journal of Banking and Finance*, Vol. 85, No. 12, pp. 30-40.

Boyer, B. H., Kumagai, T. & Yuan, K. (2006) How Do Crises Spread? Evidence from Accessible and Inaccessible Stock Indices. *The Journal of Finance*, Vol. 61, No. 2, pp. 957-1003.

Celen, B. & Kariv, S. (2004) Distinguishing Informational Cascades from Herd Behavior in the Laboratory. *American Economic Review*, Vol. 94, No. 3, pp. 484-498.

Chang, E. C., Cheng, J. W. & Khorana, A. (2000) An Examination of Herd Behaviour in Equity Markets: An International Perspective. *Journal of Banking & Finance,* Vol. 24, No. 10, pp. 1651-1679.

Chiang, T. C., Jeon. B. N. & Li, H. (2007) Dynamic Correlation Analysis of Financial Contagion: Evidence from Asian Markets. *Journal of International Money and Finance*, Vol. 26, No. 7, pp. 1206-1228.

Chiang, T. C. & Zheng, D. (2010) An Empirical Analysis of Herd Behaviour in Global Stock Markets. *Journal of Banking & Finance*, Vol. 34, No. 8, pp. 1911-1921.

Choi, N. & Sias, R. W. (2009) Institutional Industry Herding. *Journal of Financial Economics*, Vol. 94, No. 3, pp. 469-491.

Christie, W. G. & Huang, R. D. (1995) Following the Pied Piper: Do Individual Returns Herd around the Market. *Financial Analysts Journal*, Vol. 51, No. 4, pp. 31-37.

Cont, R. & Bouchaud, J.-P. (2000) Herd Behavior and Aggregate Fluctuations in Financial Markets. *Macroeconomic Dynamics*, Vol. 4, No. 2, pp. 170-196.

De Almeida, R. P., Costa, H. C. & Da Costa Jr., N. C. A (2012) Herd Behavior in Latin American Stock Markets. *Latin American Business Review*, Vol. 13, No.2, pp. 81-102.

Demirer, R. & Kutan, A. M. (2006) Does Herding Behavior Exist in Chinese Stock Markets? *Journal of International Financial Markets, Institutions & Money*, Vol. 16, No. 2, pp. 123-142.

Demirer, R., Kutan, A. M. & Chen, C.-D. (2010) Do Investors Herd in Emerging Stock Markets?: Evidence from the Taiwanese Market. *Journal of Economic Behavior & Organization*, Vol. 76, No.2, pp. 283-295.

Demirer, R., Lien, D. & Zhang, H. (2015) Industry Herding and Momentum Strategies. *Pacific-Basin Journal*, Vol. 32, No. C, pp. 95-110.

Devenow, A. & Welch, I. (1996) Rational Herding in Financial Economics. *European Economic Review*, Vol. 40, No. 3-5, pp. 603-615.

Dhaene, J., Linders, D., Schoutens, W. & Vyncke, D. (2012) The Herd Behavior Index: A New Measure for the Implied Degree of Co-movement in Stock Markets. *Insurance: Mathematics and Economics*, Vol. 50, No. 3, pp. 357-370.

Dutta, A., Gahan, P. & Panda, S. K. (2016) Evidences of Herding Behaviour in the Indian Stock Market. *Vilakshan, XIB Journal of Management*, Vol. 13, No. 2, pp. 23-40.

Economou, F., Kostakis, A. & Philippas, N. (2011) Cross-country Effects in Herding Behavour: Evidence from Four South European Markets. *Journal of International Financial Markets, Institutions & Money*, Vol. 21, No. 3, pp. 443-460.

Economou, F., Gavriilidis, K., Kallinterakis, V. & Yordanov, N. (2015) Do Fund Managers Herd in Frontier Markets – and why? *International Review of Financial Analysis*, Vol. 40, No. 1, pp. 76-87.

Ekholm, A. & Pasternack, D. (2008) Overconfidence and Investor Size. *European Financial Management*, Vol. 14, No. 1, pp. 82-98.

Froot, K. A., Scharfstein, D. S. & Stein, C. J. (1992) Herd on the Street: Informational Inefficiences in a Market with Short-Term Speculation. *The Journal of Finance*, Vol 47, No. 4, pp. 1461-1484.

Garg, A. K., Mitra, S. K. & Kumar, D. (2016) Do Foreign Institutional Investors Herd in Emerging Markets? A Study of Individual Stocks. *Decision*, Vol. 43, No. 3, pp. 281-299.

Gleason, K. C., Lee, C. I. & Mathur, I. (2003) Herding Behavior in European Futures Markets. *Finance Letters*, Vol. 1, No 1, pp. 5-8.

Gleason, K. C., Mathur, I. & Peterson, M. A. (2004) Analysis of Intraday Herding Behavior among the Sector ETFs. *Journal of Empirical Finance*, Vol. 11, No. 5, pp. 681-694.

Goodfellow, C., Bohl, M. T. & Gebka, B. (2009) Together We Invest? Individual and Institutional Investors' Trading Behaviour in Poland. *International Review of Financial Analysis*, Vol. 18, No. 4, pp. 212-221.

Graham, J. R. (1999) Herding Among Investment Newsletters – Theory and Evidence. *The Journal of Finance*, Vol. 54, No.1, pp. 237-268.

Grinblatt, M. & Keloharju, M. (2000) The Investment Behavior and Performance of Various Investor Types: A Study of Finland's Unique Data Set. *Journal of Financial Economics*, Vol. 55, No. 1, pp. 43-67.

Grinblatt, M., Keloharju, M. & Linnainmaa, J. T. (2012) IQ, Trading Behavior, and Performance. *Journal of Financial Economics*, Vol. 104, No. 2, pp. 339-362.

Grinblatt, M., Titman, S. & Wermers, R. (1995) Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior. *The American Economic Review*, Vol. 85, No. 5, pp. 1088-1105.

Guo, W.-C. & Shih, H.-T. (2008) The Co-Movement of Stock Prices, Herd Behaviour and High-Tech Mania. *Applied Financial Economics*, Vol. 18, No. 16, pp. 1343-1350.

Henker, J., Henker, T. & Mitsios, A. (2006) Do investors herd intraday in Australian equities? *International Journal of Managerial Finance*, Vol. 2, No. 3, pp.196-219.

Hirschey, M., Richardson, V. J. & Scholz, S. (2000) Stock-Price Effects of Internet Buy-Sell Recommendations: The Motley Fool Case. *The Financial Review*, Vol. 35, No. 2, pp. 147-174.

Hirshleifer, D. & Teoh, S. H. (2003) Herd Behaviour and Cascading in Capital Markets: A Review and Synthesis. *European Financial Management*, Vol. 9, No. 1, pp. 25-66.

Huang, T.-C., Lin, B.-H. & Yang, T.-H. (2015) Herd Behavior and Idiosyncratic Volatility. *Journal of Business Research,* Vol. 68, No. 4, pp. 763-770.

Hwang, S. & Salmon, M. (2004) Market Stress and Herding. *Journal of Empirical Finance*, Vol. 11, No. 4, pp. 585-616.

Javaira, Z. & Hassan, A. (2015) An Examination of Herding Behavior in Pakistani Stock Market. *International Journal of Emerging Markets*, Vol. 10, No. 3, pp. 474-490.

Jlassi, M. & Bensaïda, A. (2014) Herding Behavior and Trading Volume: Evidence from the American Indexes. *International Review of Management and Business Research*, Vol. 3, No. 2, pp. 705-722.

Kaminsky, G. L. & Schmukler, S. L. (1999) What Triggers Market Jitters? A Chronicle of the Asian Crisis. *Journal of International Money and Finance*, Vol. 18, No. 4, pp. 537-560.

Khan, H., Hassairi, S. A. & Viviani, J. L. (2011) Herd Behavior and Market Stress: The Case of Four European Countries. *International Business Research,* Vol. 4, No. 3, pp. 53-67.

Lakonishok, J., Shleifer, A. & Vishny, R. W. (1992) The Impact of Institutional Trading on Stock Prices. *Journal of Financial Economics*, Vol. 32, pp. 23-43.

Lindhe, E. (2012) Herd Behavior in Stock Markets – A Nordic Study. *Master's Thesis*, Lund Universitet Ekonomihögskolan, Deparment of Economics.

Litimi, H. (2017) Herd Behavior in the French Stock Market. *Review of Accounting and Finance*, Vol. 16, No. 4, pp. 497-515.

Lux, T. (1995) Herd Behavior, Bubbles and Crashes. *The Economic Journal*, Vol. 105, No. 431, pp. 881-896.

Messis, P. & Zapranis, A. (2014) Herding Behaviour and Volatility in the Athens Stock Exchange. *The Journal of Risk Finance,* Vol. 15, No. 5, pp. 572-590.

Mobarek, A., Mollah, S. & Keasey, K. (2014) A Cross-Country Analysis of Herd Behavior in Europe. *Journal of International Financial Markets, Institutions & Money*, Vol. 32, pp. 107-127.

Nobel Media (2018) All Prizes in Economic Sciences. [WWW Document]. [Referred on 26th of March 2018]. Available https://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/

Nofsinger, J. R. & Sias, R. W. (1999) Herding and Feedback Trading by Institutional and Individual Investors. *The Journal of Finance*, Vol. 54, No. 6, pp. 2263-2295.

Ohlson, P (2010) Herd Behavior on the Swedish Stock Exchange. *Master's Thesis*, Jönköping International Business School.

Saastamoinen, J. (2008) Quantile Regression Analysis of Dispersion of Stock Returns – Evidence of Herding? *Keskustelualoitteita #57*, Joensuun yliopisto, Taloustieteet.

Scharfstein, D. S. & Stein, J. C. (1990) Herd Behavior and Investment. *The American Economic Review*, Vol. 80, No. 3, pp. 465-479.

Schiller, R. J. (1995) Conversation, Information, and Herd Behavior. *American Economic Review*, Vol. 85, No. 2, pp. 181-185.

Schiller, R. J. & Pound, J. (1989) Survey Evidence on Diffusion of Interest Among Institutional Investors. *Journal of Economic Behavior and Organization*, Vol. 12, No. 1, pp. 47-66.

Schmeling, M. (2008) Investor sentiment and stock returns: some international evidence. *Discussion papers, School of Economics and Management of the Hanover Leibniz University*, No. 407.

Shah, M. U. D., Shah, A. & Khan, S. U. (2017) Herding Behaviour in the Pakistani Stock Exchange: Some New Insights. *Research in International Business and Finance*, Vol. 42, No 1, pp. 865-873.

Sias, R. W. (2004) Institutional Herding. *Review of Financial Studies*, Vol. 17, No. 1, pp. 165-206.

Smith, L. & Sørensen, P. (2000) Pathological Outcomes of Observational Learning. *Econometrica*, Vol. 68, No. 2, pp. 371-398.

Sulasalmi, I. (2014) Together Everyone Achieves More? Herd Behavior in the Finnish Stock Market. *Master's Thesis*, Lappeenranta University of Technology, School of Business and Management.

Tan, L., Chiang, T. C., Mason, J. R. & Nelling, E. (2014) Herding Behaviour in Chineses Stock Markets: An Examination of A and B Shares. *Pacific-Basin Finance Journal,* Vol. 18, No. 1-2, pp. 61-77.

Thaler, R. H. (1999) The End of Behavioral Finance. *Financial Analysts Journal*, Vol. 55, No. 6, pp. 12-17.

Wang, D. & Canela, M (2006) Herd Behavior towards the Market Index: Evidence from 21 Financial Markets. *IESE Business School, Working paper,* No. 776, pp. 1-47.

Welch, I. (1992) Sequential Sales, Learning, and Cascades. *The Journal of Finance*, Vol. 47, No. 2, pp. 695-732.

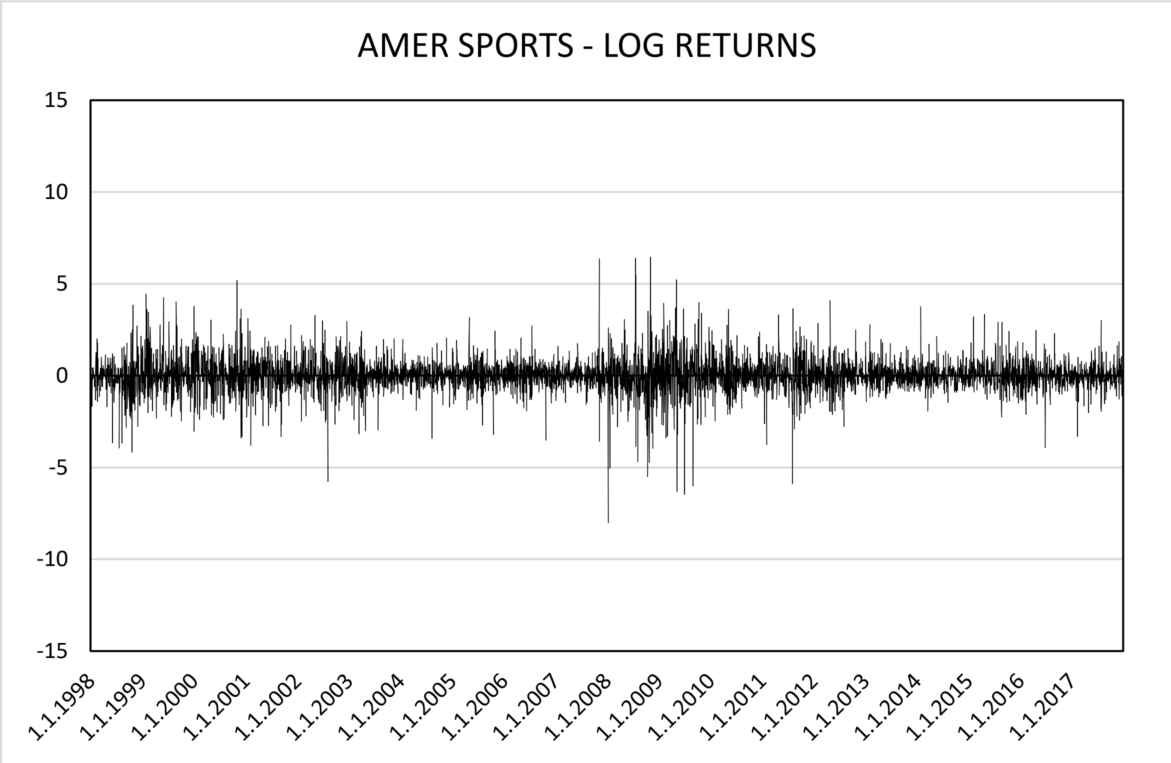
Welch, I. (2000) Herding Among Security Analysts. *Journal of Financial Economics*, Vol. 58, No. 3, pp. 369-396.

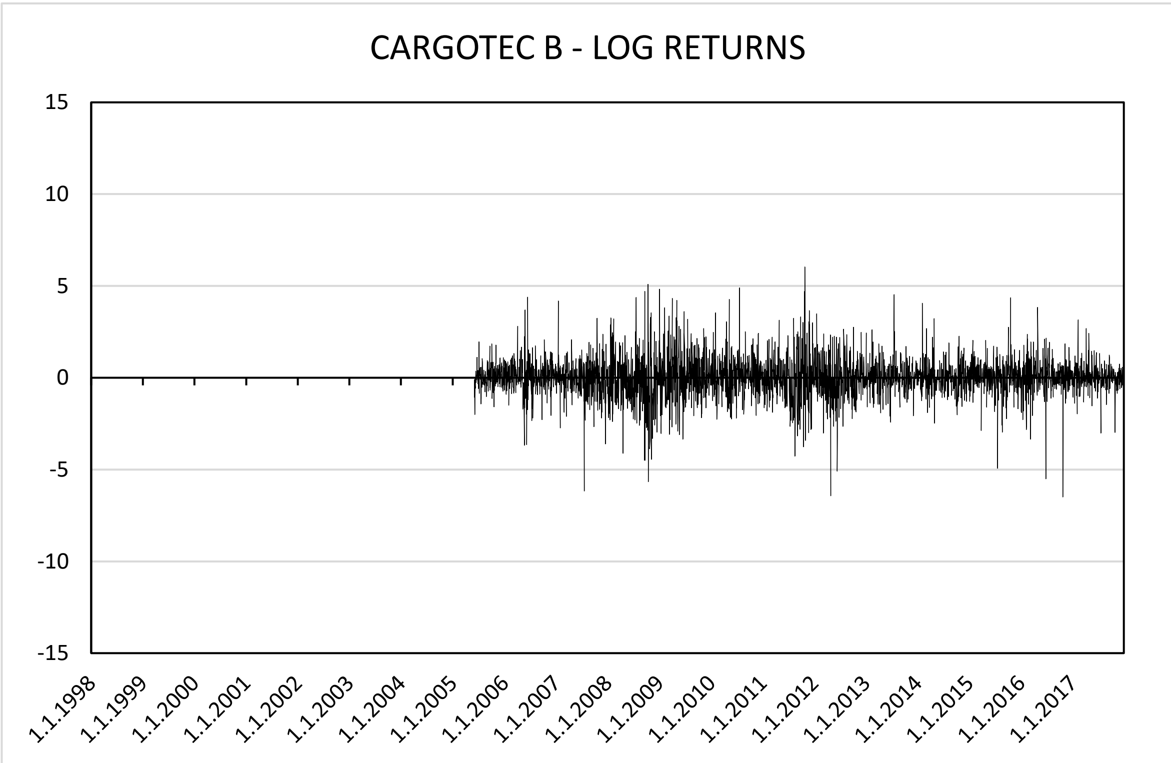
Wermers, R. (1999) Mutual Fund Herding and the Impact on Stock Prices. *The Journal of Finance*, Vol. 54, No. 2, pp. 581-622.

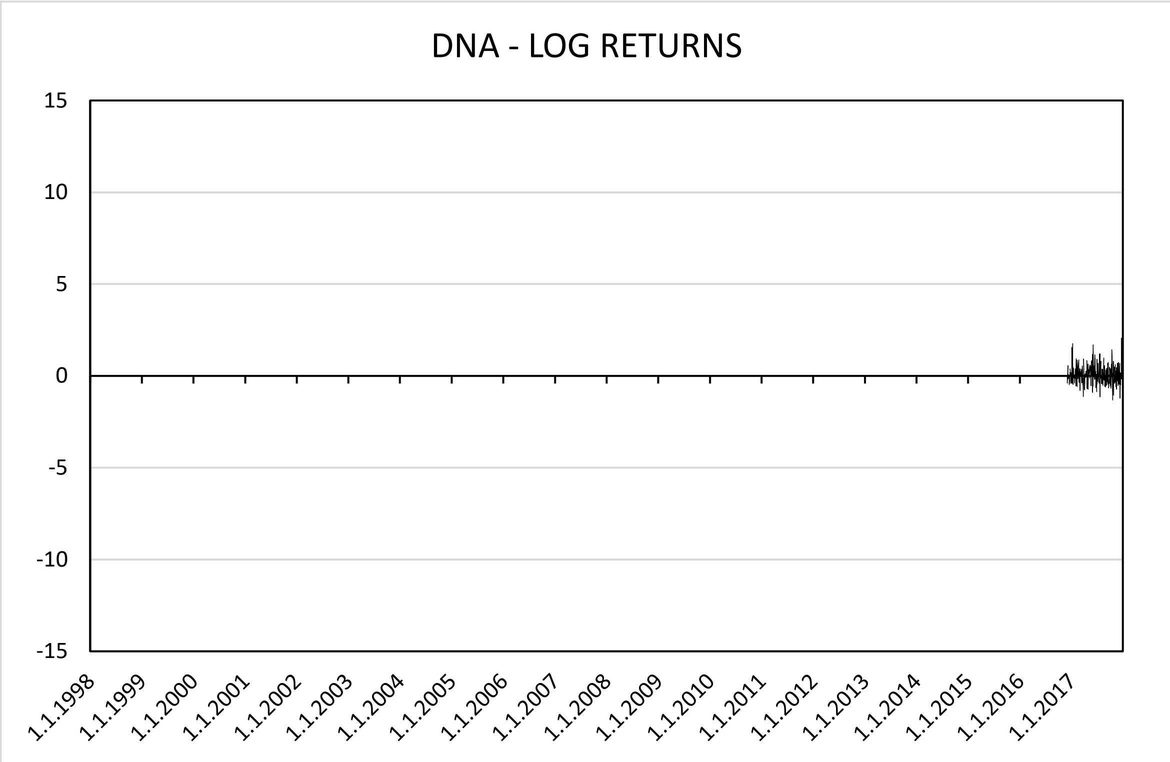
Yao, J., Ma, C. & Peng He, W. (2014) Investor Herding Behaviour of Chinese Stock Market. *International Review of Economics and Finance*, Vol. 29, No. 1, pp. 12-29.

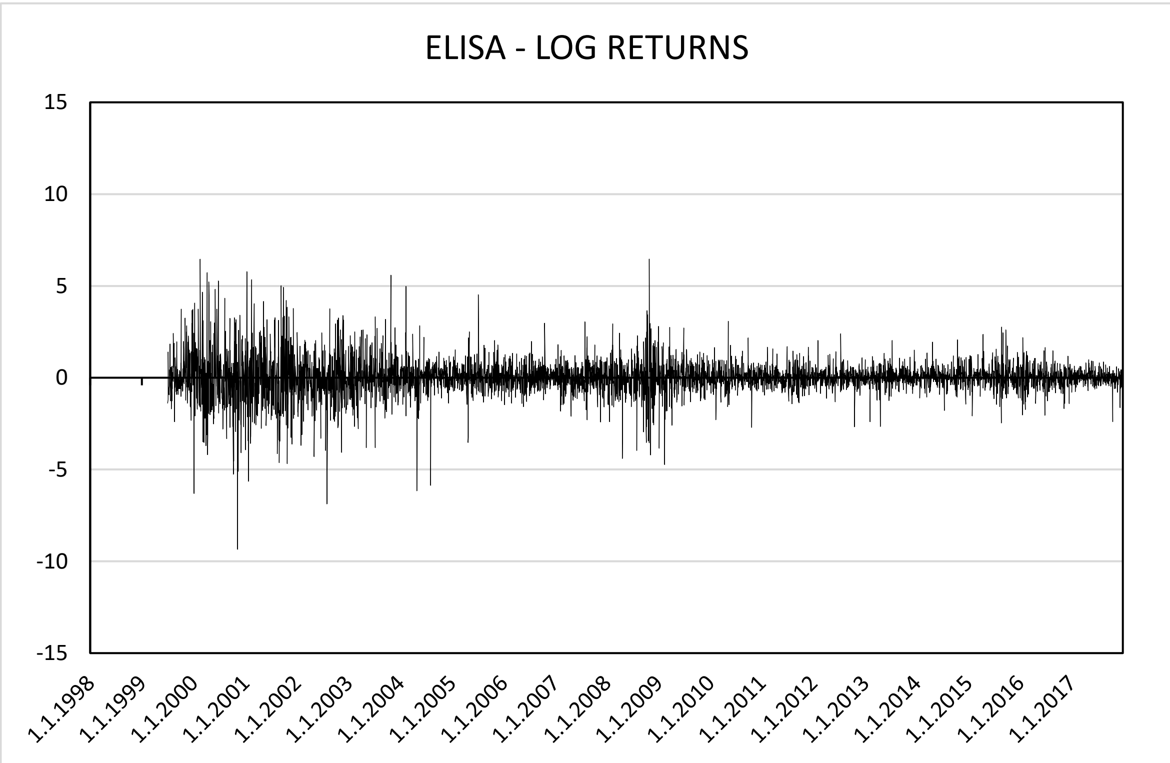
Zheng, D., Li. H. & Zhu, X. (2015) Herding Behaviour in Institutional Investors: Evidence from China’s Stock Market. *Journal of Multinational Financial Management*, Vol. 32-33, No. 4, pp. 59-76.

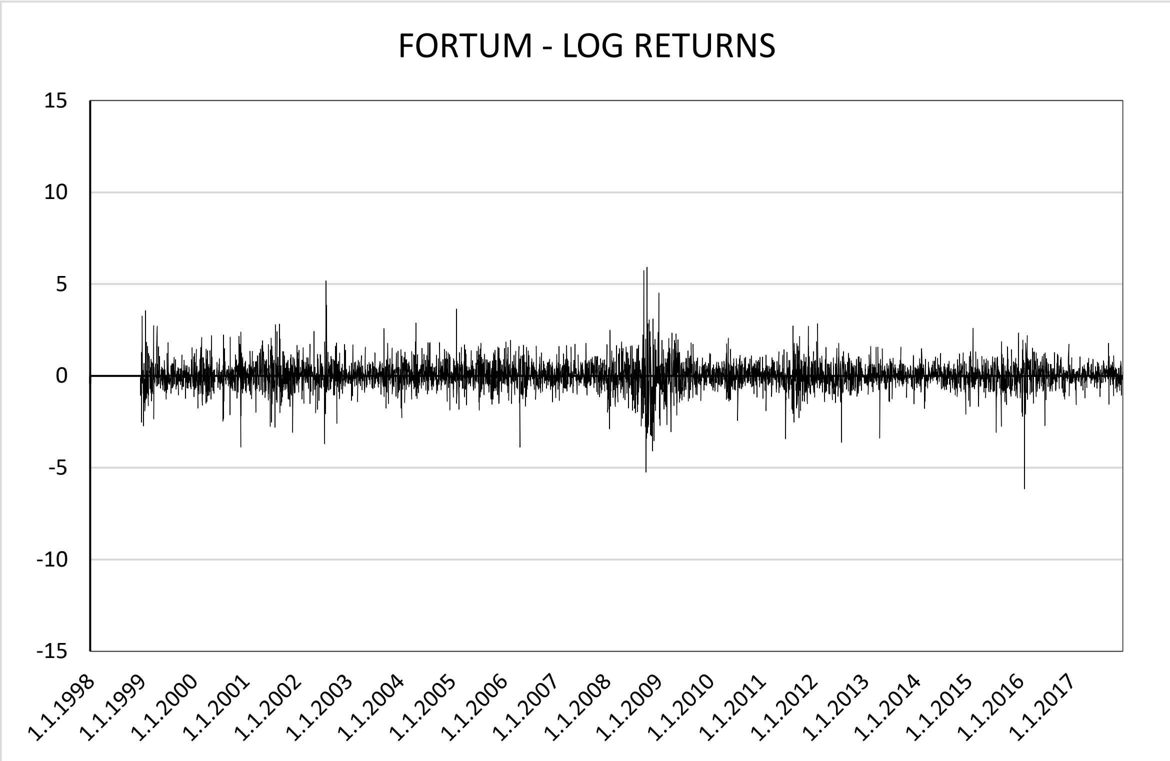
Appendix 1. Logarithmic returns of individual OMXH25 companies

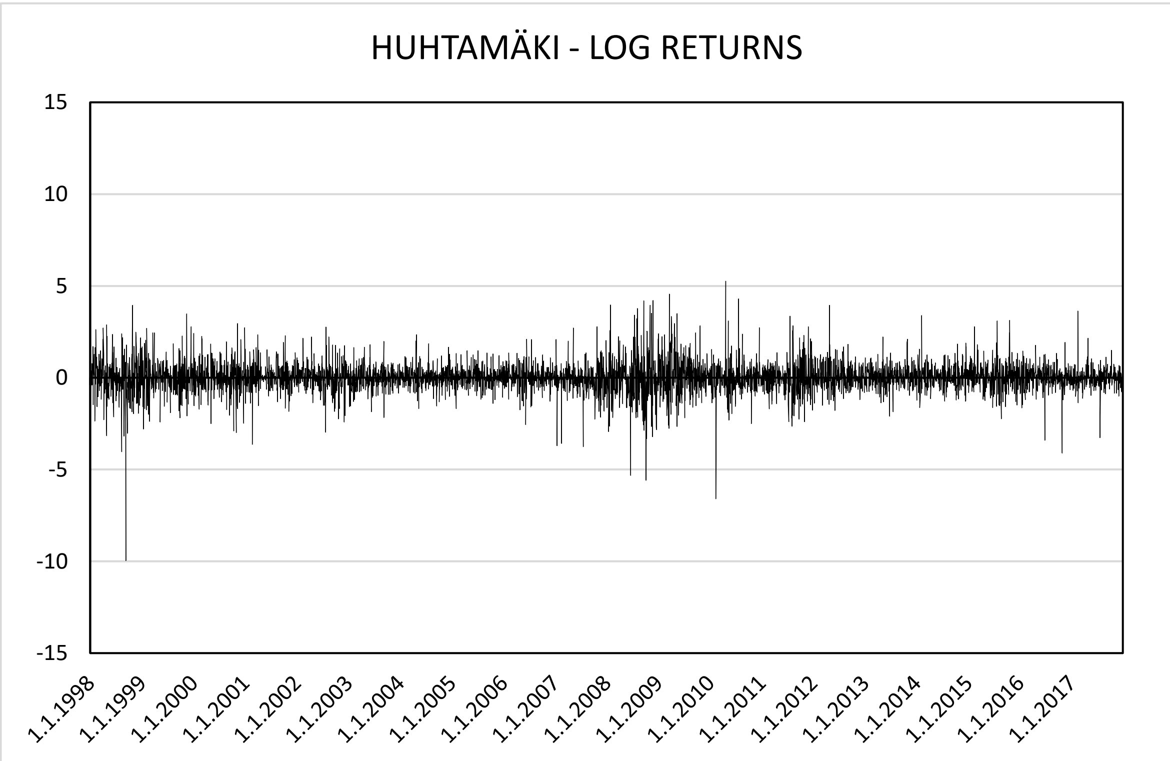


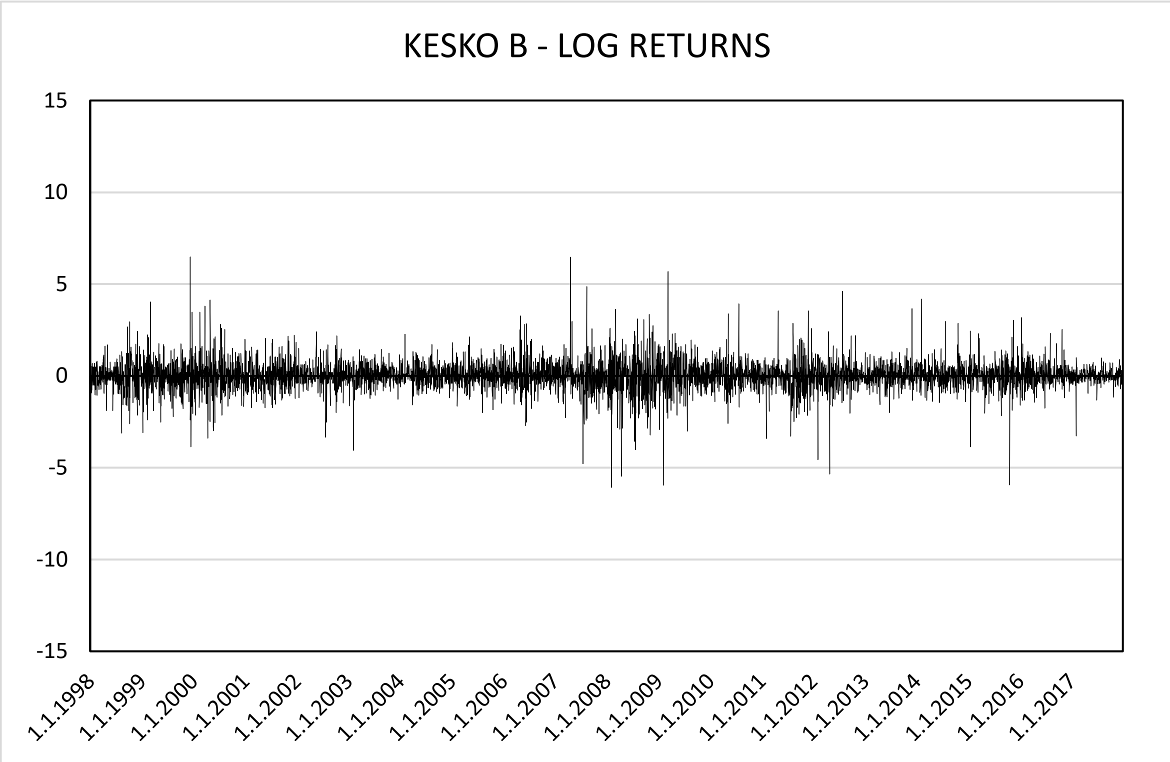


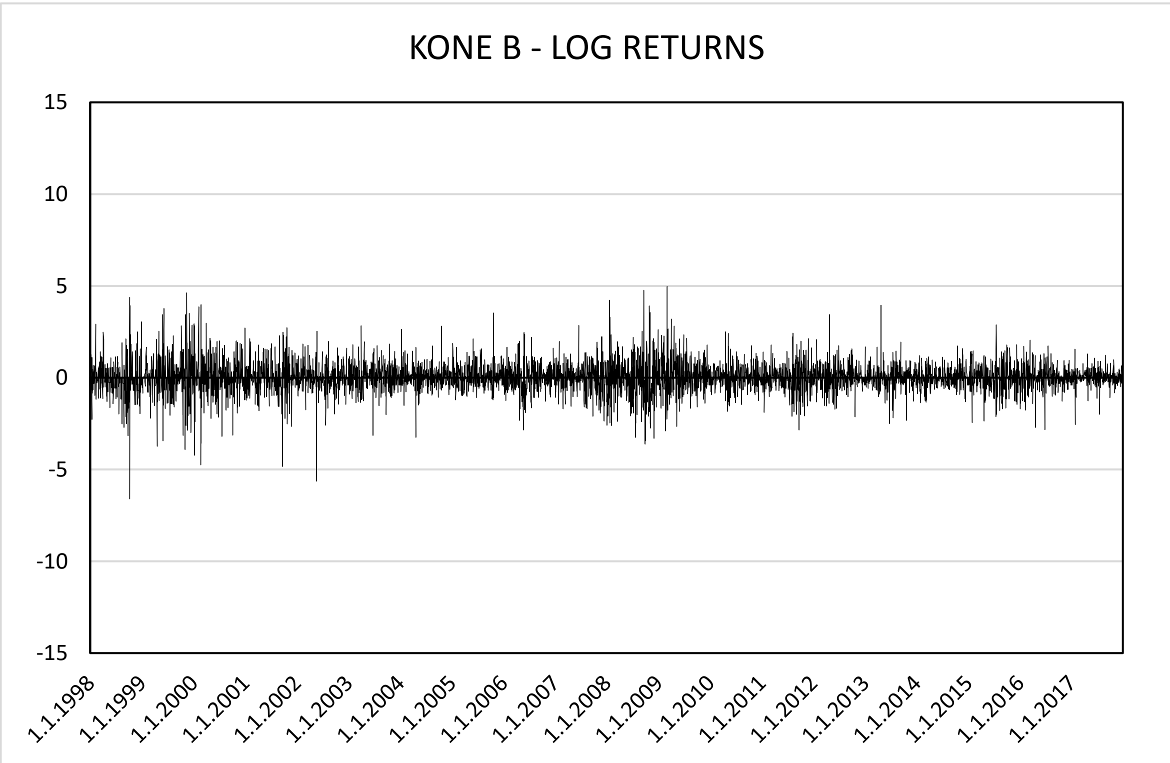

DNA - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

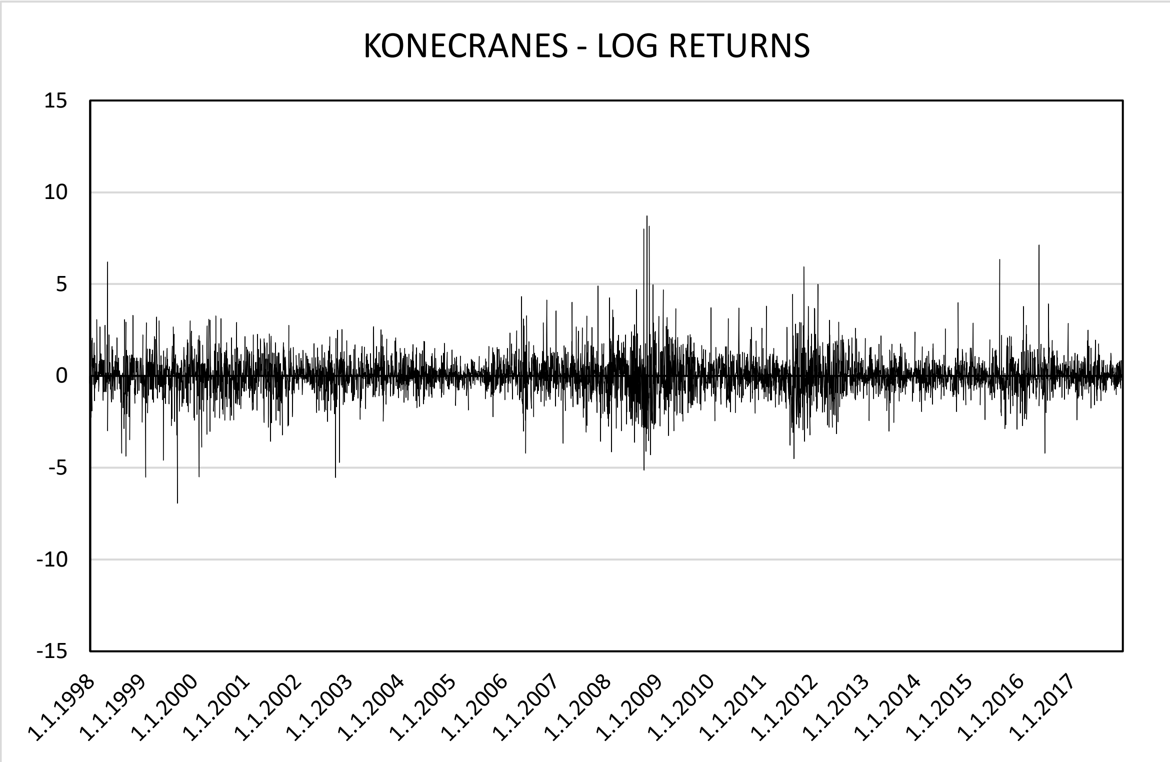

ELISA - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

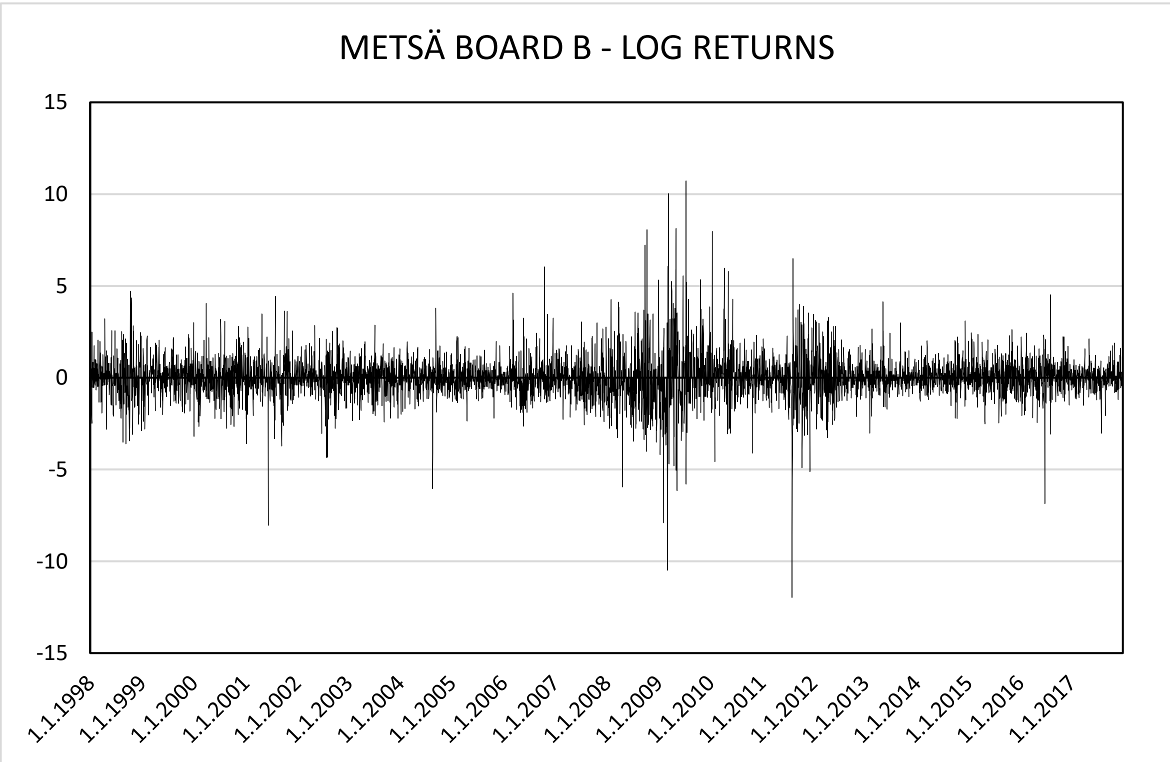

FORTUM - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

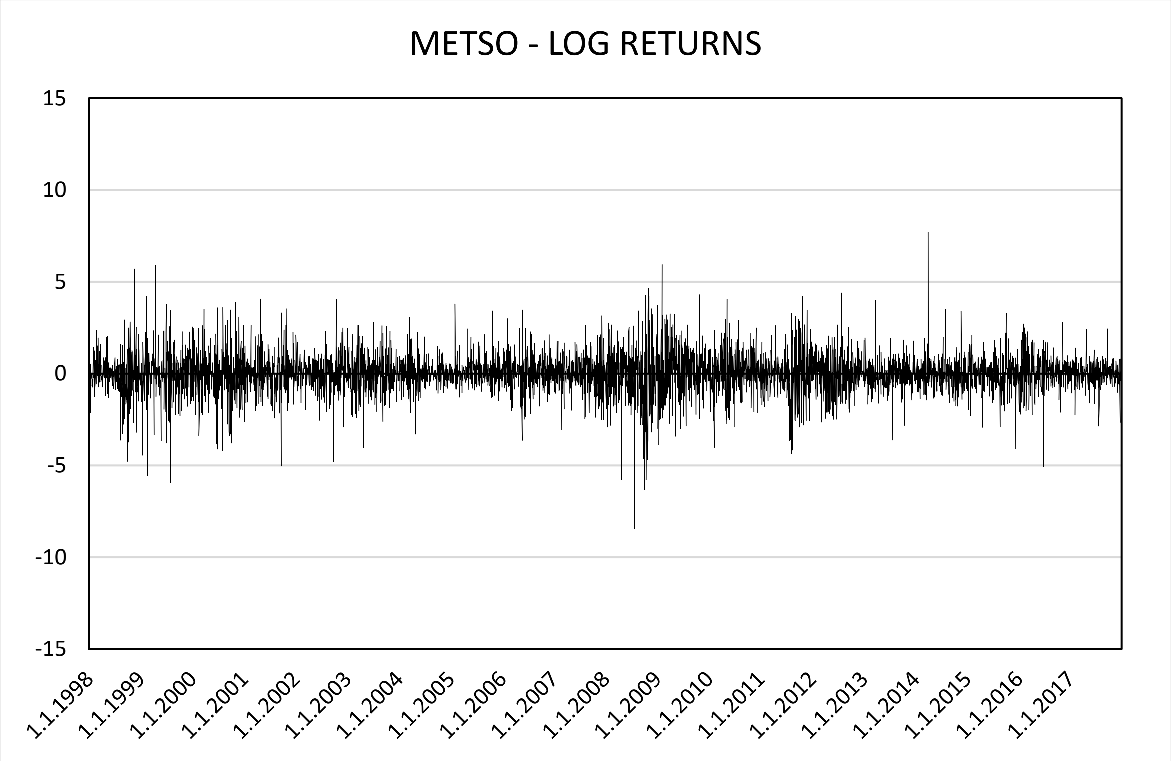

HUHTAMÄKI - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

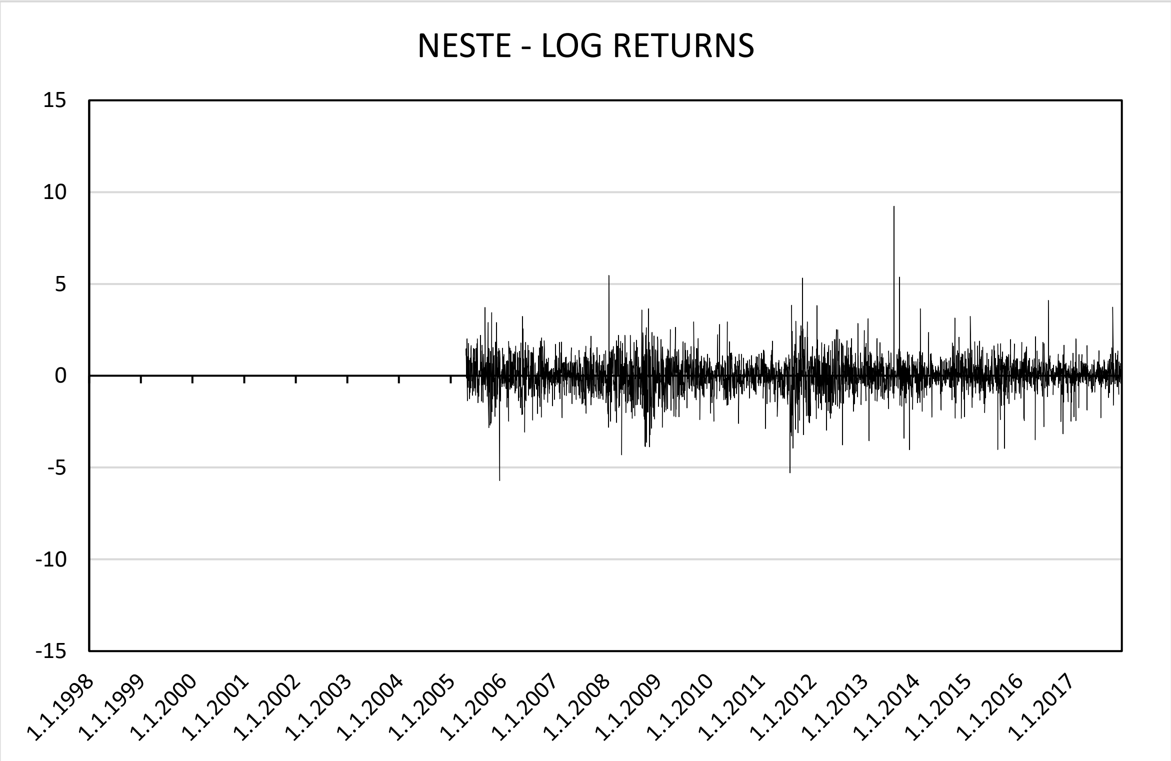

KESKO B - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

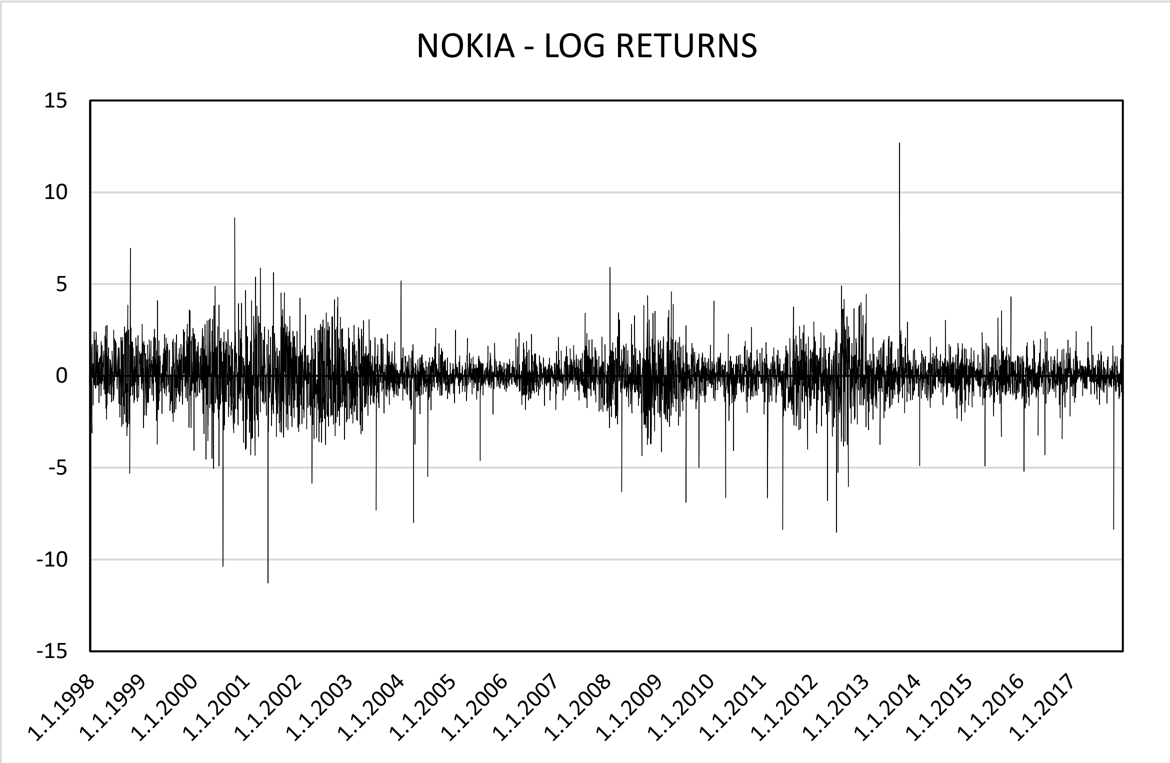

KONE B - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

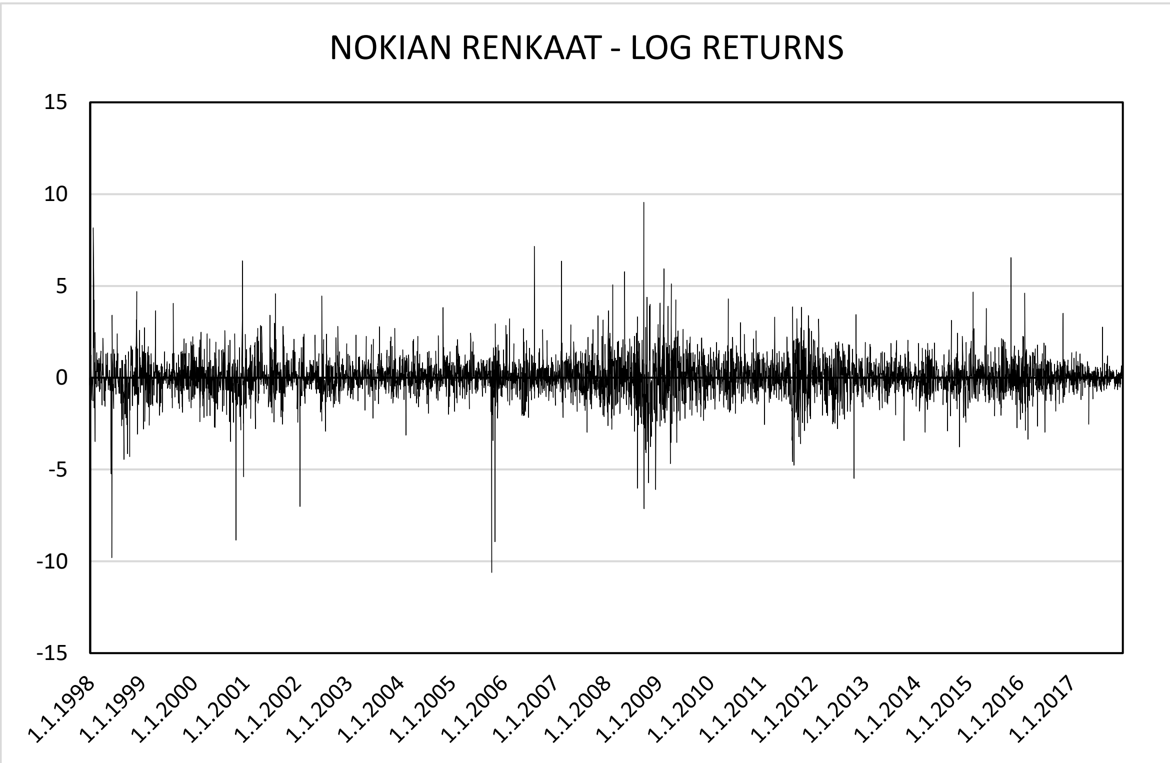

KONECRANES - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

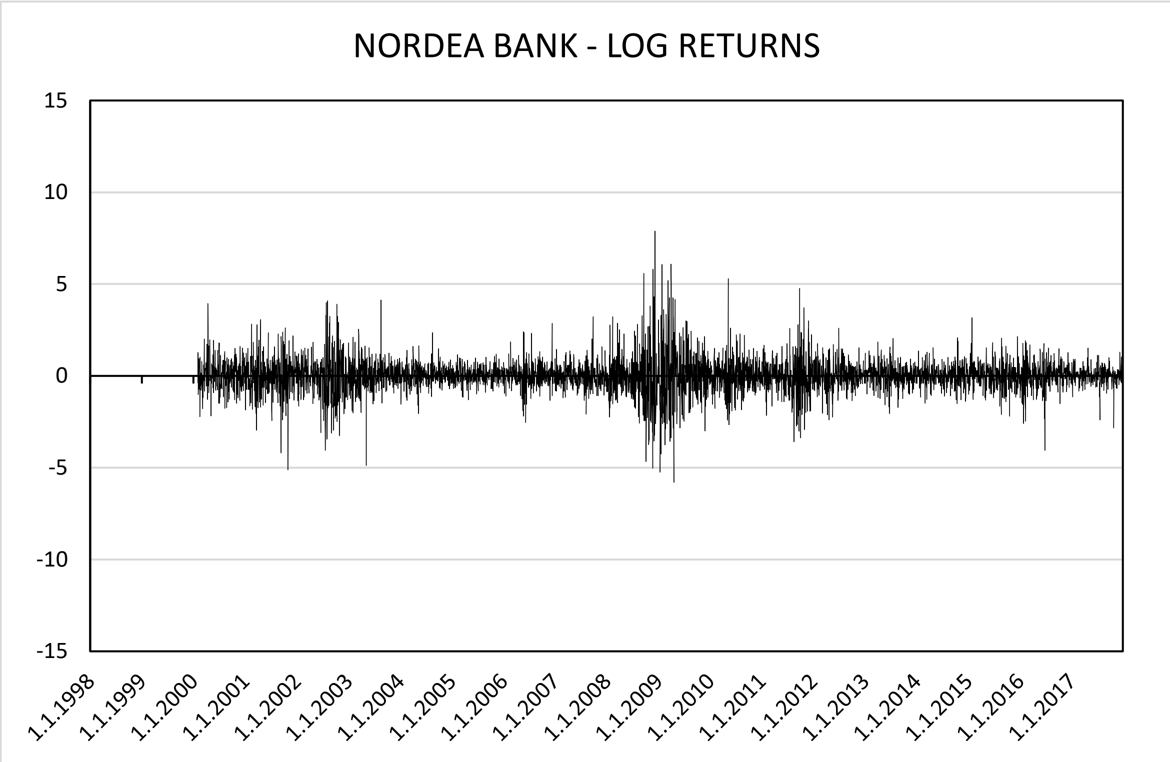

METSÄ BOARD B - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

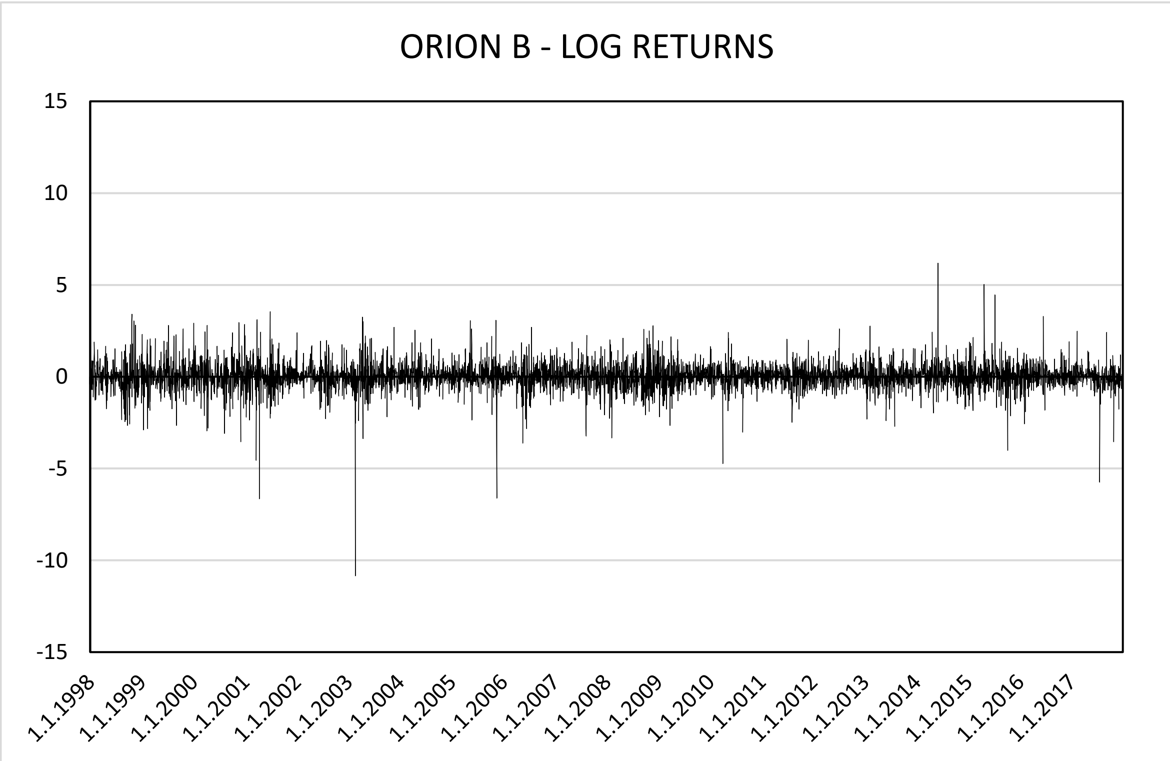

METSO - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

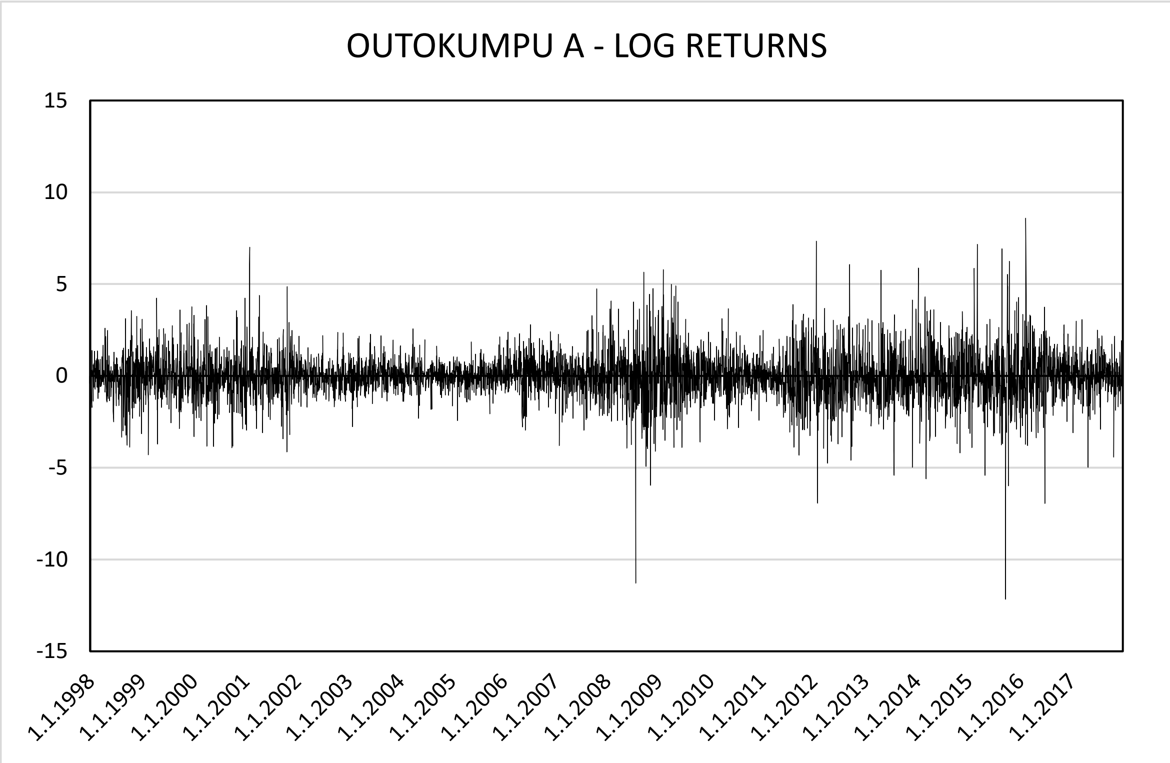

NESTE - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

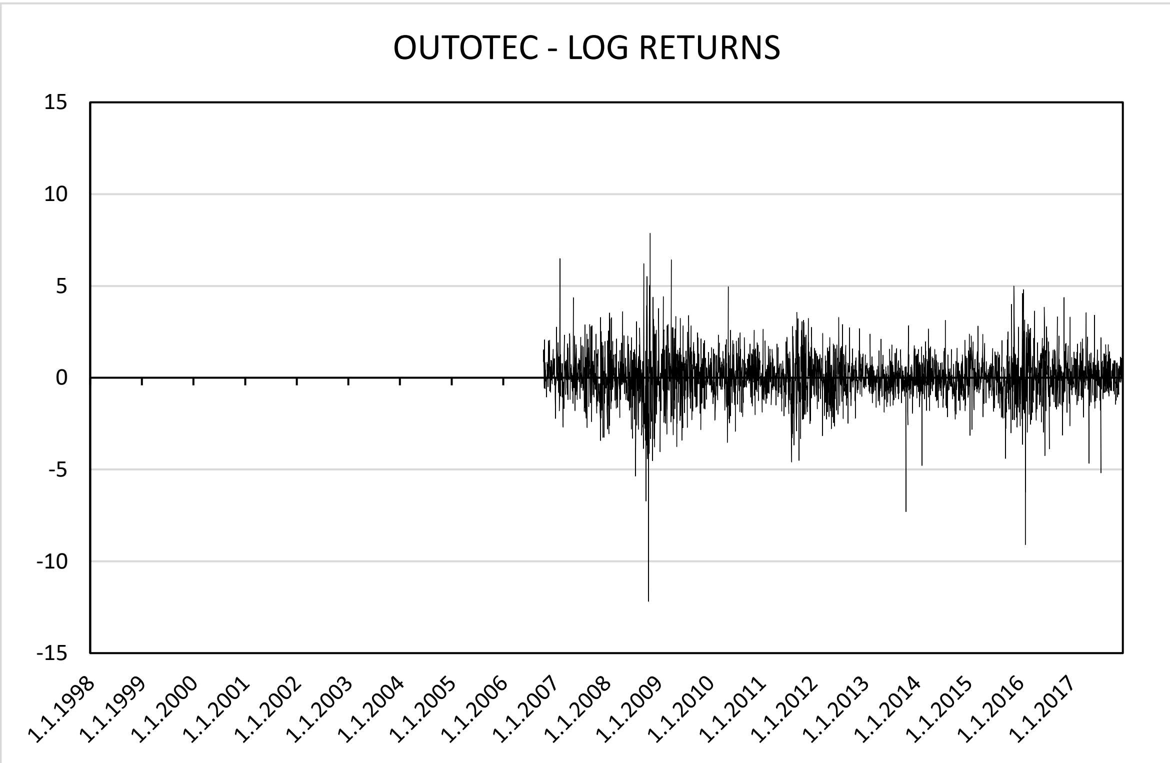

NOKIA - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

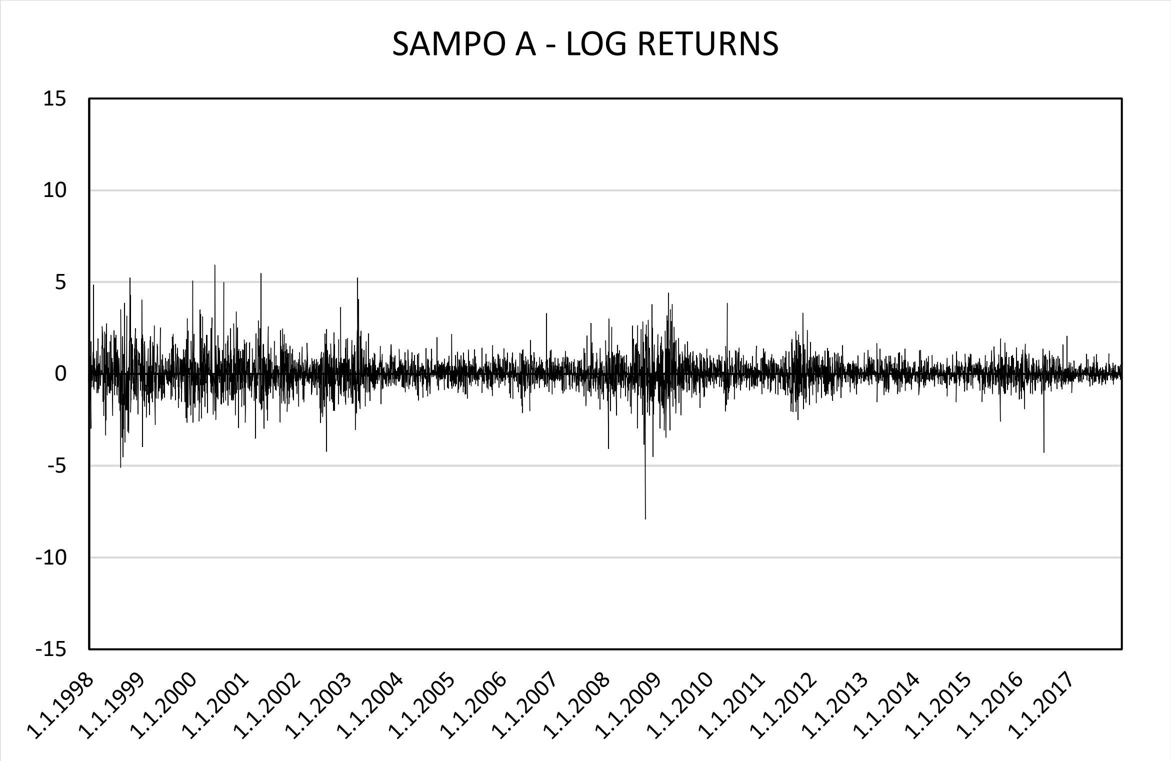

NOKIAN RENKAAT - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

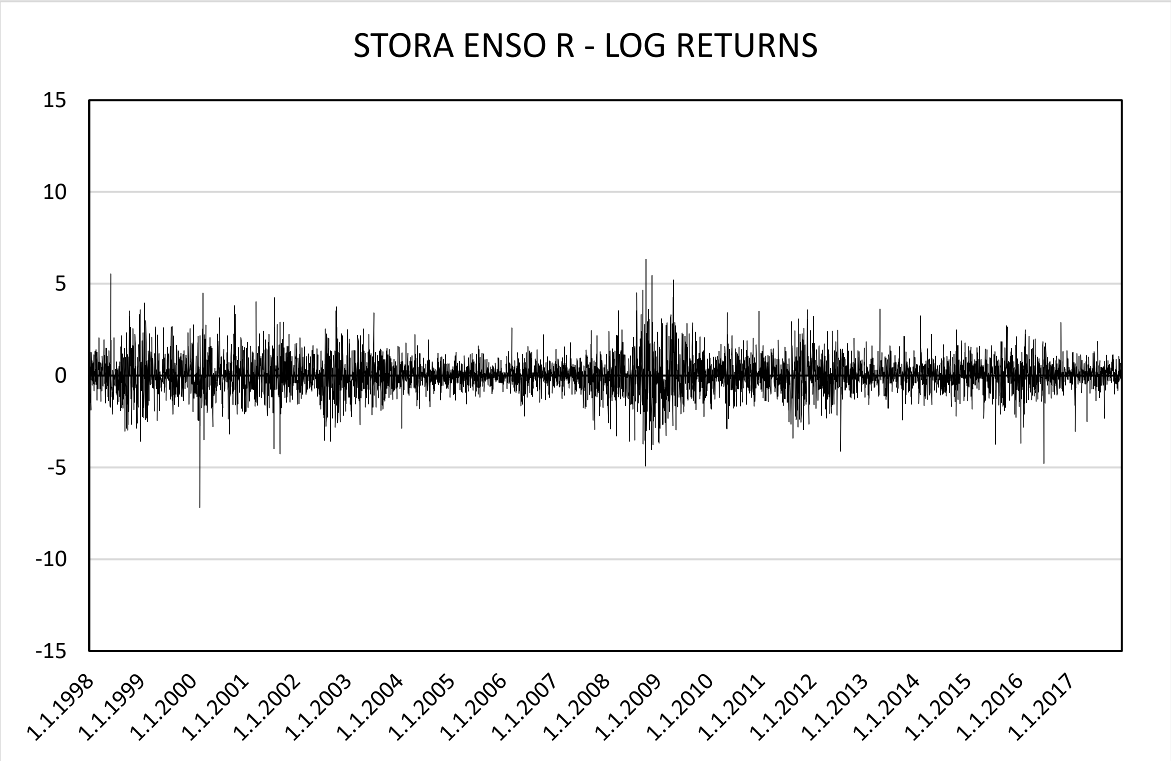

NORDEA BANK - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

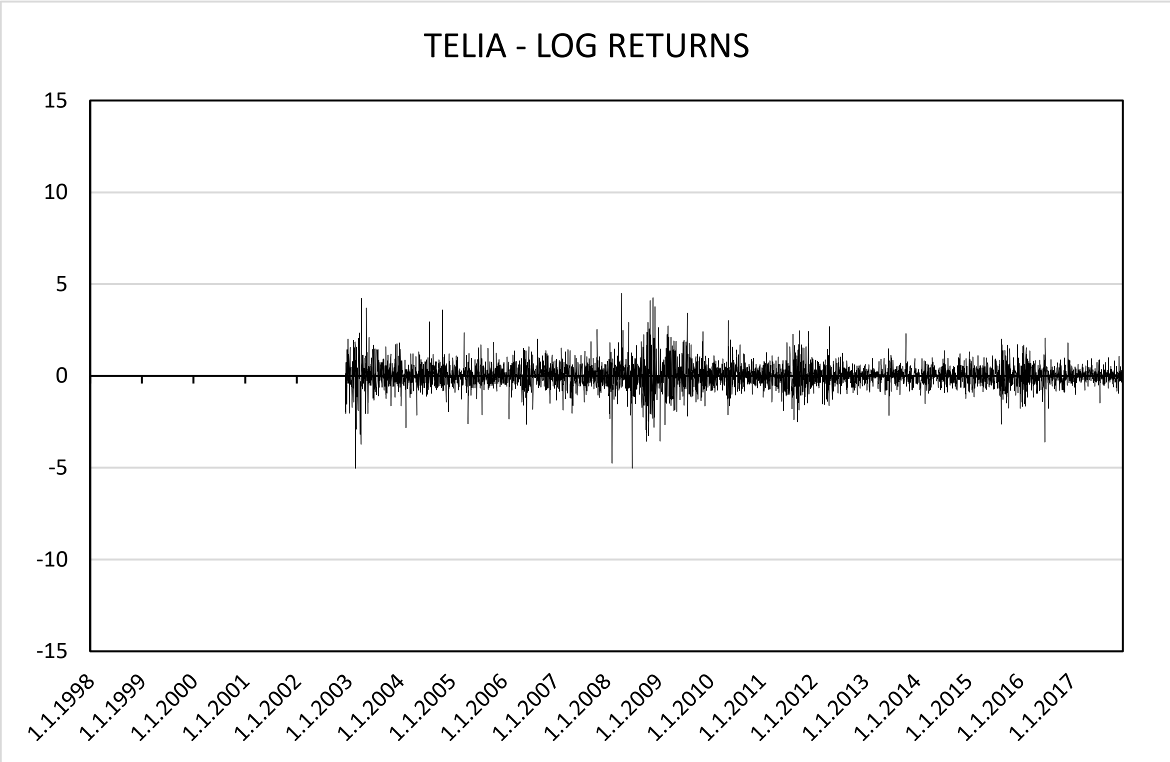

ORION B - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

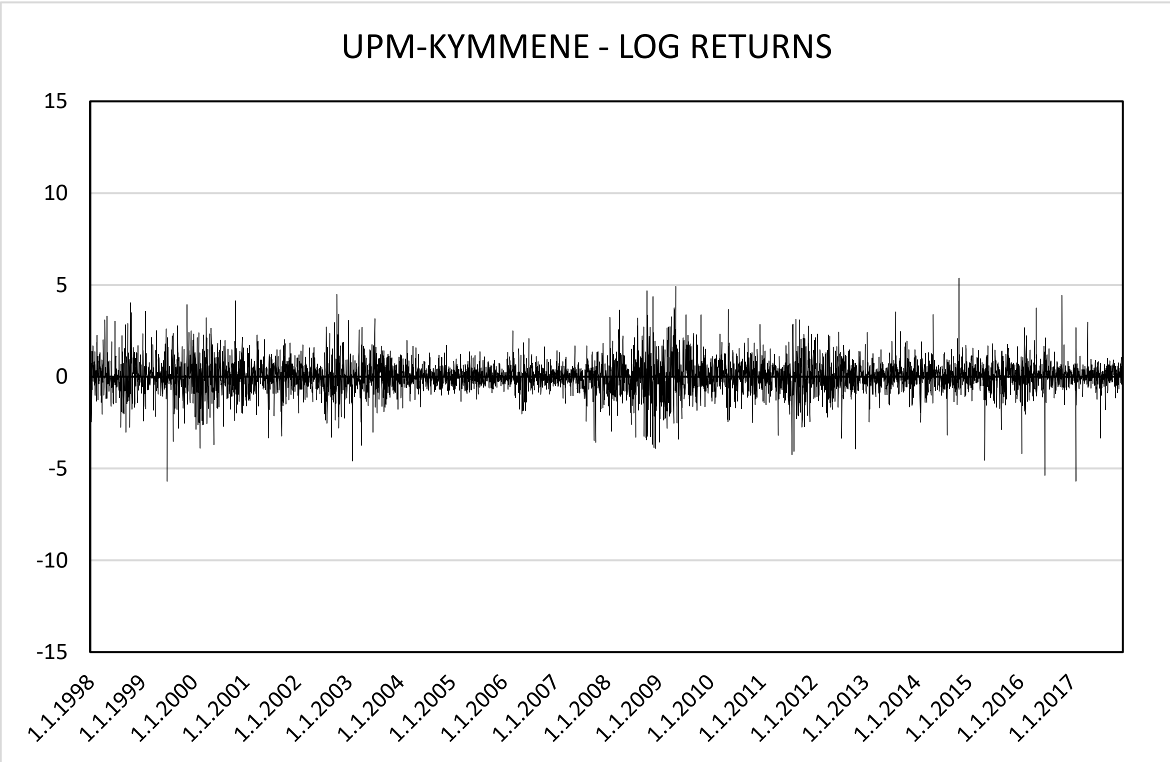

OUTOKUMPU A - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

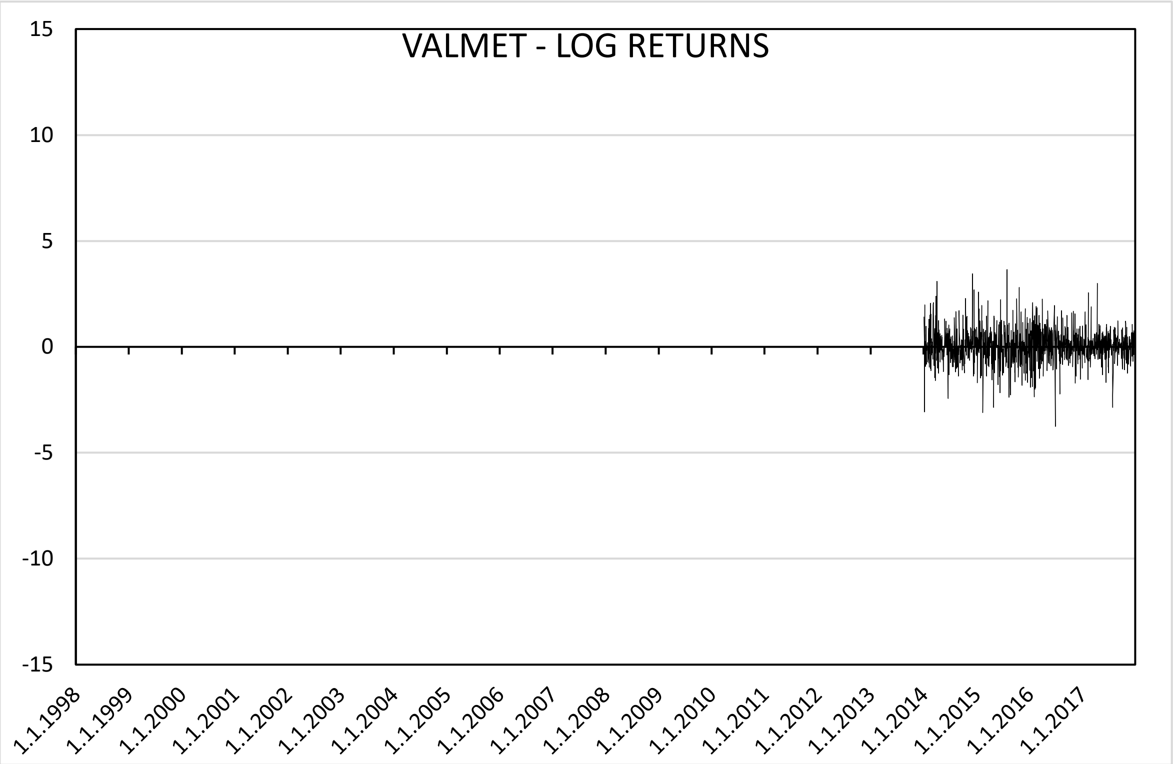

OUTOTEC - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

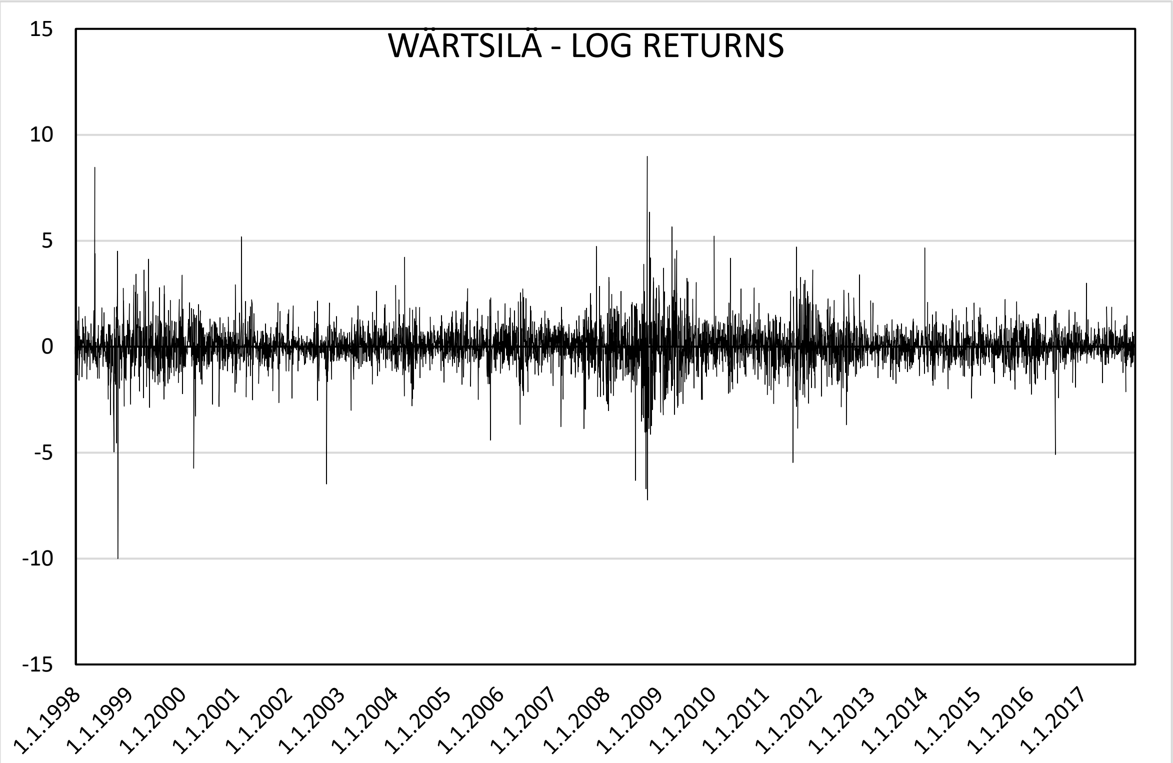

SAMPO A - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

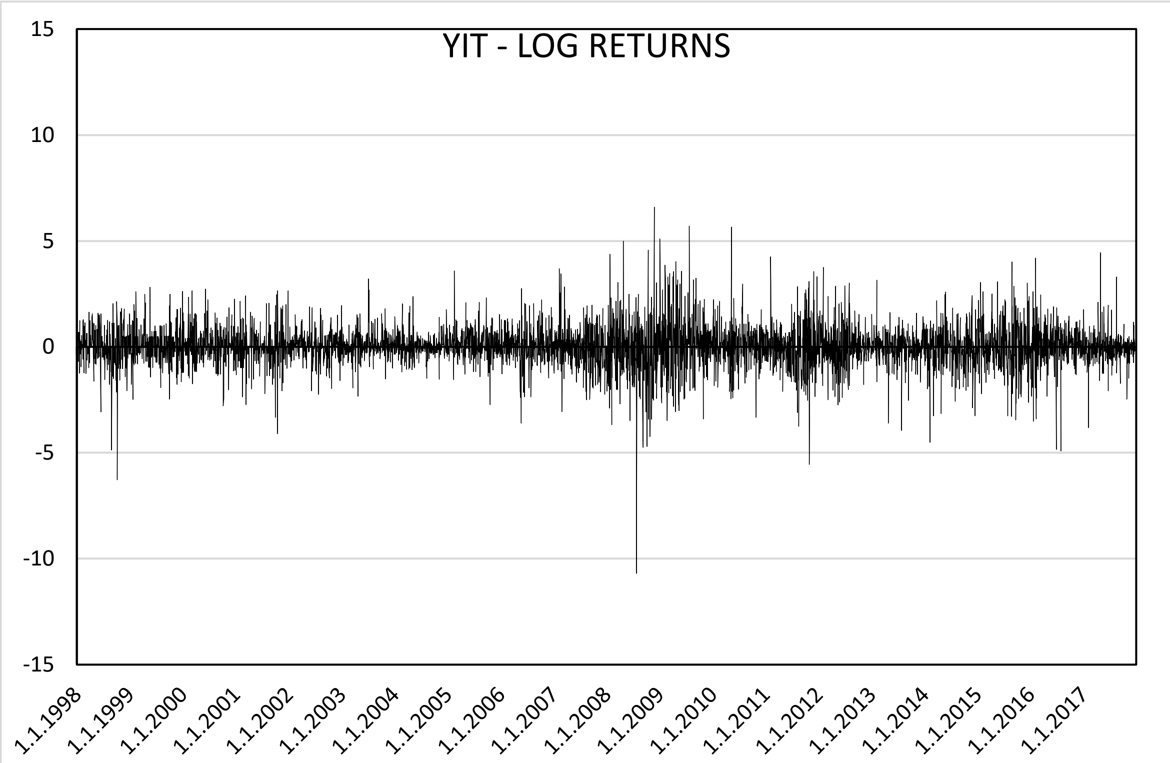

STORA ENSO R - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017


TELIA - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

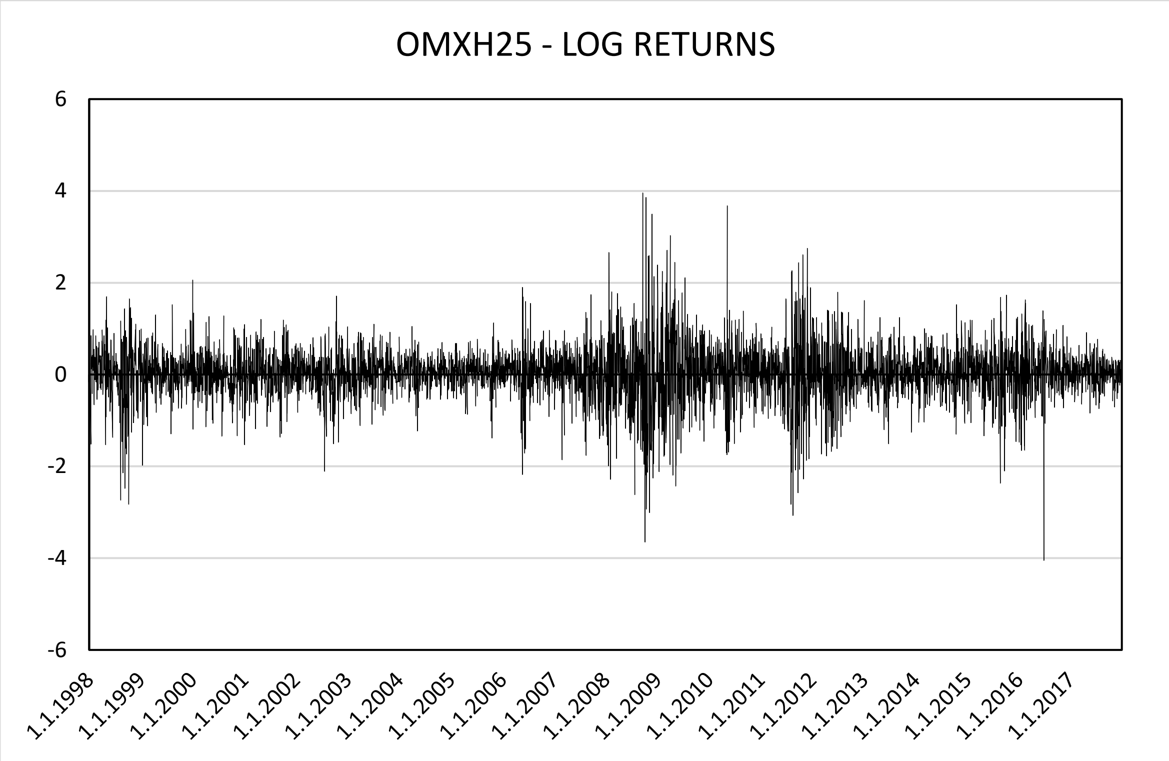

UPM-KYMMENE - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

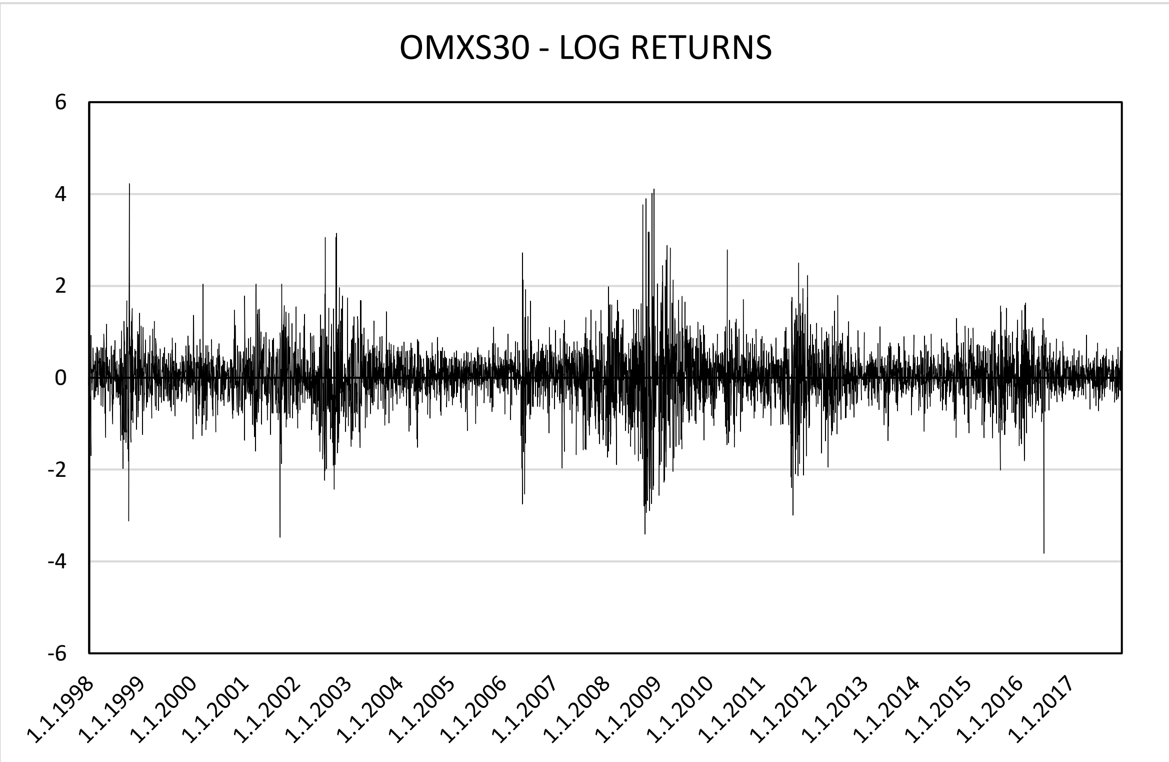

VALMET - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

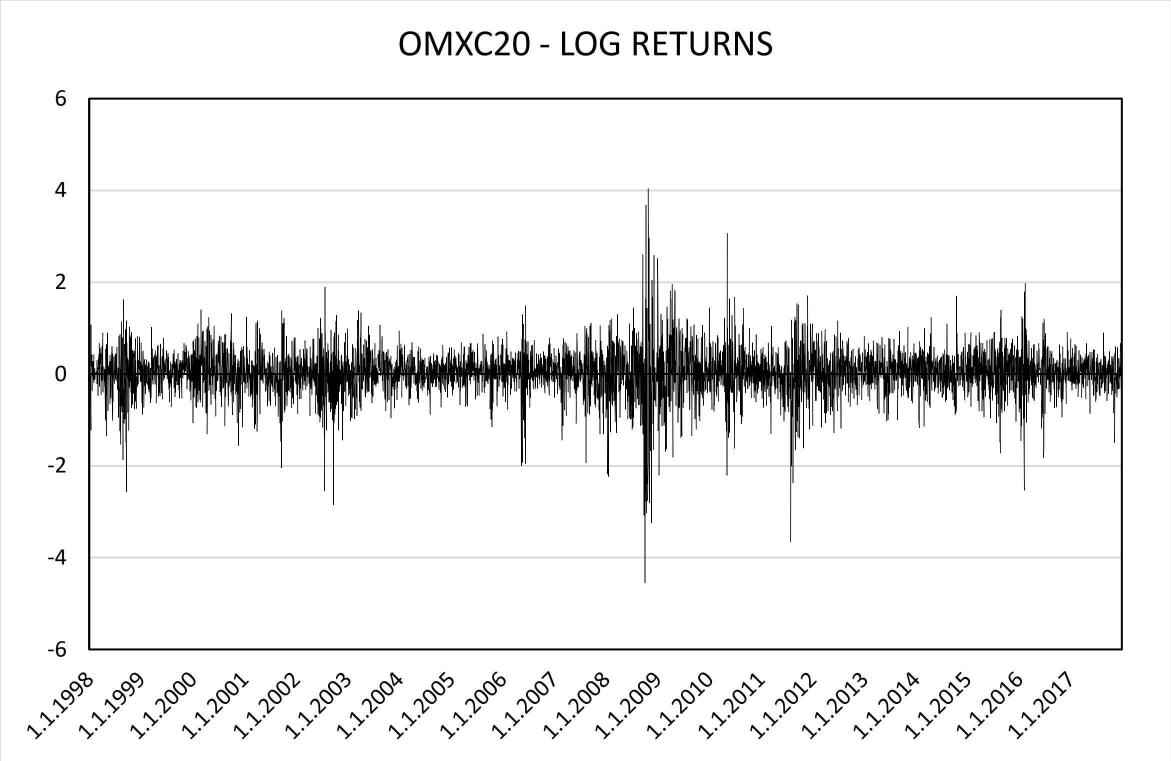

WÄRTSILÄ - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

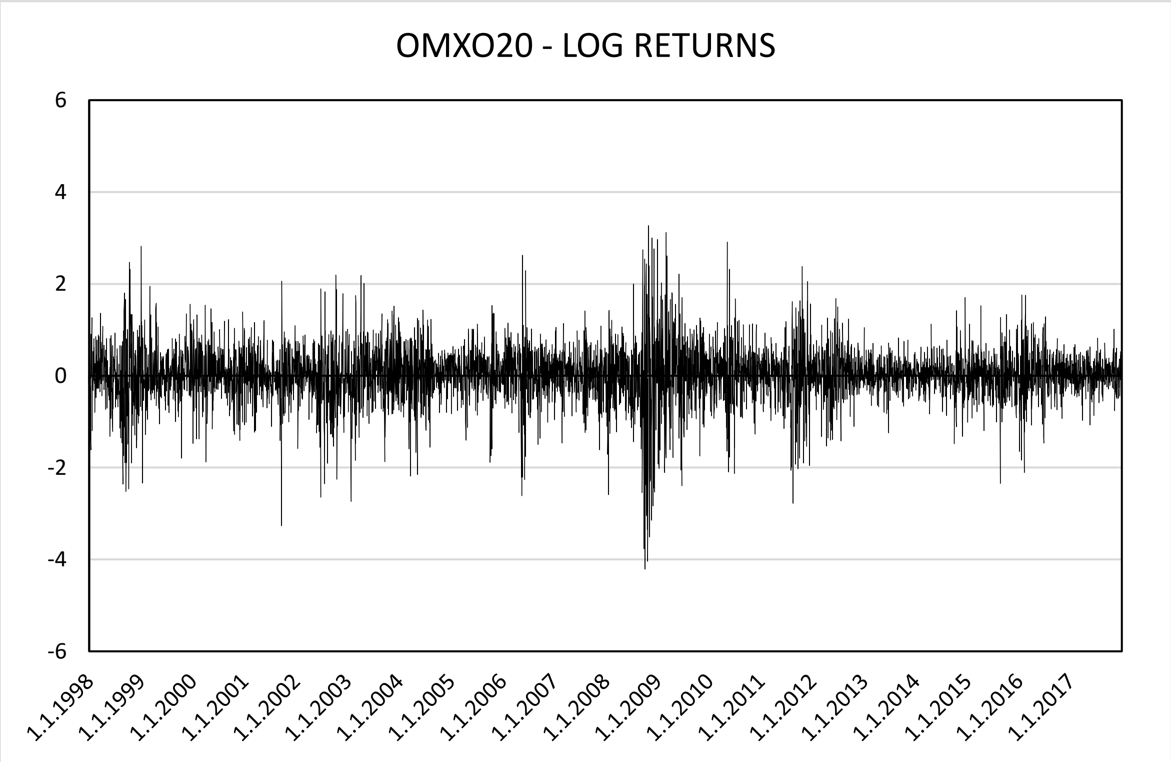

YIT - LOG RETURNS
15
10
5
0
-5
-10
-15
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017

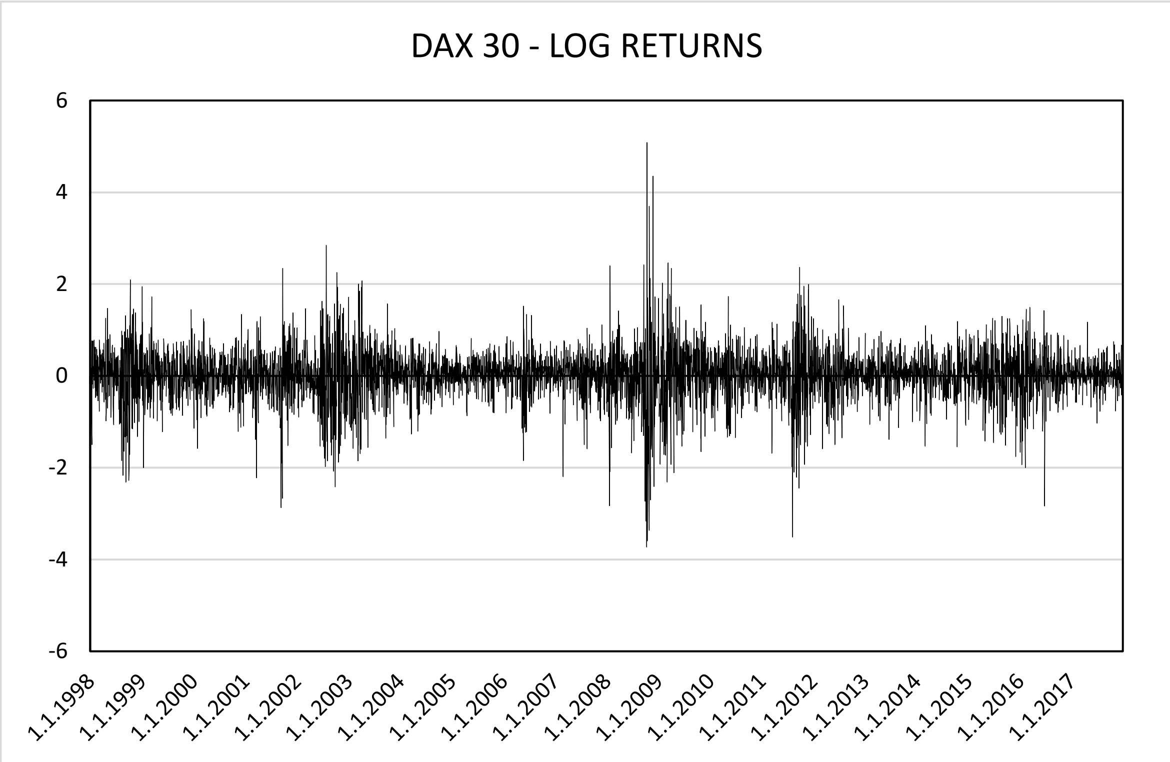
Appendix 2. Logarithmic returns of the selected indices

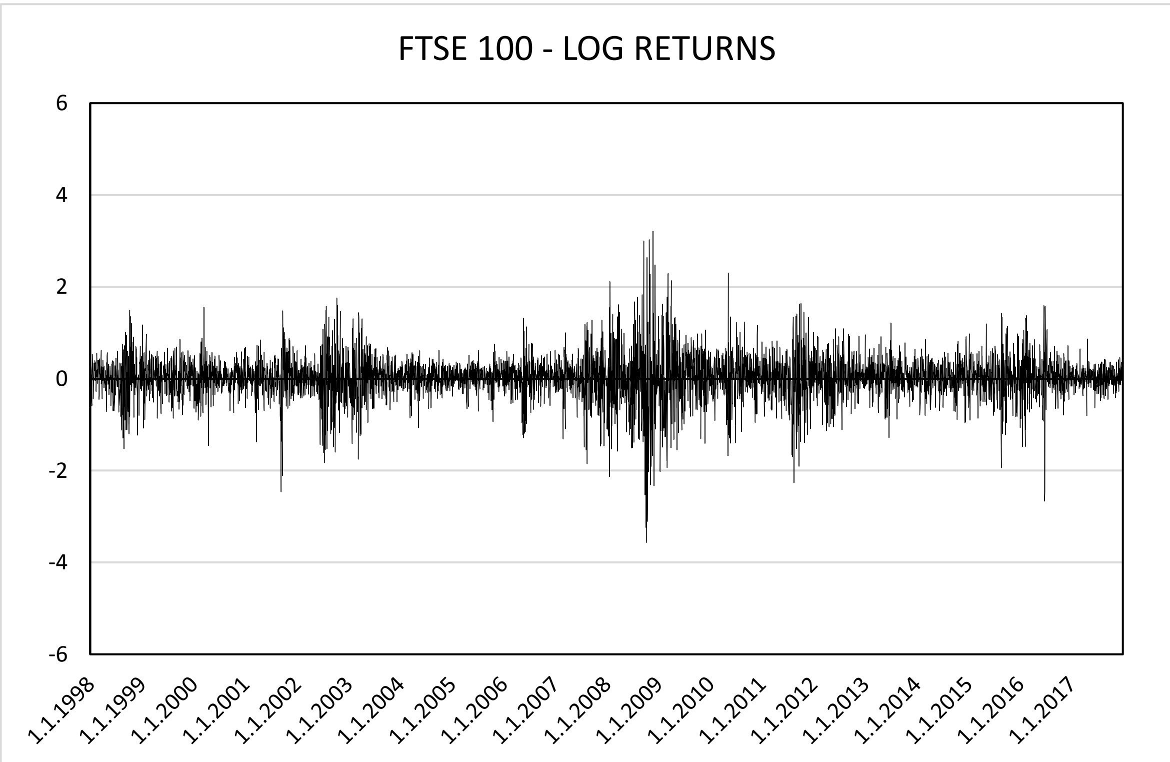


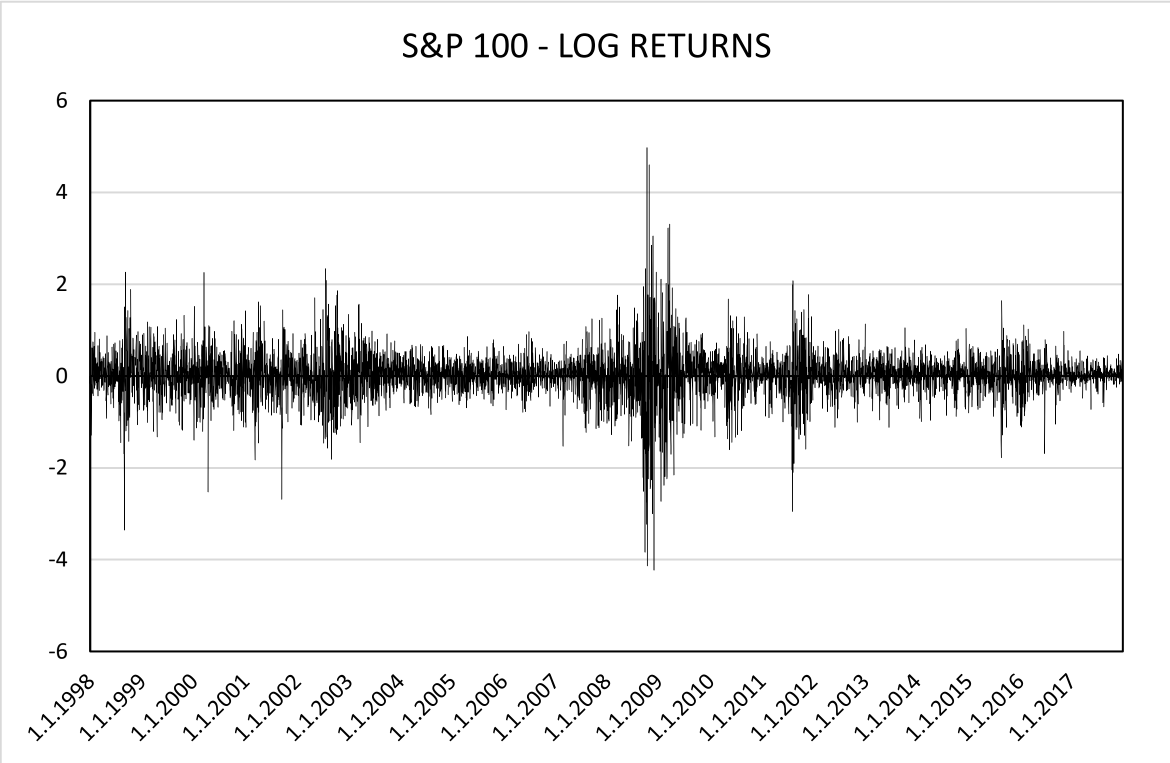



OMXC20 - LOG RETURNS
6
4
2
0
-2
-4
-6
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017


OMXO20 - LOG RETURNS
6
4
2
0
-2
-4
-6
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017


DAX 30 - LOG RETURNS
6
4
2
0
-2
-4
-6
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017


FTSE 100 - LOG RETURNS
6
4
2
0
-2
-4
-6
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017


S&P 100 - LOG RETURNS
6
4
2
0
-2
-4
-6
1.1.1998
1.1.1999
1.1.2000
1.1.2001
1.1.2002
1.1.2003
1.1.2004
1.1.2005
1.1.2006
1.1.2007
1.1.2008
1.1.2009
1.1.2010
1.1.2011
1.1.2012
1.1.2013
1.1.2014
1.1.2015
1.1.2016
1.1.2017