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Herd Behavior in the NASDAQ OMX Baltic Stock Market

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Abstract

This thesis investigates whether the stock market in the Baltic countries exhibit herd behavior during the period 2006-2014. A quantitative approach is used to see if investors show group oriented mentality in Estonia, Latvia, and Lithuania, and in the Baltics as whole. This is further complemented with a qualitative approach. The quantitative part is based on a market wide approach. The models proposed by Chang et al. (2000), Chiang and Zheng (2010) and Philippas et al. (2013) are used as major guidelines. Apart from testing herd behavior in the Baltic markets under different market conditions, the role of the US market is examined. In addition, the impact of investors' sentiment on herd behavior is tested.

We find supportive evidence for herding formation mostly in Tallinn and Riga. Overall, Vilnius shows the least amount of herd behavior. When considering up and down days and substantial up and down days, we find mixed results. Notably, we do not find evidence of herding during the crisis in 2008. Further on, evidence suggests that investors in the Baltics are influenced by the US, but they do not herd around the US market. Deterioration of investors' sentiment is found to be related with herd behavior. Investors in Tallinn and Riga exhibit herd behavior when they are anxious about future market conditions. However, this relationship is not observed during turbulent periods.

Key words: The Baltic States, stock market, traditional finance, behavioral finance, herd behavior, cross-sectional absolute deviation, investors' sentiment

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Chapter 1. Introduction

The question of whether investment behavior is showing group mentality is yet to be explored in the Baltic stock market. In general, the twenty-first century is characterized by market inefficiencies such as growing and bursting bubbles, stock prices that deviate considerably from what they *should* be worth according to fundamental analysis, and stock markets that crash for no apparent reason. These previously inexplicable anomalies in the financial markets have made room for a relatively recent study area, namely behavioral finance. Behavioral finance incorporates psychology in order to explain market participants' investment behavior (Shiller, 2003). A well-documented behavioral pattern within this area is herding; that is, investors tendency to mimic the actions of others (Devenow & Welch, 1996). In this study, we examine herd behavior within the three Baltic markets, Estonia, Latvia, and Lithuania, by evaluating the stock return dispersions in relation to the market returns.

In early 1960s Eugene Fama introduced the efficient market hypothesis as an investment theory (1965). He argues that markets are efficient, investors make rational decisions and there are no arbitrage opportunities since security prices always reflect all information. However, this description is applicable to an ideal world and in reality investors are instead governed by their emotions, making them to behave in unanticipated irrational ways (Shiller, 2003). Behavioral finance, as discussed by Shiller (2003), attempts to answer why the market is sometimes ineffective by assuming that people are not always rational. He explains how psychological factors affect individual investors and how that in turn affects the financial markets. He further explains that it is important to take into account that the human being is unique and multifaceted and that it is almost impossible to predict an individual's behavior in order to make sound investment decisions. He claims that taking the behavior traits into consideration could help to identify bloated markets easier and thus aid to eliminate future bubbles.

Herd behavior is one of many forms of irrational behavior and has been proposed as an alternative explanation of investor's behavior in stock markets (Devenow & Welch, 1996). Notably, there is no single strict definition of herd behavior. Still, it is widely accepted that herd behavior is related to a social behavior that rests on ignoring one's personal information and following the crowd (Bikhchandani et al., 1992). There are several reasons why it is crucial to consider whether investors in financial markets are herding. A particularly interesting aspect of herding is the lack of centralized coordination (Raafat et al., 2009). When it comes to stock markets, herding trends have been noticed both in developed and emerging markets, in both cases especially strongly during market up- and down- turns, as these times can be driven more by emotions rather than rationality (Chiang & Zheng, 2010). Thus, herding activities are of great concern to policymakers due to their impact on the market stability, for such behavior might cause excess volatility, particularly in periods of financial crises (Demirer & Kutan, 2006). In addition, if asset returns are co-moving, then it is harder for investors to maintain a diversified portfolio because asset correlation is increasing (Chang et al., 2000; Chiang & Zheng, 2010).

Thus, herd behavior is related to mispricing and decreasing market efficiency as prices deviate from their fundamental values (Devenow & Welch, 1996). Nevertheless, for some market participants herd behavior actually creates profitable opportunities to buy and sell stocks (Hwang & Salmon, 2004; Tan et al., 2008). However, herd behavior leads to suboptimal decision making (Werners, 1999).

On the basis of the statistical measures, the cross-sectional standard deviation (Christie & Huang, 1995) and the cross-sectional absolute deviation (Chang et al., 2000), several studies have examined herding activities internationally (e.g. Christie & Huang, 1995; Chang et al., 2000; Caparrelli et al., 2004; Demirer & Kutan, 2006; Chiang & Zheng, 2010). For instance, the studies of Christie and Huang (1995) were applied on the US stock market. Chiang & Zheng (2010) on the other hand focussed on advanced European countries with a sample consisting of 18 countries. Economou et al. (2011) contributed to the research by investigating four south European markets. A well-examined market is the Chinese stock market, which was studied by Demirer and Kutan (2006), Tan et al. (2008) and Chiang et al. (2010). The results obtained differ from area to area. However, no study has been conducted in the Baltic stock market. In general, the Baltic States are three geographically relatively small and economically rather homogenous countries. Due to that, it could be interesting to compare the Baltic countries in order to determine if there are any differences regarding the herd behavior. The region has undergone major changes such as the currency transition to Euro during the last three decades (Mezo & Bagi, 2012), which may make this herding study particularly relevant.

The general aim of this study is to examine investors' behavior in the Baltic countries. This study aims in particular to contribute to the limited existing literature by examining the presence of market wide herd behavior in the Baltics as a whole and in the three countries Estonia, Latvia, and Lithuania separately for the time period 2006-2014. Particularly, this thesis will examine the return dispersion of all traded stocks during the chosen time period. In addition, we investigate herd behavior under up and down markets as well as substantial up and down days. Furthermore, the study is extended by investigating the role of the US market. More specifically, if the Baltic market is influenced by or herd around the US market. In addition, the impact of investors' sentiment on herd behavior will be tested.

The rest of the thesis is organized as following: Chapter 2 provides an overview of the historical development of the economy and the stock market in the Baltic countries. Chapter 3 introduces theoretical findings related to traditional finance theory and behavioral finance. In this chapter a thorough presentation of herd behavior in stock markets is provided. Chapter 4 outlines previous empirical research on herd behavior. Chapter 5 presents the methodology used in this study. In chapter 6 data and descriptive statistics are discussed. An empirical analysis and discussion of findings are provided in Chapter 7. Chapter 8 presents the findings from the interviews.

Finally, a conclusion is given in chapter 9. Practical implications and suggestions for further studies are provided in this chapter as well.

Chapter 2. Background: The Baltic Market

The Baltic region has undergone major economic changes in the last decades. This chapter presents the past development of the chosen area, which enables a better understanding of investors' behavior.

2.1 The Economic Development of the Baltic States

Historic development or path dependence is considered as a main driver of a country's institutional and economic efficiency (Adam et al., 2009). Rudzkis and Valkaviciene (2014, p.783) describe the Baltic market as "small open economy with immature stock markets". Furthermore, the financial and economic situation in the Baltics is similar, although Estonia is considered slightly more successful than other Baltic countries (Panagiotou, 2001).

Initially, a strong pro-market tactic enabled the Baltic countries in the transition process from a planned system to a market oriented economy (Kattel & Raudla, 2013). Further on, fiscal and monetary policies were some of many sovereignty signals in the transition processes (Knöbl & Haas 2003). In general, the market has exhibited several ups and downs, including the recent financial crisis (Aslund, 2009). In the last twenty years different macroeconomic policies have been implemented to gain stability (Darvas, 2011). Furthermore, Reiner (2010) argues that the economic and geographic similarities among the three countries have helped the Baltics in the market liberalization process. One of the reasons, as he states, was the injection of foreign capital in the three Baltic countries, particularly in the banking sector. Further on, he specifies that some important characters during this period were high consumption, foreign investment, and low unemployment. According to him, this is one of the reasons why the area was referred as "the Baltic tigers" during the period 2000 to 2007. After joining the EU in 2004, the Baltic countries experienced continuous economic improvements, where, for example, the GDP showed an upward movement with yearly growth rates of 8-12% (Mezo & Bagi, 2012). At that time, the Baltic region developed faster than the overall EU (Syriopoulos, 2007). In addition, the EU membership allowed for higher integration within the Baltics, as the countries had to work towards common targets that had to be achieved (Maneschiöld, 2006), which can also be said about the stock market.

In 2008 the countries experienced a notable economic downturn (Aslund, 2009). Overoptimistic financing circumstances in pre-crises period made the economic downturn severe (Brixiovaa et al., 2010). GDP dropped sharply leading to further consequences such as illiquidity issues and high unemployment, and eventually in a decreasing demand (Darvas, 2011). Staehr (2013) claims that in order to address the growing issues, each country applied different anti-crisis policies and fiscal austerities that were closely related on internal factors, for example, the socio-political situation.

He states that Estonia showed higher flexibility and more advanced technological development, for example, the country applied the biggest fiscal consolidation in 2009. He further states that as a result, some signs of recovery started to appear by the end of 2009. The author claims that at the same time Latvia showed a close link between politics and business, where the policy development was entrenched as different interest groups had high influence. Overall, the outcome of economic and social crisis and policies implemented is regarded as a success story (Hilmarsson, 2014). Currently, according to Khan (2015), the Baltic States show a positive investment outlook, where Latvia is ranked as the 9th most-promising emerging market, while Estonia takes the 2nd place and Lithuania 4th in most-promising frontier markets. Furthermore, he estimates that the growth rate of GDP will be around 3% in the Baltic region.

2.2 The NASDAQ OMX Baltic Stock Market

The transition process to a market economy in these countries included a development of the stock market, which has grown steadily (Čekauskas et al., 2012). In general, stocks listed in emerging markets have low capitalization and small turnover as the market suffers from a weak legal protection and general macroeconomic issues (Claessens et al., 2000). As it can be seen in the NASDAQ OMX Baltic website (2015), Tallinn and Riga had only 6 and 4 companies listed when the stock exchange was opened, but the number of listed companies in both countries has increased. As of April 2015 there are 15 companies listed in Tallinn, and 28 companies in Riga. Further on, when the stock exchange in Vilnius opened, 55 companies were listed. However, the number has steadily decreased, reaching 33 in 2015. Delisting as well as IPO has occurred on an ongoing basis. Vaiciulis (2013) states that the growth of listed companies on the stock exchanges lately has been slowed down due to many factors. As an example he mentions the market illiquidity and weak capitalization in Lithuania, which has occurred due to bankruptcy cases and takeovers by multinational companies.

Several studies are done in the Baltic stock market (e.g. Maneschiöld, 2006; Rudzkis & Valkaviciene, 2014). Maneschiöld (2006) finds that in the short run the Latvian and Lithuanian markets influence the Estonian market. However, Rudzkis and Valkaviciene (2014) claim that the stock market is becoming more integrated. They specify that the differences between the three countries are decreasing and trading activities are more focused in a common Baltic market, rather than in the individual countries. Initially, each country had its own stock exchange, but in 2004 Vilnius, Riga, and Tallinn joined NASDAQ OMX Group and thus became more integrated with international stock markets (Čekauskas et al., 2012). It is in accordance with Claessens et al. (2000) suggestion that due to worldwide stock market consolidation, stock markets in transition economies benefit from an integration with leading players. Since 2001 the Baltic equity list is split in two parts: main and secondary list (NASDAQ OMX Baltic, 2015). As of April 2015 the main list consists of 34 blue-chip companies and the secondary list (companies that do not meet quantitative requirements for the main list) consists of 42 companies.

Equity investors in the Baltics have over time benefited from the continuous improvements such as higher liquidity, increased trading hours, and lower commission fees (NASDAQ OMX Baltic, 2015). However, Čekauskas et al. (2012) find that stocks market are not equally developed across the Baltics. They show that the market in Tallinn and Vilnius outperform the market in Riga in terms of market quality. They assert that the liquidity was highly affected by the market crash in 2008-2010 while informational efficiency remained rather stable over time.

Chapter 3. Literature Review

The following section discusses the relevant theoretical literature for this study. Firstly, two broad finance categories, namely, traditional finance theory and behavioral finance theory, are compared. Secondly, the scope is narrowed down to behavioral finance. Thirdly, a subcategory of behavioral finance, herd behavior and its drivers are discussed. Finally, an overview of investors' sentiment is presented.

3.1 Traditional Finance Theory vs. Behavioral Finance Theory

Market models that are based on rationality, for example, the efficient market hypothesis (EMH) and the capital asset pricing model (CAPM) emerged in the 1960s and are considered as the traditional financial theory (Sharpe, 1964; Fama, 1965; Lintner, 1965). These models share the same considerations: expected utility maximization, market equilibrium, and fundamental analysis. Commonly, the market is assumed to move towards equilibrium (Fama, 1965). However, in 1980s different anomalies that the EMH was unable to explain started to emerge, often making the available asset-pricing models inadequate (Schwert, 2003). Further on, Shiller (2003) points out EMH weaknesses by arguing that people are not always rational and tend to refrain from a passive investment strategy. Nevertheless, the EMH is often considered as a cornerstone in the finance theory, even if studies are mostly in academic setting and do not consider natural environment (Fama, 1965). According to Fama (1970), the EMH has three subcategories in distinct forms: strong, semi-strong, and weak form. While the semi-strong form is commonly used in a research, he states that a more extreme version, namely, the strong form, has been neglected due to the strong underlying assumptions. One of the assumptions that he mentions is that all available information (including private information) is incorporated in prices at any time.

A market with perfect information, in other words, strong form or efficient market suggested by Fama (1970), is claimed to be impossible as individuals would not gain from gathering information and trade in general, eventually leading to a collapse (Grossman, 1976; Grossman & Stiglitz, 1980). Nonetheless, Fama (1970) assumes that stock prices are unpredictable, meaning, they follow a *random walk* and nobody can beat the market in the long run. He claims that in such marketplace, no investor can get abnormal returns on an on-going basis. Also, Fama (1965) assumes that the market is rational. However, as he argues, it does not mean that all investors need to be rational. In particular, he claims that irrationality is assumed to be occasional and cancelled out with other irrational trades, so it has no influence on security prices.

Thus, according to the author, the arbitrage will eliminate the price effect arising from irrationality if it happens in a similar pattern.

Behavioralist view supporters propose several challenging twists to examine the validity and applicability of the EMH, for example, the applicability of rationality and arbitrage (Smith, 1991; Thaler, 2005). To alter the efficient market standpoint, Fama and French (1996) propose a three-factor model. In this model they add two new factors to the CAPM, which allows accounting for value and small cap stocks tendency to outperform the market. Further on, Fama (1998) meets the criticism that comes from behavioral finance supporters. He argues that the new studies on behavioral aspects do not find definite evidence that indicates that the theory of market efficiency does not hold. Moreover, he explains that the anomalies, that were found, occurred in an equal frequency both due to investor underreaction and overreaction, and that the anomalies tend to disappear over time. Shiller (2003) continues the debate and claims that the findings of Fama (1998) are not surprising since there is no psychological rule that states that individuals consistently underreact or overreact. He argues that the statement that anomalies tend to disappear is weak since it is not sufficient enough to assure that markets are efficient and that prices will adjust over time. Further on, he criticizes the idea of fundamental values since it is difficult to measure them and they can be observed only in a very long sample period. Even though the EMH implies that it is impossible to beat the market, Coval et al. (2005) conclude that some individuals in certain situations are able to constantly beat the market. Further on, Fenzl and Pelzmann (2012) argue that widely used classical economic and financial theories fail to estimate future market behavior and to predict price movements, especially in booms and crises, when market participants show particularly irrational behavior.

3.2 Behavioral Finance: An Overview

Behavioral finance as a research field emerged comparatively recently- in 1980s- by combining previously two distinct fields: neo-classical economic theory and psychology (Shiller, 2003). Shleifer (2000, p.23) has defined behavioral finance as “study of human fallibility in competitive markets”. It means that behavioral finance enables to explain what preferences people actually have, which the expected utility theory fails to do precisely (Hens & Rieger, 2010). One of the first ideas in this field was that informed and efficient markets are highly unlikely, and in contrast to the EMH, behavioral finance is not based on arbitrage and rationality assumptions (Grossman & Stiglitz, 1980). Especially irrationality can be observed in many ways, for example, as hesitation towards loss realization (Odean, 1999), which can be further linked to one’s unwillingness to sell losing stocks but tendency to sell winning stocks (Shefrin & Statman, 1985). In contrast, a rational behavior would exhibit the opposite (Badrinath & Lewellen, 1991).
Behavioral finance researchers frequently discuss many biases, when considering various market conditions (e.g. Shefrin, 2000, Shiller, 2003). The biases are arising since limited cognitive resources make individuals to use heuristics to finalize decisions (Hirshleifer, 2001). Kahneman and Tversky (1979) introduced the first pillar of behavioral finance, the so-called prospect theory. Their study claims that individuals evaluate the losses and gains using certain heuristics,

for example, representativeness heuristics. This type of heuristic, according to the authors, refers to the concept of selective interpretation of information whereby individuals seek for a pattern in a set of random events. They argue that individuals base their judgment about the likelihood of an event on information that already exists in their minds and resembles a typical situation. Even though representativeness heuristics is seen as a mental shortcut enabling individuals to take quick decisions, the authors also acknowledge that these decisions are likely to be biased since they are based on representativeness. In the financial markets heuristics are observed when, for example, traders in a fast manner have to interpret incoming information (Bondt & Thaler, 1985; Gilovich et al., 2002). Anchoring is another concept introduced by Kahneman and Tversky (1979). They state that individuals make their decisions considering information known to them, even though the information may be irrelevant for the particular case. Interestingly, according to the authors, anchoring behavior is both responsive to information and persistent when information is absent. They further claim that investors on an aggregate level tend to make mistakes due to some investors irrationality that leads to pricing irregularities. Clearly, cognitive biases induce people to easily make mistakes as the way they process information can be seen as incomplete, resulting in decisions which have limited rationality (Kahneman & Tversky, 1979; Bondt & Thaler, 1985; Gilovich et al., 2002).

Even though it may seem that behavioral finance has the power to explain the market participants, considerable criticism to weaken the theory is present (e.g. Fama, 1998; Thaler, 1999). Although there is no single model that could explain all anomalies in the market, empirical papers present a wide array of alternatives, which enable to detect irrationality more often than before (Thaler, 1999). Hirshleifer (2001) and Barberis and Thaler (2009) claim that one of the main reasons why behavioral finance is criticized is due to the assumptions that one can anticipate investors' reaction by selecting which bias to highlight. They argue that this happens when a model is dredged for a certain case. Also, they argue that behavioral finance models tend to be ad hoc, meaning, models that are designed to explain specific events or facts cannot be applied for other purposes. Further on, Thaler (1999) indicates that certain level of data mining could be involved, as some researchers in the behavioral finance field may be eager to find reasons why traditional finance models are not valid. He claims that even if there is no general theory underlying behavioral finance, this field is less controversial as it used to be. Levinson and Peng (2007) argue that investor behavior differs, for example, due to geographical location, and thus no general model can be created to incorporate psychological factors. They claim that individuals need to be considered by their culture and other aspects that eventually are related to finance, for example, decision making patterns and value estimation. Nevertheless, the field of behavioral finance is still in progress and new methods are often suggested, mainly as the existing theories tend to be fragmented. Despite the critique, proponents of behavioral finance claim that their aim is to make a neoclassical approach better applicable to real life situations, rather than to create a separate field (Ritter, 2003). According to Shefrin (2008), a combination of neoclassical approach and behavioral finance would allow to describe the market in a psychological light, thereby having a higher coherence. In any case, the importance of behavioral finance as a part of financial economics is increasing (Hens & Rieger, 2010).

3.3 Herd Behavior in Financial Markets

Herd behavior is one of the core concepts in cognitive economics and is often linked to financial markets (Parker & Prechter, 2005). The existing literature covers a wide array of studies from various perspectives, mainly in economy and psychology (e.g. Christie & Huang, 1995; Prechter, 2001). Moreover, herd behavior is an important consideration not only for market participants, but also for economists and academics, enabling them to assess market movements and to evaluate risk and return relationship and applicability of asset pricing models (Shiller, 2006). As herd behavior itself is a generally observable phenomenon, studies are applied on both micro and macro levels (e.g. Christie & Huang, 1995; Goodfellow et al., 2009).

Shiller (2006) claims that humans have belonged to herds since the first tribes and group migrations. A recent study done by Easley and Kleinberg (2010) show that it is part of human behavior to imitate, even if there is no informational cause to do so. Also Freud (1922) has focused his research on group psychology and concludes that individuals comply with a herd that has a strong leader. His findings show that when a herd is formed, an authority is automatically chosen. He claims that the herd instinct limits one's ability of critical assessment and emotional impulses become stronger. When it comes to financial markets, Keynes (1937) claims that the market is driven by an animal spirit, which easily transmits to other market participants. He argues that the critical issue with the animal spirit is the investors' inability to logically respond to new information and categorize its relevance. He further argues that eventually private information is neglected and individuals follow other market participants. Bikhchandani and Sharma (2001) assert that a herd is created if investors acknowledge actions taken by others and allow their decisions to be affected. An essential element of herding, according to them, is market participant interaction, where individuals react on signals they get from other individuals. Basically, they claim that herding occurs when individuals mimic others. However, such signals may be misleading since speculators create impulses in the market (Froot et al., 1992). In any case, correlated trading activities emerge when investors interact with each other (Chiang & Zheng, 2010). However, Hwang and Salmon (2004) make a distinction between common movements and correlated movements. They explain that the former may result in an inefficient market, whereas the later simply occurs when stocks are traded based on fundamental news. In general, market movements may be influenced by social pressure, which can be either real or illusionary, that makes an individual to change his or her behavior, opinion or expectation (Oehler & Chao, 2000).

Herd behavior has various effects on the financial markets. Olsen (1996) claims that herding makes it difficult to make accurate forecasts, as stock prices do not reflect their fundamental value. He further claims that this happens due to market inefficiencies that arise from anxiety. Keynes (1937) argues that fundamental data and facts are often neglected or even irrelevant in the market. He asserts that investors base their decisions on rumors and speculations, without applying critical thinking. The emergence of financial bubbles can be explained by investors' irrational behavior in the stock markets, when they follow the crowd and draw information on what others do (Lux, 1995; Malkiel, 2003). In addition, herding can be seen as a regret aversion, because if a failure occurs to several individuals then the regret is lower, rather than when an individual experiences it alone, which means that individuals are afraid to be left alone with their convictions (Yahyazadehfar et al., 1985). The willingness to engage in herding, in other words, mimicking market participants, shows that individuals act in order to preserve (Prechter, 2001). However, if investors are imitating each other's decisions, some practitioners might spot profitable trading possibilities due to price deviation from the fundamental value (Tan et al., 2008). Furthermore, investors that seeks to invest in the short term might herd in order to capture the information other investors hold (Froot et al., 1992).

Following the movements of other investors' previous decisions and ignoring private information might be optimal for market participants who look for signals from better-informed investors (Bikchandani et al., 1992). Banerjee (1992) argues that this type of herd behavior can be observed directly since investors behave in an irrational way, which may eventually cause bubbles. He explains that different price movements cause a bubble due to diverse stages of uncertainty among investors about the correct price of an asset and the likelihood of extraordinary events to occur. However, he claims that the uncertainty has one apparent consideration, namely, it is difficult for investors to distinguish informed investors from uninformed. In addition, Lakonishok et al. (1992) argue that herding is more present in stocks with small market capitalization as publicly available information is lacking, inducing market participants to follow market consensus. They observe that a simultaneous and homogenous reaction is common among investors who invest in small cap stocks, especially after news announcements or price movements. Conversely, they notice that the opposite is true for large cap stocks as individuals are able to form their own opinion due to higher transparency.

Herding can be categorized in several ways. Theoretically, herding can be categorized depending on how information is transmitted (Demirer & Kutan, 2006). According to Caparrelli et al. (2004), if individuals, that have access to the same information, make investment decisions in a similar pattern, they exhibit spurious herding. The authors further claim that if individuals disregard private information in favor for market-shared information, they herd intentionally. In such cases it can often be a sign that market participants tend to passively follow their predecessors and they perceive it as a social norm (Christie & Huang, 1995). Further on, Devenow and Welch (1996) state that herding is rational if institutional investors mimic each other as an urge to maintain their reputation as their performance is evaluated based on results. The authors clarify that investors are enticed to ignore private information and instead mimic other better-informed investors in order to improve their results. This behavior is also likely to occur among individual investors if they believe that somebody has superior information (Demirer & Kutan, 2006). According to Devenow and Welch (1996), market liquidity and information acquisition can be considered as payoff externalities that steer rational herding. Unfortunately, in practice herding types are hard to separate from each other because of difficulties to collect precise information of investment decisions and due to investors' biases (Burghardt, 2011).

3.3.1 Herding under Market Up and Down Days

Herding is asymmetric as it can occur both in market up and down days and by accounting for these differences, optimistic and pessimistic views can be segregated (Christie & Huang, 1995). The asymmetries arise as individuals react differently to market movements, for example, some individuals buy stocks in a *bear* market and sell stocks in a *bull* market (Neal & Wheatley, 1998). On the opposite, Prechter and Parker (2007) suggest that people tend to buy stocks during *bull* market periods and sell them during *bear* market periods, believing they are lowering their risks by following the aggregate market trend. The authors claim that the risk is actually increasing and that the majority of investors have a misperception of underlying risks due to collective behavior. Prechter (2001) argues that herd behavior is driven by a willingness to gain as much as possible and lose as little as possible. He claims that myriad measures are used to link investor sentiments with the market trends in order to determine whether there is a market optimism or pessimism.

Some authors find that herding is present, when a market experiences large price movements (Caparrelli et al., 2004; Keasey et al., 2014). Further on, Gleason et al. (2004) claim that market participants tend to align with some general opinion in downward periods. Moreover, Demirer and Kutan (2006) note that herd behavior may be extra harmful to financial stability in turbulent markets. As they explain, negative shocks may intensify the magnitude of market movements. Also, Cajueiro et al. (2009) find evidence that shows herding activities only in extreme down markets. Fenzl and Pelzmann (2012) argue that a spiral is created in market downward situations as bad news makes market participants to panic. Nevertheless, the pattern cannot be taken as given, for example, Gleason et al. (2004) find no herding during periods of extreme market movements in the US, but still they detected an asymmetric market behavior.

Further on, herd behavior often occurs in market up days (e.g. Christie & Huang, 1995; Saastamoinen, 2008). Even though Saastamoinen (2008) finds no herding during average trading days, the author finds that the Helsinki stock exchange shows herd behavior during up days. Similar results are observed by Christie and Huang (1995): herd behavior among financial market participants historically has been more evident during *bullish* periods. They claim that herding in the up days has a tendency to create a bubble. A bubble occurs if a price temporarily moves away from its fundamental value due to excessive future expectations, which do not have a reasonable justification (Sornette et al., 2009). Booms create a situation where investors neglect fundamental information and instead take decisions by considering other investors behavior (Fenzl & Pelzmann, 2012). In certain cases such as this, investors may actually benefit by ignoring their own judgment and by following the crowd and copying its behavior

(Bikhchandani et al., 1992; Banerjee, 1992; Easley & Kleinberg, 2010). Shiller (2006) implies that such situations can often be linked to speculative behavior. He claims that if there is a too high optimism in the market, the stock prices experience a continuous increase. Even though some may expect the trend will result in high profits, he argues that the majority of market participants are unfamiliar with inherent risks. He concludes that in such cases, analysts are faced with difficulties to make forecasts. The market pace increases and its participants end up taking risk they would never consider to take (Earl et al., 2007). Bishop (1987) claims that if the market consisted of the same traders all the time, extreme situations such as bubbles and crashes would occur less frequently. However, he further claims that such situation is impossible to verify and it is unlikely to occur. Minsky (1975) asserts that market shifts away from a boom when a certain threshold is reached and a certain number of market participants show disbelief that the market trend is sustainable. He argues that if this happens, people may experience difficulties to switch from *bull* to *bear* markets, mainly due to pressure from other people around them. Fenzl and Pelzmann, (2012) note that the two driving forces in extreme situations are sentiment and greed rather than fundamental analysis. They suggest that in such case herd behavior indicates the market's direction.

3.3.2 Retail and Institutional Investors

Burghardt (2011) suggests that when the chosen research approach is investor specific, stock market participants can be grouped as either retail or institutional investors. He claims that while professionals work for institutional investors or mutual funds, non-professional investors buy and sell securities in order to invest their savings for future consumption. In general, two approaches may be applied when studying herding: researchers may choose either low frequency data that is investor specific (Lakonishok et al., 1992; Sias, 2004; Wermers, 1999) or high frequency data that contains no information about investors and their private signals (Barber et al., 2009). Notably, Fenzl and Pelzmann (2012) assert that sometimes market participants may not be aware that they are part of a herd because they either do not understand such a behavioral trend or may not notice it. They argue that both groups may also have speculative motives.

The research about herding in the stock market started from the institutional investors' perspective, where Kraus and Stoll (1972) were pioneers. Since then, several studies have tried to determine the herding level for professionals, for example, by studying behavior of fund managers, equity market analysts, or institutional investors (e.g. Hong et al., 2000; Nofsinger & Sias, 1999; Sias, 2004). In general, institutional investors have a tendency to mimic each other, when buying and selling securities, mainly as their performance is continuously compared to the market consensus (Sias, 2004; Choi & Sias, 2009). Burghardt (2011) claims that a single institutional investor often has proportionally higher access to funds than a single retail investor, thus increasing institutional power in the market and enabling to affect prices and the market's direction. In addition, he asserts that institutional investors are dependent on professional tools, such as different models and expert opinions rather than on market sentiment. Devenow and Welch (1996) state that institutional investors are affected by agent-principal problems. Overall, institutional herding is often studied on a national level and the results are mixed, for example, German institutional investors showed signs of herding, while equity fund managers in the UK showed only a weak sign of institutional herding (Wylie, 2005). The findings about Germany are also in accordance with the study of Walter and Weber (2006). Kim and Nofsinger (2005) compare investors in the US and Japan, and conclude that institutional herding in Japan is lower than in the US. Sometimes it is even suggested that institutional investors improve the market efficiency, for instance, as it was found in Athens (Caporale et al., 2008). Furthermore, institutional investors also herd across industries (Choi & Sias, 2009).

The research on individual investors has been carried out only since mid-1980s; where Black's (1986) study can be considered as one of the pioneering studies. Retail investors are often considered as "dumb money", since these investors tend to engage in frequent security reallocations, which eventually lead to lower wealth (Frazzini & Lamont, 2008). Further on, Black (1986) considers retail investors as noise traders. He states that basically, a noise trader is anyone who cannot distinguish between noise and information. He claims that eventually as noise is assumed to be information, trading becomes inefficient, because noise is not related to fundamental facts. He further claims that such trading can be more related to historical information or some breaking news. Burghardt (2011) argues that in comparison to institutional investors, retail investors have a limited ability to show negative sentiment, as they cannot short sell stocks. He claims that it creates an asymmetry between positive and negative expectations. In general, he states that there are several crucial sources that can influence sentiment, for example, gut feeling, facts, news, and psychological characteristics. He argues that sentiment often drives retail investors trading decisions, which eventually leads to biased choices and higher correlation among retail investors. The author asserts that some investors may be more willing to become a part of a herd, because they do not have access to information or ability and knowledge to process it. This mainly occurs as retail investors lack the knowledge to value stocks and they do not possess advanced models to evaluate securities. He further asserts that this can be acknowledged as a "free riding" issue. This is in accordance with Sirri and Tufano's (1998) findings that retail investors engage in positive feedback trading, meaning, their decisions are biased towards stocks that have had superior historical performance.

Further on, analyst reports are said to influence retail investors due to individuals' social instinct, where they compare themselves to others in a better position on an ongoing basis (Veblen, 1899). Schiller (1984) suggests that since retail investors may be unable to evaluate firm specific information, they rely more on macroeconomic factors thus they mainly do not use their own judgment, but to some extent base it on others. Barber et al. (2009) expand the argument and claim that the main source of passive reaction is related to psychological biases, where some individuals may observe others, but not necessarily engage in a herd. Only few studies have compared retail and institutional investors in a certain geographic area due to limited data availability (Burghardt, 2011). As one example a study by Goodfellow et al. (2009) can be mentioned, where they examine the two-investor types in Poland. They find that institutional investors do not herd, while individual investors herd, although this behavior diminishes over time.

3.3.3 Reputational Herding

Reputational herding is a type of herding which occurs when professionals, such as portfolio managers, are judged on their performance (Devenow & Welch, 1996). There are two general reasons why institutional investors may ignore fundamental information and start to herd: firstly, to avoid bad reputation and secondly, to avoid underperformance when they are benchmarked (Scharfstein & Stein, 1990; Trueman, 1994; Welch, 2000; Sias, 2004). In order to avoid underperformance and bad reputation, institutional investors chose to disregard private-information by instead follow the behavior of other professionals who are assumed to be better informed (Scharfstein & Stein, 1990; Trueman, 1994). Institutional investors clearly demonstrate herd behavior, when they announce prognoses similar to their peers despite what their own information implies (Trueman, 1994).

Fama (1965) argues that, even though naive investors may push security prices away from intrinsic values, more sophisticated traders will find it worthwhile to correct any mispricing. However, the argument seems weak as institutional investors can easily create a bubble anyway, and more advanced investors may not always correct the situation as they may benefit from herding if prices are increasing (Shiller, 2003). Also, Scharfstein and Stein (1990) study proves that sophisticated traders may not always adjust mispricing. They introduce a model that captures "smart" managers and "dumb" investors. In their study, the former is assumed to obtain revealing information that is correlated, while the latter is supposed to obtain independent and meaningless information. They find that managers showed an enticement to mimic others in order to appear as "smart" and show the market that they obtained the same information as other manager. Graham (1999) made similar assumptions about the two different types of investors, where the private information of the "smart" investors is positively correlated and the information of the "dumb" investors is independent. He argues that investors that are considered "smart" have a tendency to invest in the same securities, whereas the "dumb" investors choose to invest independently according to their private information. The author observes that the need for reputational herding increases with investors' reputation and wage and thus, institutional investors follow the herd to maintain their current position and salary. Also, Scharfstein and Stein (1990) argue that institutional investors reduce reputational costs if they follow the herd. They claim that it is more costly to be the one that differs from the market and that makes the wrong investments than to mimic the market and collectively invest in securities.

3.4 Investors' Sentiment

Market sentiment and limited arbitrage are two core assumptions of behavioral finance (Baker & Wurgler, 2007). In general, Barberis et al. (1998) explain that investors' sentiment refers to how market participants form beliefs. They suggest that the psychological traits in the market can be split in two subcategories: underreaction and overreaction. They further suggest that if underreaction to news is present, then prices do not reflect investor behavior immediately but rather lead to positive autocorrelations. Recently, the focus has shifted towards effects of sentiment, where it is measured by a volatility index (Baker & Wurgler, 2007). Lei et al. (2012) also suggest that higher volatility index indicates higher trading volume, and thus liquidity. They argue that noise traders can be linked to trading volume. They claim that sentiment itself is a signal of noise and essentially drives the stock price away from its fundamental value. Baker and Wurgler (2007) in their study identify that investor sentiment is particularly observable in low capitalization, high volatility, unprofitable or even distressed stocks. They explain this by stating that market participants are concerned about future cash flows and investment risks. They conclude that if it is difficult and subjective to determine a true value, then a security is exposed to speculation. In addition, they assert that retail investors are more probable to be influenced by sentiment than institutional investors. According to Barber and Odean (2008) and Burghardt (2011), individual investors have less access to information and they lack the knowledge to process it. They also claim that individual investors, in contrast to institutional investors, are more likely to be affected by psychological factors and market sentiment. This confirms the conjecture of Nofsinger and Sias (1999) that individual investors herd because of unreasonable and organized reaction to sentiment, while institutional investors herd as a consequence of agency problems. Further on, Barberis et al. (1998) argue that sophisticated market participants can earn abnormal returns without having to take extra risk, thus underreaction and overreaction are challenging the EMH assumptions. Nevertheless, they further argue that since investor sentiment is unpredictable and prices can continue to deviate from their fundamental values, arbitrage opportunities become limited.

Chapter 4. Previous Empirical Research on Herd Behavior

Several models have been proposed to detect herding mentality among stock investors. The studies have been done in different countries and also by considering the influence of US on investors' behavior.

4.1Empirical Models

The empirical method introduced by Christie and Huang (1995) is a commonly used approach to detect herding. Their model is based on cross-sectional standard deviation of returns (CSSD), which is considered as the pioneering indicator of herd behavior. Their reasoning behind using CSSD as a herd measure is that if stock returns get closer to the market rate of return, correlation among returns increases, which signals herding. They further try to detect herd behavior during periods of market stress in the US. In order to measure stock return dispersion under stress periods they set a threshold of 1% and 5%. Notably, their results display no evidence of herd behavior in the US market. Up till now, the model of Christie and Huang (1995) is broadly acknowledged as a measurement for herd behavior and multiple studies have employed their approach in altered forms (e.g. Chang et al., 2000; Chiang & Zheng 2010). The model is easy to apply to stock prices and the underlying reasoning is easy to grasp: the level of herding is stronger if the stock returns show lower dispersion (Christie & Huang, 1995). The reasoning is contrasting the CAPM, which is one of the rational asset pricing models, where individual stocks have a linear relation with the market return as investors are assumed to rely on their own information (Fama & French, 2004). However, Christie and Huang (1995) acknowledge some drawbacks in their model, as it does not control for movements in fundamentals, making it difficult to determine whether the market is efficient or inefficient. Further on, they assert that their measure is dependent on times series volatility and may be sensitive to outliers. The authors apply a robustness check by using cross-sectional absolute deviation (CSAD), which made the results more aligned with the rational asset-pricing models. Since their study only focuses on stressed periods in the US stock market, the possibility to compare investor behavior across geographical areas is limited.

A study by Chang et al. (2000) adopts a similar approach to measure herding activities by using cross-sectional absolute deviation (CSAD) of individual betas in the US and Asian markets. They split the market returns in upward and downward moving markets, which are used as extra variables. They claim that the CSAD has an advantage over the CAPM as it does not entail beta estimations, reducing the possibility of errors in the model specification, which may occur in the CAPM. They state that their approach automatically considers the impact of time series volatility. They claim that the improvements in the specification make it possible to measure herding both in volatile periods and in normal market conditions, which was neglected in Christie and Huang's model (1995). The results of Chang et al. (2000) study show evidence of co-movements during both down and up market days. A later study by Demirer et al. (2010) confirms the results of Chang et al. (2000). Their study on the Taiwanese stock market shows that investors, who behave irrationally, tend to follow the market and ignore their private information. Even though Chang et al. (2000) improve the mentioned model by adding a nonlinear term, Demirer et al. (2010) claim that the findings do not change when the non-linear term is added. An explanation, as suggested by Hirshleifer and Teoh (2003), could be that the nonlinear term in the model may not be considered as a definite evidence of herd behavior. They claim that the nonlinear term instead can be a combination of imperfect rationality, direct payoff interactions, and several effects, such as preference reputation and information. In any case, the effect of the phenomenon remains the same whatever model is applied, namely, extra changes in stock prices are created, resulting in volatility (Chang et al., 2000). This occurs since securities are not priced according to their fundamental values (Tan et al., 2008). Even if some criticism is present, Christie and Huang (1995) and Chang et al. (2000) studies have strongly influenced the research field of herd behavior. In addition, the methods in the research papers are often applied interchangeably.

Hwang and Salmon (2004) propose a different model to detect herd behavior. They criticize the model of Christie and Huang (1995) by pointing out an important drawback: the limitations to clearly verify the causality between investors' behavior and equity return nonlinearities. They instead suggest that the measure should be based on cross-sectional dispersion of betas, also called “beta herding”. They explain that if cross-sectional variance of betas becomes lower and investors herd around the market consensus. By using the CAPM equilibrium they distinguish herd behavior from nonlinearities. In comparison to the model proposed by Christie and Huang (1995), this model is linked to fundamentals and betas can be seen as a risk measure. Hwang and Salmon (2009) further developed their model by including nonparametric measures. However the results remained the same.

Moreover, several empirical studies have examine the herd behavior during financial crises such as the US stock market crash in 1987, the Mexican peso devaluation in 1994 and the Asian financial crises in 1997 (Forbes & Rigobon, 2002; Hwang & Salmon, 2004; Baur & Fry, 2009; Corsetti et al., 2005; Chiang et al., 2007). During these three crises, strong evidence of market return correlation is found. For instance, Hwang and Salmon (2004) results indicate that the Asian crisis at a large extent influenced the markets in US, UK and South Korea. In addition, they find that herding is more evident during pre-crisis when the market is less active, which contrasts the common assumption, that herding occurs mainly during market stress. In general, some contradictions exist, for instance, Kremer and Nautz (2013) find that herding decreased during the crisis in Germany. On the opposite, Chiang and Zheng (2010) find that herding is increasing during crisis. Also the study of Keasey et al. (2014) confirms that several European countries showed signs of asymmetric herd behavior during periods of crisis and extreme market movements.

In addition, some studies use several methods simultaneously, for example, Chiang et al. (2010) and Lao and Singh (2011) apply two different methods to examine herding activities: a least square method and a quantile regression analysis. Notably, Chiang et al. (2010) arrive at different results. A drawback with the least square method is that it does not address tail information and thus does not account for market stress (Chang et al., 2000). In contrast, the quantile regression is more beneficial since it considers tail information and reduces statistical problems (Barnes & Hughes, 2002).

4.2 Studies in Individual Markets

Herd behavior has been investigated in both local markets and global markets (e.g. Chang et al., 2000; Caparrelli et al., 2004; Demirer & Kutan, 2006; Chiang & Zheng, 2010). In general, developed markets such as the US and the UK exhibit fewer herding activities than emerging markets such as South Korea (Hwang & Salmon, 2004). Also, an alternative study by Barberis et al. (2005) done in the US contradicts the models that show no herding in this particular market, for example, Christie and Huang’s (1995) model. However, a recent study conducted in the US finds evidence of herding when essential macroeconomic information is announced (Galariotis et al., 2015). Furthermore, another developed stock market, Australia, shows no signs of herding (Henker et al., 2006). Similarly, a study performed by Tessaromatis and Thomas (2009) in the

Athens stock market shows no indication of herd behavior. When their sample is divided into sub-periods, evidence of herd behavior is found.

Most of the studies on herd behavior are focused in the Asian markets, which are mainly emerging ones (e.g. Chang et al., 2000; Ashiya & Doi, 2001; Bikchandani & Sharma, 2001). In the study of Chang et al. (2000), herding activities are found in South Korea and Taiwan and at some extent in Japan but not in the US and Hong Kong. According to the authors, several factors could explain why herd behavior is more apparent in emerging markets. Firstly, they mention that Asian countries may herd due to economic conditions. Secondly, they point out that as the financial markets are emerging, firm based information is not available. Instead, investors base their decisions considering macroeconomic information (Chang et al., 2000). Historically Asian countries have shown a trend to copy each other when macro-economic predictions are provided (Ashiya & Doi, 2001). In the same manner Bikchandani and Sharma (2001) claim that the main sources of herd mentality are informational asymmetry and liquidity issues. According to Easley et al. (1996), herd behavior is highly influenced by information risk, which increases if trading is driven by more informed market participants. In addition, Tan et al. (2008) claim that institutional factors, for example, government intervention and lacking accounting legislation lead to herd behavior. However, they further claim that this may not apply to all cases.

Many studies have been conducted in the Chinese stock market (e.g. Demirer & Kutan, 2006; Tan, et al., 2008; Chiang, Li & Tan, 2010). However, these studies have lower explaining power than the studies done in the US. Demirer and Kutan (2006) explain this with the Chinese stock market relatively recent establishment and its explicit specification in A and B shares, which divides foreign and domestic investors in two distinct groups and often impose liquidity constraints. Some results from the studies done in the Chinese market are contradicting: while Demirer and Kutan (2006) do not find herd behavior, Tan et al. (2008) and Chiang et al. (2010) find evidence of herding. Tan et al. (2008) find evidence of investors following the crowd rather than their own private information in both rising and falling market conditions in China. Furthermore, their study shows that this behavior is evident in the A-share market, which is aimed for the local investors. On the opposite, the B-share market, which consists of international investors, shows no herding in their study. The authors claim that this can be explained as the A-share market and the B-share market have different characteristics. In an additional study, both types of stock markets in China proved the presence of herd behavior (Tan et al., 2008). However, a later study that employs several methods detects that some models identify herding in the A-share markets, but other models identify herding in both A-share market and B-share market (Chiang et al., 2010). Additionally, studies have been conducted to discover whether volatile market conditions influence investors' behavior in Chinese stock market. For example, Fu (2010) finds that herding is more evident during down market days. Lao and Singh (2011) find similar results that herd behavior in the Chinese market is more significant during market down days and when there is low trading volume. However, they find the opposite in India. Their results show stronger evidence of herd behavior during market up days in the Indian market.

4.3 International Studies

The increasing globalization is seen as a source of market wide herding since it may influence investors incentives for collecting costly information (Calvo & Mendoza, 2000). Chiang and Zheng (2010) account for globalization by applying an adjusted version of the methodology introduced by Chang et al. (2000). The model is adjusted to account for the US influence and extends the geographical scope to a sample of 18 countries, consisting of advanced markets, Latin American markets and Asian markets. They find contradictory results to the study of Chang et al. (2000). Their study clearly indicates evidence of herding in advanced markets, except in the US market. Surprisingly, they find that the markets show lower levels of herd behavior during periods of market stress. The US market is found to have a major role as many countries herd around the US market, confirming its importance as a crucial global leader. Their results show that investors besides their domestic market also herd with the US market. The authors find evidence of herd behavior in the Asian market while the Latin American markets showed no sign of herding activities. Unexpectedly, their findings show that investors in the Latin American markets herd only with the US market. They conclude that foreign markets influence local herding. Similarly, Economou et al. (2011) test the influence of the US stock market in international markets. They claim that extreme price moments in the US have a dominant impact on investors' behavior in other countries. The authors find that four European markets exhibit a positive relationship with the US market. Also, Galariotis et al. (2015) study recent financial crisis and more specifically, whether there are spill-over effects from the US to the UK. Contrary to Chiang and Zheng (2010) results, their findings indicate that herding is driven by either specific time period or by the country itself. They conclude that when local markets are considered, the US has a minor impact on individuals' investment behavior.

Chapter 5. Methodology

This study mainly uses a quantitative approach and is further complemented with a qualitative approach. For the quantitative approach market data of all stocks, both listed and delisted, is gathered. A corresponding market portfolio of stocks for each country and the Baltics as a whole is considered. The market data is analyzed using statistics, more specifically, regression analysis. In order to determine market wide herding, OLS regressions are estimated. The qualitative approach consists of two interviews with representatives from NASDAQ OMX Baltic. By conducting interviews we can attain a more specific insight about the types of investors being active in the Baltic stock market and their trading activities, as this cannot be determined by solely using a quantitative approach. Furthermore, the interviews also facilitate us to evaluate differences in the Baltic stock market. Thus, a combination of a quantitative and a qualitative approach enables a deeper understanding of the investors' behavior and to see whether or not the Baltic States exhibit herd behavior. In addition, secondary data from previous studies is compared with the results of this study.

5.1 Research Design of the Quantitative Method

The quantitative approach of this study is based on cross-sectional absolute deviations of stock returns (CSAD), which is a measure proposed by Chang et al. (2000). The CSAD is a commonly used measure to estimate return dispersion and allows determining the level of herding among market participants. The measure is estimated according to the following formula:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \qquad (1)$$

Where R_m, here and onwards, is a market index for either the specific country or the Baltics as a whole. $R_{i,t}$ is the observed stock return of firm i on day t. N is the number of assets in the portfolio.

The evolution of the CSAD for each country and the Baltics as a whole are presented in figures A2-A5 in Appendix. In general, as can be seen the CSAD is rather stable in the chosen time period. Notable exceptions occur during the crisis in 2008 when deviations from the market consensus are higher in all cases, with the most explicit findings for Vilnius.

All our models are based on a non-linear relationship between the cross-sectional absolute deviation of returns and the market return, which is in accordance with the model proposed by Chang et al. (2000). A low CSAD value indicates that market participants are following the overall market behavior. In other words, co-movements in stocks result in a decreased dispersion.

The level of market-wide herding is detected by the following non-linear OLS regression as suggested by Chang et al. (2000):

$$CSAD_t = \gamma_0 + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \qquad (2)$$

Where R_m enters the equation twice: first, in absolute terms, and second, as a squared variable to measure the non-linear relationship between CSAD and R_m. The model specification, which is used as a baseline model in this study, is applied to each country separately and to all three countries combined. The CSAD is expected to either decrease or proportionally increase less than the market return if herd behavior is present. In such case the coefficient γ_2, which responds to the non-linear variable, is expected to be negative and statistically significant as argued by Chang et al. (2000). We further expect γ_1 to be greater than zero and γ_2 equal to zero in case of no herd behavior. Nevertheless, Chiang and Zheng (2010) suggest a variation for the Eq. (2), where R_m enters the right side of the equation three times: in normal terms, as an absolute term, and as a squared term. They claim that it helps to identify asymmetric investor behavior. Here, the equation is not applied because the goal is to determine if herding is present in general.

This study also accounts for herd behavior during various market conditions. It is examined in a similar manner as previous research. Chang et al. (2000) and Chiang and Zheng (2010) find indications of irregularity in herd behavior between up and down market days. The authors claim that herding activities are more prevalent during periods of large market movements as investors are more likely to ignore their own private information in favor of the collective behavior in the market. This study adopts the same model as Philippas et al. (2013) to determine whether herd behavior shows asymmetries between up and down days. Days with negative market returns are referred to as down days and days with positive market returns as up days.

The following model specification is employed to account for asymmetries in herd behavior:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 D^{down}\left|R_{m,t}\right| + \gamma_3 R_{m,t}^2 + \gamma_4 D^{down} R_{m,t}^2 + \varepsilon_t \qquad (3)$$

Where D^{down} is a dummy variable taking the value of 1 on days when the market returns is negative and the value of 0 on days when the market returns are non-negative. This model specification allows us to examine whether herd behavior is more prevalent during down days in comparison to up days. We expect a statistically negative γ_3 coefficient and $\gamma_4<\gamma_3$ when herding effects are more explicit during down days. In case of no herding activities we expect γ_1 to be positive and γ_3 to be equal to zero. An alternative for the model is to estimate up and down days separately (Tan et al., 2008). However, our chosen approach is more robust as the dummy variables are applied in a single equation (Chang et al., 2000).

We further examine herding activities during volatile market periods by employing Fabozzi and Francis' (1977) proposed classification of trading days. They categorize substantial up months as months where market return is larger than half of standard deviation during the sample period. The opposite applies to substantial down months. We apply the same categorization for our daily data. An alternative model specification could be a quantile study, however, that would substantially reduce the sample size, as more extreme market conditions (either 1% or 5% of returns) are considered.

In order to account for the turbulent market periods, the following model specification proposed by Chang et al. (2000), is applied to each country and for all Baltic countries combined:

$$CSAD_t = \gamma_0 + \gamma_1 D^{down}\left|R_{m,t}\right| + \gamma_2 D^{up}\left|R_{m,t}\right| + \gamma_3 D^{down} R_{m,t}^2 + \gamma_4 D^{up} R_{m,t}^2 + \varepsilon_t \qquad (4)$$

Where D^{down} and D^{up} are dummy variables that take the value of 1 on substantial market return days and 0 otherwise. Here, a significant and negative γ_3 and γ_4 are expected, which implies that investors exhibit herd behavior during volatile market conditions. If there is no evidence of herding activities under these market conditions, then $\gamma_3 = \gamma_4 = 0$ is expected.

Further on, the increasing globalization has made countries more financially integrated. Unlike previous studies, Chiang and Zheng (2010) take this aspect into consideration by studying herding activities across national borders. They argue that previous research, for example the study of Chang et al. (2000) contain certain weaknesses. They claim that previous models overlook important variables and only display local behavior. Therefore, such method is only applicable to countries that are not influenced by other countries. Chiang and Zheng (2010) adjust their model to include the impact of US, as the US plays an important role in the world market. Since the three Baltic countries, Latvia, Lithuania and Estonia, in our study are countries that are subject to foreign influence; the matter of herd behavior across national border is tested.

We examine if the three Baltic countries herd around the US market by using the following model specification proposed by Chiang and Zheng (2010):

$$\mathrm{CSAD_t} = \gamma_0 + \gamma_1 \mathrm{R_{m,t}} + \gamma_2 \left|\mathrm{R_{m,t}}\right| + \gamma_3 \mathrm{R^2_{m,t}} + \gamma_4 \mathrm{CSAD_{us,t-1}} + \gamma_5 \mathrm{R^2_{us,m,t-1}} + \varepsilon_t \qquad (5)$$

In this model specification we use $\mathrm{CSAD_{us,t-1}}$ and $\mathrm{R^2_{us,m,t-1}}$ due to time lag as suggested by Chiang and Zheng (2010). $\mathrm{CSAD_{us,t-1}}$ refers to the US return dispersion of all stocks in S&P 100. $\mathrm{R^2_{us,m,t-1}}$ measures the squared market return for the US index. The S&P 100 index is used as a proxy for the US market return. All other variables are defined in the same way as previously mentioned. The same as in the baseline model, market-wide herd behavior is present if γ_3 is negative and statistically significant. While a negative and statistically significant γ_5 would indicate that the area in question herds around the US market. A positive and highly statistically significant γ_4 implies that the US has a major influence on the markets.

To extend our study we also take investors' sentiment into consideration. More specifically, we test if investors have a tendency to follow the crowd and suppress their private information in periods of increased anxiety of upcoming market conditions. One way to capture the uncertainty about future conditions is to use CFE-VIX as a proxy as proposed by Baker and Wurgler (2007). Their motivation to incorporate this measure in the regression is that an increase in investors' anxiety will raise implied volatilities, as they would be more prone to follow hedging strategies.

We examine investors' sentiment according to the following model specification proposed by Philippas et al. (2013):

$$CSAD_t = \gamma_0 + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + \gamma_3 R_{CFE-VIXt} + \varepsilon_t \qquad (6)$$

Where $R_{CFE-VIXt}$ is the percentage return of CFE-VIX futures index on day t. The CFE-VIX futures index is published by CBOE and tracks the market's expectation of economic prospects. If investors' sentiment is linked to a decreasing trend in the return dispersions, we expect the coefficient γ_3 to be negative and statistically significant.

5.2 Research Design of the Qualitative Method

The qualitative approach consists of one phone interview and an e-mail exchange with two representatives from NASDAQ OMX Baltic. The interviews were conducted by telephone and e-mail due to the geographic location of the interviewees. The phone interview lasted around 30 minutes. One of the interviewees Liene Dubava is a member of the management board with a particular insight in the Latvian stock market. The other interviewee Kristo Sepp holds the title Trading Surveillance Manager and is responsible for monitoring trading activities in the three Baltic markets. A semi-structured approach with open questions was applied. This approach facilitates the initial question to be followed up by more specific questions depending on the answers obtained (Denscombe, 2007). The questions used in the interviews can be seen in the Appendix.

Chapter 6. Data and Descriptive Statistics

In this section data collection and descriptive statistics are presented and discussed.

6.1 Data

Daily stock prices for all three Baltic countries as well as the OMXBBGI, OMXT, OMXR, and OMXV indices are retrieved in Euro from NASDAQ OMX Baltic website, which is the core source for stock prices in the chosen region. All four indices are weighted according to the market values. The development of these indices can be seen figure A1 in Appendix. The OMXBBGI is a benchmark index that represents the largest and the most liquid shares in the Baltic market (NASDAQ, 2015). As can be seen on the NASDAQ website, on April 13, 2015 OMXBBGI covers respectively 54,9% of the Baltic market considering the whole market capitalization. The index composition can be seen in table A1 in Appendix. The sample in our study consists of both individual stock returns and market level data. All stocks traded in the Baltics are considered; both delisted and listed. Thus, our dataset is free of survivorship bias. The sample period in this study is 2006-2014, with 2006-01-02 as starting date and 2014-12-30 as end date. The length is sufficient to cover different market phases: both *bull* and *bear* periods. It means that the study covers various economic conditions. The sample period is of interest as it comprises the financial crisis in 2008, the currency transition to Euro in all three countries and hence gives an indication of psychological pressure on investors when the market experience high uncertainty. The final dataset consists of 2271 daily observations when the whole Baltic market is considered together. However, when the three countries are considered separately, the dataset ranges from 2214-2255 daily observations.

The individual stock returns are calculated as logarithmic changes in stock prices. As can be seen in trading statistics on the NASDAQ website (2015), some stocks in the Baltic markets are thinly traded. Thus, the data are adjusted for thin trading by only including liquid stocks. Kallinterakis (2007) describes thinly traded stocks as illiquid stocks, which have a tendency to underestimate herd behavior. Following his approach, a liquidity criterion of 70% had to be accomplished for a stock to be included in this study. As can be seen in table A2 in Appendix, 86 stocks meet this requirement, while 45 stocks are excluded. A list of the illiquid stocks can be seen in table A3 in Appendix. Furthermore, non-trading days were excluded from the sample. In addition, the sample was adjusted for outliers. Hawkins (1980) describes outliers as observations that deviate too much from the sample and thus may have risen due to other sources. As herding is studied from a market wide perspective, an adjustment for company specific outliers is done in order to increase result robustness. We set a threshold of 6 standard deviations. In cases where the outliers in CSAD arise due to a single security, the return of that particular security on that date was excluded from the sample. However, when the whole market underwent abnormal returns, no adjustments were done. Overall, the outlier adjustment improved the quality of the data.

Moreover, the data for additional variables to test for the influence of the US market and investors' sentiment are obtained from Thomson DataStream database. The data is obtained for the same period as the data for the Baltic countries. The dataset consist of daily stock prices of all firms included in S&P 100. The S&P 100 consists of the 100 major US stocks with a market cap of 724 773,39 million US dollar (S&P Dow Jones Indices, 2015) and covers nearly 45% of the market capitalization of the US equity markets. In addition, daily S&P 100 index is also collected. Also, the CBOE implied volatility index (VIX) prices is obtained from Thomson DataStream database for the time period 2006-01-02 to 2014-12-30.

6.2 Descriptive Statistics

Table 1 presents descriptive statistics of the CSAD in the three countries and the Baltics as a whole. As it can be seen in the table, Riga shows the highest mean value, which suggests significantly higher market variations across stock returns for Riga compared to the other two countries and the Baltics as a whole. Vilnius has the lowest mean value of CSAD. Notably, Vilnius also has the highest maximum value of CSAD. A minimum value of zero for CSAD implies that all individual stock returns move together with the market. None of the markets reaches 0 as the minimal value, which means that none of the markets is in full consensus with the market index. Further, all three countries have high standard deviations; the highest is in Riga, and the lowest in Vilnius. A high standard deviation might imply that the market had unusual cross-sectional variations due to unanticipated events or distress. Skewness is positive in all three cases and departs from normality. Tallinn and Vilnius show higher skewness than Riga. In addition, excess kurtosis can be seen in all cases and thus it implies departure from a normal distribution, meaning high probability of extreme values. The Jarque–Bera test statistics show significant result at 1% level for all markets, indicating a rejection of the null hypothesis of a normal distribution. However, the closest distribution to the normal one is observed in Riga. In addition, a high and significant level of serial correlation is apparent for CSAD in all four markets, where Baltics as a whole shows the highest value of 0,648 followed by Tallinn 0,563. The serial correlation is significant even at lag 20. This can be explained by the high frequency time series market data.

Table 1 Summary statistics of cross-sectional absolute standard deviation (CSAD).

								Serial correlation at lag				
Market	**Mean**	**Max**	**Min**	**Std. d.**	**Skew.**	**Kurt.**	**Jarque-B.**	**1**	**2**	**3**	**5**	**20**
The Baltics	0,82	6,40	0,08	0,46	3,08	22,48	39510	0,65	0,56	0,52	0,45	0,38
Tallinn	0,87	5,50	0,07	0,56	2,09	10,40	6790	0,56	0,47	0,45	0,39	0,35
Riga	0,95	6,06	0,01	0,57	1,76	8,90	4397	0,49	0,40	0,39	0,31	0,24
Vilnius	0,78	8,65	0,02	0,54	4,15	37,85	118410	0,56	0,47	0,43	0,38	0,27

Notes: This table reports the daily mean, standard deviation, skewness, kurtosis of the cross-sectional absolute standard deviation (CSAD) over the sample period for stock markets in Tallinn, Riga and Vilnius and all three markets combined. In addition, serial correlation of the CSAD and is reported for lags 1, 2, 3, 5 and 20. Calculations of CSAD are given by Eq. (1).

Table 2 depicts the descriptive statistics for the market return, which in this case are different indices. The average daily return as it can be seen in the table is close to zero, while the maximum and minimum returns varies – the highest return is in Tallinn, while the lowest return is for the index applied to the Baltics as a whole. Furthermore, the standard deviations are similar to findings presented in table 1. Vilnius and the Baltics show negative skewness. This means that the return distribution has a long left tail. Furthermore, excess kurtosis can be seen in all cases. As can be seen in table 2, market returns have lower serial correlation than CSAD. Even though the Jarque–Bera test statistics in table 2 are lower than in table 1, the results are still statistically significant at 1% level. The null hypothesis that CSAD and market returns have a normal distribution is rejected. However, the sample used in this study is sufficiently large to conduct the regression analysis.

Table 2 Summary statistics of market return.

								Serial correlation at lag				
Market	**Mean**	**Max**	**Min**	**Std. d.**	**Skew.**	**Kurt.**	**Jarque-B.**	**1**	**2**	**3**	**5**	**20**
The Baltics	0,00	3,89	-3,83	0,48	-0,46	13,17	9870	0,14	0,05	0,07	0,05	-0,03
Tallinn	0,00	5,25	-3,06	0,53	0,13	11,96	7549	0,14	0,06	0,06	0,06	-0,03
Riga	-0,01	4,42	-3,41	0,58	0,16	9,47	3905	-0,04	0,02	-0,01	0,01	0,04
Vilnius	0,01	4,78	-5,18	0,52	-0,38	21,07	30178	0,14	0,05	0,04	0,05	0,02

Notes: This table reports the daily mean, standard deviation, skewness, kurtosis of the market index (Rm) for Tallinn, Riga and Vilnius and the Baltic stock market over the sample period 2006-01-02 to 2014-12-30. In addition, serial correlation of the Rm is reported for lags 1, 2, 3, 5 and 20.

Chapter 7. Empirical Analysis

In this section we present the results of all estimated regressions in this study. Further on, a discussion of our results is provided.

7.1 Baseline Model

In the first set of empirical tests we assess whether the Baltics exhibit herd behavior using Eq. (2), also considered as the baseline model. To test for heteroscedasticity and autocorrelation issues, several statistical tests are applied to the residuals from Eq. (2). As the regression analysis is based on time series data, residual diagnostics are applied on the baseline model. The obtained results are summarised in table 3. The Engle's ARCH test confirmed that there is heteroscedasticity in residuals. Thus, the null hypothesis of no heteroscedasticity is rejected. Also the results from the White test, which considers nonlinearity of independent variable on the error variance, support the argument that homoskedasticity hypothesis is rejected. The Breusch-Godfrey Serial Correlation LM Test presented in table 3 shows that there is a serial dependence in the model, as a high autocorrelation is indicated. In addition, the autocorrelation test applied to the residuals confirms serial dependence. However, in comparison to the CSAD, residuals show lower serial correlation. All tests in table 3 show p-values that are close to zero, implying that estimators do not have a minimum variance. The statistically significant results of serial correlation and heteroscedasticity motivate the use Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors. Thus, statistical corrections proposed by Newey and West (1987) are applied to all of our regressions.

Table 3 Results from the statistical tests.

Engle's ARCH test (number of lags: 1)			
F-statistic	284	Prob. F(1,2268)	0,000
Obs*R-squared	253	Prob. Chi-Square(1)	0,000
White's general test for heteroskedasticity			
F-statistic	89	Prob. F(4,2266)	0,000
Obs*R-squared	307	Prob. Chi-Square(4)	0,000
Scaled explained SS	1675	Prob. Chi-Square(4)	0,000
Breusch-Godfrey Serial Correlation LM Test			
F-statistic	222	Prob. F(1,2267)	0,000
Obs*R-squared	203	Prob. Chi-Square(1)	0,000
Serial correlation at lag			
1: 0,293		5: 0,247	
3: 0,259		20: 0,227	

Notes: This table reports the Engle's Arch test, White's general test for heteorskedasticity, Breusch-Godfrey Serial Correlation LM Test for the Baltic, Tallinn, Riga and Vilnius stock markets over the sample period 2006-01-02 to 2014-12-30. In addition, serial correlation of the residuals is reported for lags 1, 3, 5 and 20.

The estimated coefficients for Eq. (2) can be seen in table 4. The coefficient of interest in this model is the one of $R^2_{m,t}$, which allows testing if the CSAD increases or decreases over the sample period. We expect the coefficient of $R^2_{m,t}$ to be negative and statistically significant. As can be seen in table 4, this only occurs in Tallinn at a significance level of 10%. In Riga the coefficient is negative but not statistically significant, while it is positive in Vilnius and when all countries are considered together. Notably, Vilnius and all three countries combined have the best model fit as the adjusted R^2 has the highest value. Similarly, Galiroitos et al. (2015) find no evidence of herding in UK and US during their full sample period.

Table 4 Estimates of herd behavior using the baseline model for all markets.

Market	Constant	$\left\|R_{m,t}\right\|$	$R^2_{m,t}$	$\overline{R^2}$
The Baltics	0,574***	0,796***	0,027	0,464
	(40,214)	(13,277)	(0,683)	
Tallinn	0,568***	0,914***	-0,040*	0,355
	(32,152)	(17,889)	(-1,927)	
Riga	0,613***	0,906***	-0,054	0,364
	(30,658)	(13,645)	(-1,261)	
Vilnius	0,522***	0,770***	0,042	0,468
	(35,051)	(13,000)	(1,216)	

Notes: This table reports the regression results of CSAD based on Eq. (2). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.
* The coefficient is significant at the 10% level.
** The coefficient is significant at the 5% level.
*** The coefficient is significant at the 1% level.

Table 5 Estimates of herd behavior for coefficients of Rm^2 in the baseline model.

Year	The Baltics	Tallinn	Riga	Vilnius
2006	-0,044	0,208	-0,023	-0,029
2007	0,028	0,033	0,275	0,058
2008	0,017	-0,020	0,048	0,109
2009	0,054*	0,029*	-0,064*	0,014
2010	0,212*	-0,081	0,102*	0,068
2011	0,112	0,053	-0,016	0,047*
2012	0,103	0,128	0,701*	0,398
2013	0,152	-0,135	0,001	-0,097
2014	0,179	0,058	0,035	-0,039

Notes: This table reports the regression results of CSAD coefficient that refers to the market return squared term based on Eq. (2). The date range from 2006-01-02 to 2014-12-30.
* The coefficient is significant at the 10% level.
** The coefficient is significant at the 5% level.
*** The coefficient is significant at the 1% level.

We further test herding effects in yearly sub-periods by applying Eq. (2). In this way we can determine if herd behavior is a short-lived phenomenon or if it spreads over several years. Table 5 reports coefficients of the non-linear term $R^2_{m,t}$. As can be seen in this table, herd behavior was not present in the pre-crisis period, 2007. The same results were obtained for 2008, even though this year is characterized as a year of large market movements with high market stress and uncertainty. This implies that the market participants in the Baltics did not herd during the financial crisis in 2008. These results are consistent with the findings obtained by Demirer and Kutan (2006), Tan et al. (2008) and Yao et al. (2014), which did not find evidence of herding activities during crisis periods. In contrast, Fenzl and Pelzmann (2012) show that market participant react irrationally, especially during crisis and booms. As depicted in table 5 Tallinn is the only country in 2008 that has a negative coefficient, but the result is not statistically significant. In 2009 the coefficient of $R^2_{m,t}$ is negative and statistically significant only in Riga. That is similar to the findings of Philippas et al. (2013), where herd behavior was more evident after the market bubble than during the bubble. In other words, the market participants in the Baltics did not show group mentality in a *bear* market, when the market indices and stock prices dropped. Further on, Riga only shows group mentality in one sub-period and not for the whole sample period, which imply that herd behavior overall is not common and it does not spread over several years. This is consistent with the study done by Tessaromatis and Thomas (2009). They argue that herd behavior does not have a permanent effect on investors, as their study also indicated herding in some sub periods, while not in the whole sample period. As table 5 shows, the coefficients of the non-linear term are in most of the cases positive, which implies that herd behavior is not present. The full regression estimates can be seen in tables A4-A7 in Appendix.

For robustness purposes we classify the sample according to market capitalization. The sample is separated in two portfolios: a main list consisting of large stocks and a secondary list containing small stocks (NASDAQ, 2015). Such an approach is in accordance with the robustness test done by Chang et al. (2000), which examine small and large stocks separately. We apply Eq. (2) to both portfolios. The estimated coefficients from the robustness test are shown in table 6, where the main list is presented, and table 7, where the secondary list is presented. As the tables show, the main list and the secondary list exhibit nearly the same level of herd behavior. The only exception is Tallinn, where the coefficient of $R^2_{m,t}$ in the secondary list is negative and statistically significant at the 1% level. The coefficient of $R^2_{m,t}$ for the main list however is negative and statistically insignificant. The results in Tallinn are consistent with the study of Yao et al. (2014) where herding activities were more evident in smaller stocks than in larger ones. The reasoning can be supported by Lakoniskok et al. (1992) findings that smaller stocks are less analysed and that there is less publicly available information making investors more prone to follow the market and eventually herd. Furthermore, they claim the opposite for large cap stocks, where there is more publicly available information, enabling investors to base their investment decision on their own beliefs. We find robust evidence of no herd behavior in Vilnius and when all three countries are considered together. Overall, the results are robust across these two size-based portfolios. Further on, these findings confirm robustness of the full sample results.

Table 6 Estimates of herd behavior using the baseline model for the main list.

Market	Constant	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$\overline{R^2}$
The Baltics	0,507***	0,835***	0,008	0,434
	(33,380)	(14,137)	(0,228)	
Tallinn	0,542***	0,855***	-0,023	0,383
	(33,096)	(17,393)	(-1,204)	
Riga	0,550***	0,946***	-0,074*	0,328
	(27,555)	(13,300)	(-1,820)	
Vilnius	0,454***	0,778***	0,040	0,452
	(29,157)	(13,189)	(1,241)	

Notes: This table reports the regression results of CSAD based on Eq. (2). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.
* The coefficient is significant at the 10% level.
** The coefficient is significant at the 5% level.
*** The coefficient is significant at the 1% level.

Table 7 Estimates of herd behavior using the baseline model for the secondary list.

Market	Constant	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$\overline{R^2}$
The Baltics	0,689***	0,721***	0,059	0,361
	(37,154)	(9,268)	(1,103)	
Tallinn	0,658***	1,132***	-0,102***	0,189
	(23,989)	(15,302)	(-2,978)	
Riga	0,662***	0,847***	-0,027	0,261
	(26,278)	(11,462)	(-0,583)	
Vilnius	0,639***	0,716***	0,053	0,348
	(34,636)	(10,682)	(1,423)	

Notes: This table reports the regression results of CSAD based on Eq. (2). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.
* The coefficient is significant at the 10% level.
** The coefficient is significant at the 5% level.
*** The coefficient is significant at the 1% level.

7.2 Herding under Market Up and Down Days

Next, asymmetries under market up and down days are examined using Eq. (3). Table 8 displays the estimated coefficients for all three markets separately and combined. The results show that the coefficient of $D^{down}R^2_{m,t}$ is smaller than the coefficient of $R^2_{m,t}$ for Riga and when all three countries are combined. This implies that herding in these two markets is more evident when market returns are negative. Our results indicate that when the market is experiencing a downturn, investors have a tendency to be more group oriented. The opposite is found in Tallinn where herding effects are more pronounced in rising market conditions. A likely explanation for our findings can be related to the stock market development in the Baltic States. As the stock market in Tallinn is more developed compared to the other two Baltic countries, investors may express their optimistic views about this market by herding in the up days. Similarly, Tan et al. (2008) find that rising markets show decreasing return dispersion. Overall, our findings show statistically significant herding effects when considering the market returns' sign. These asymmetries arise as individuals react differently to market movements. Consistent with our findings, several studies (Chang et al., 2000; Demirer et al., 2010; Yao et al., 2014) have found that investors react differently on days with non-negative or negative market returns. When considering all the Baltic countries combined no highly significant results neither in up or down days were found. Furthermore, Vilnius shows low level of herding than Riga and Tallinn. This may be explained by the higher stock market development in Vilnius.

Table 8 Estimates of herd behavior under up and down days.

Market	Constant	$\lvert R_{m,t} \rvert$	$D^{down} \lvert R_{m,t} \rvert$	$R^2_{m,t}$	$D^{down} R^2_{m,t}$	$\overline{R^2}$
The Baltics	0,570***	0,809***	0,002	0,097	-0,133*	0,477
	(37,288)	(7,947)	(0,026)	(1,113)	(-1,725)	
Tallinn	0,563***	0,969***	-0,056	-0,037*	-0,035	0,357
	(31,108)	(15,805)	(-0,757)	(-1,795)	(-0,844)	
Riga	0,606***	0,919***	0,051	-0,023	-0,108*	0,369
	(31,158)	(10,967)	(0,617)	(-0,393)	(-1,911)	
Vilnius	0,519***	0,772***	0,013	0,095	-0,103	0,481
	(35,057)	(8,314)	(0,118)	(1,304)	(-1,248)	

Notes: This table reports the regression results of CSAD based on Eq. (3). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted R^2. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.

* The coefficient is significant at the 10% level.

** The coefficient is significant at the 5% level.

*** The coefficient is significant at the 1% level.

In addition, extreme markets movements are considered. An examination of substantial up and down days enables a verification of investors trading activity in changing market conditions. The sample period covers both *bull* and *bear* markets. As table 9 shows, the coefficient of $D^{down} R^2_{m,t}$ is only negative and statistically significant for Riga. This implies that herding is present during substantial down days in Riga. It shows that investors are more inclined to ignore their private information and follow the market consensus during periods of market stress. Furthermore, the results indicate that none of the markets exhibit herd behavior during substantial up days, except Tallinn, where the sign of the coefficient of $D^{up} R^2_{m,t}$ is negative but not statistically significant. Although Vilnius has the highest adjusted R^2 values, the market does not exhibit herd behavior in neither substantial up or down days. Similarly, Demirer and Kutan (2006), Tan et al. (2008) and Yao et al. (2014), found no evidence of herding activities during crisis periods in the Chinese stock market. Our results however, contrast the results provided by Chang et al. (2000) and Fenzl and Pelzmann (2012) that show that investors have a tendency to herd especially in booms and crises.

Table 9 Estimates of herd behavior under substantial up and down days.

Market	Constant	$D^{down}\lvert R_{m,t}\rvert$	$D^{up}\lvert R_{m,t}\rvert$	$D^{down}R^2_{m,t}$	$D^{up}R^2_{m,t}$	$\overline{R^2}$
The Baltics	0,649***	0,662***	0,651***	0,011	0,145*	0,470
	(53,616)	(11,253)	(6,643)	(0,356)	(1,610)	
Tallinn	0,657***	0,747***	0,830***	-0,018	-0,007	0,356
	(42,486)	(10,353)	(14,754)	(-0,406)	(-0,282)	
Riga	0,716***	0,790***	0,731***	-0,077**	0,027	0,363
	(44,591)	(12,335)	(9,220)	(-1,967)	(0,452)	
Vilnius	0,596***	0,671***	0,652***	0,017	0,121	0,477
	(48,955)	(9,791)	(7,179)	(0,596)	(1,654)	

Notes: This table reports the regression results of CSAD based on Eq. (4). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.
* The coefficient is significant at the 10% level.
** The coefficient is significant at the 5% level.
*** The coefficient is significant at the 1% level.

7.3 The Role of the US Market

After using Eq. (2) to test herding effects in a closed system, the model is extended to consider the influence of the US stock market on investors in the Baltic stock market. Table 10 reports the estimated results of CSAD based on Eq. (5), for each country separately and all three countries combined. The coefficients of interest here are $CSAD_{US,t-1}$ and $R^2_{US,t-1}$.

Table 10 Estimates of herd behavior by incorporating the US factor.

Market	Constant	$R_{m,t}$	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$CSAD_{US,t-1}$	$R^2_{US,t-1}$	$\overline{R^2}$	Wald test
The Baltics	0,331***	0,117***	0,653***	0,043	0,647***	-0,006	0,560	0,654***
	(13,619)	(4,107)	(12,497)	(1,270)	(10,369)	(-0,388)		
Tallinn	0,287***	0,083***	0,762***	-0,031*	0,746***	0,009	0,446	0,737***
	(9,873)	(3,261)	(18,071)	(-1,750)	(10,855)	(0,467)		
Riga	0,454***	0,069***	0,845***	-0,055	0,422***	-0,008	0,390	0,429***
	(13,495)	(3,104)	(13,362)	(-1,437)	(5,220)	(-0,450)		
Vilnius	0,264***	0,115***	0,636***	0,058**	0,675***	-0,011	0,547	0,685***
	(9,325)	(2,665)	(11,834)	(2,119)	(8,531)	(-0,487)		

Notes: This table reports the regression results of CSAD based on Eq. (5). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors. The last column presents the results from the Wald test of herding for coefficients of $R_{(US,t-1)}^2$ and $CSAD_{(US,t-1)}$. H_0: γ_4-γ_5=0, which is used to test the equality between the coefficients.
* The coefficient is significant at the 10% level.
** The coefficient is significant at the 5% level.
*** The coefficient is significant at the 1% level.

As can be seen in table 10 the adjusted R^2 is relatively high for all geographic specifications. Therefore, by including $CSAD_{US,t-1}$ and $R^2_{US,t-1}$ into the baseline model the explanatory power is improved. All markets show positive and highly statistically significant results for the $CSAD_{US,t-1}$ coefficient. Our results show that the return dispersion in the US is transmitted to the Baltics. This indicates that the US has a considerable influence in all three markets separately as well as combined. This is consistent with the findings of Chiang and Zheng (2010), where the US return dispersion is found to be a major influence on other countries. According to table 10 the coefficient of $R^2_{US,t-1}$ is negative, but not statistically significant in all three countries combined as well as in Riga and Vilnius, while only Tallinn shows an insignificant positive value. This implies that no herding around the US market can be observed. As we do not find statistically significant coefficients of $CSAD_{US,t-1}$ and $R^2_{US,t-1}$, a contagion effect is not present. A possible explanation could be that there is no close interaction between these markets.

In addition, a Wald test is performed to test for the joint significance of the coefficients of the $CSAD_{US,t-1}$ and $R^2_{US,t-1}$The results in table 10 confirm that the null hypothesis that the two coefficients are equal is rejected at the 1% level.

Further, we examine whether large market movements in the US influence the behavior of investors in the Baltics. In the following specification we apply the same procedure as used in the Eq. (4):

$$CSAD_t = \gamma_0 + \gamma_1 D^{down}_{US,t-1}\left|R_{m,t}\right| + \gamma_2 D^{up}_{US,t-1}\left|R_{m,t}\right| + \gamma_3 D^{down}_{US,t-1} R^2_{m,t} + \gamma_4 D^{up}_{US,t-1} R^2_{m,t} + \varepsilon_t \quad (7)$$

In a similar manner as before, if group mentality is apparent in substantial up and down days, then accordingly negative values of the coefficients of $D^{down}R^2_{m,t}$ and $D^{up}R^2_{m,t}$ are expected. As depicted in table 11 Riga and Vilnius show positive and significant results during down days, while all three countries combined show a positive and significant result for days with negative returns.

As can be seen in table 11, none of the coefficients are negative, which insinuates that there is no herding around the US market during volatile periods, neither in the up nor down days. This is in contrast to the study of Galariotis et al. (2015) who find a spill-over effect from the US to the UK during market downturns. Furthermore, it was expected that investors would herd more during substantial up and down days. Conversely, as the results show, the US does not influence the behavior of Baltic investors during volatile periods. A possible interpretation of this is that investors in the Baltic markets are more affected by economic conditions in Europe and Russia rather than events in the US. This is supported by the findings of Chiang and Zheng (2010). They show that during turbulent periods countries in the same geographical area are more influenced by each other than by the US. However, they claim that the significance of the US may appear lower than it actually is because the local market return already reflects some events in the US.

As table 10 and table 11 show, the model has a higher explanatory power when all market conditions are considered.

Table 11 Estimates of herd behavior under substantial up and down days considering the US market.

Market	Constant	$D^{down}\lvert R_{m,t}\rvert$	$D^{up}\lvert R_{m,t}\rvert$	$D^{down}R^2_{m,t}$	$D^{up}R^2_{m,t}$	$\overline{R^2}$
The Baltics	0,707***	0,630***	0,703***	0,097*	0,036	0,360
	49,197	7,467	9,235	1,751	1,378	
Tallinn	0,746***	0,598***	0,729***	0,114	0,004	0,253
	40,129	5,308	9,618	1,463	0,231	
Riga	0,838***	0,460***	0,547***	0,126***	0,086	0,215
	40,504	5,607	5,911	2,887	1,351	
Vilnius	0,660***	0,608***	0,660***	0,092**	0,036*	0,365
	41,366	7,297	8,898	2,126	1,853	

Notes: This table reports the regression results of CSAD based on Eq. (7). The date ranges from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.
* The coefficient is significant at the 10% level.
** The coefficient is significant at the 5% level.
*** The coefficient is significant at the 1% level.

7.4 Investors' Sentiment

The estimated coefficients for Eq. (6), where VIX is introduced, can be seen in table 12. As mentioned before, we expect the coefficient of $R_{CBOEVIXt}$ to be negative and statistically significant. In such case an increasing VIX is negatively related to the return dispersion. It emphasizes the assumption that if investors' sentiment becomes worse, the level of herding increases.

The results in table 12 demonstrate that the implied volatility index is negatively related to the CSAD for all markets. However, it is only statistically significant for Tallinn and Riga. This indicates that investors in these two markets exhibit herd behavior when they are anxious about future market conditions. Our results are consistent with those of Philippas et al. (2013): if investors' sentiment deteriorates, market participants are more prone to follow the market consensus. As a consequence it becomes more difficult to make precise predictions since stock prices deviates from their fundamental values due to the market inefficiency caused by investors' anxiety (Olsen, 1996). Considering the findings of Schmeling (2009), a probable reason for our findings may be that these two markets are culturally more inclined to herd and overreact than the stock market in Vilnius. It appears that sentiment in the Baltics as whole does not to drive trading decisions.

Table 12 Estimates of herd behavior by incorporating implied volatility.

Market	Constant	$R_{m,t}$	$R^2_{m,t}$	$R_{VIX,t}$	$\overline{R^2}$
The Baltics	0,572***	0,800***	0,012*	-0,008	0,452
	(39,124)	(12,146)	(0,249)	(-1,906)	
Tallinn	0,576***	0,878***	-0,036	-0,005*	0,340
	(30,955)	(16,673)	(-1,676)	(-1,076)	
Riga	0,608***	0,932***	-0,085	-0,006*	0,345
	(26,627)	(11,953)	(-1,762)	(-1,035)	
Vilnius	0,524***	0,747***	0,044	-0,003	0,466
	(34,512)	(12,007)	(1,275)	(-0,640)	

Notes: This table reports the regression results of CSAD based on Eq. (6). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.

* The coefficient is significant at the 10% level.

** The coefficient is significant at the 5% level.

*** The coefficient is significant at the 1% level.

As a further examination of the implications of implied volatility on the CSAD, we apply the same procedure as used in the Eq. (4) by estimating the dummy variables based on VIX changes rather than market return changes. We apply the following model specification:

$$CSAD_t = \gamma_0 + \gamma_1 D^{down}_{CFE-VIX}\left|R_{m,t}\right| + \gamma_2 D^{up}_{CFE-VIX}\left|R_{m,t}\right| + \gamma_3 D^{down}_{CFE-VIX} R^2_{m,t} + \gamma_4 D^{up}_{CFE-VIX} R^2_{m,t} + \varepsilon_t \quad (8)$$

If herding effects are present in substantial down days and up days, then the coefficients of $D^{down}_{CFE-VIX} R^2_{m,t}$ and $D^{up}_{CFE-VIX} R^2_{m,t}$ are negative and statistically significant. The modification allows testing if there is a relation between substantial movements in implied volatility and the CSAD.

As it can be seen in table 13, we find a positive relationship between implied volatility and CSAD in both substantial up and down days, in other words, an increase in VIX is related to an increase in CSAD. Thus, investors in each country separately and in the Baltics as a whole do not herd. This implies that the market participants' expectations of future market conditions do not have an effect on their investment behavior in volatile market conditions. Our results show that the level of herding does not increase when investors' sentiment changes. The findings can be related to the sub-period analysis where no herding activity was detected in 2007 and 2008 when the market underwent *bull* and *bear* periods. Thus, market participants appear not to be influenced by psychological factors when taking investment decisions. A possible explanation for these results may be that since extreme market conditions are associated with high market illiquidity, investors in the Baltics have limited trading possibilities. As our findings from table

12 and table 13 show herd behavior is not related to investors' sentiment in Vilnius and all three countries combined.

Table 13 Estimates of herd behavior during substantial up and down days by incorporating implied volatility.

Market	Constant	$D^{down}\|R_{m,t}\|$	$D^{up}\|R_{m,t}\|$	$D^{down}R^2_{m,t}$	$D^{up}R^2_{m,t}$	$\overline{R^2}$
The Baltics	0,726***	0,478***	0,373***	0,204**	0,159***	0,268
	(40,859)	(4,843)	(5,198)	(2,283)	(3,634)	
Tallinn	0,775***	0,257**	0,420***	0,407***	0,107**	0,173
	(35,032)	(2,061)	(4,649)	(3,145)	(2,063)	
Riga	0,851***	0,551***	0,253***	0,024	0,189***	0,161
	(39,414)	(4,635)	(3,473)	(0,238)	(4,869)	
Vilnius	0,686***	0,376***	0,409***	0,228***	0,126***	0,276
	(34,023)	(3,878)	(4,325)	(3,247)	(3,082)	

Notes: This table reports the regression results of CSAD based on Eq. (8). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.

* The coefficient is significant at the 10% level.

** The coefficient is significant at the 5% level.

*** The coefficient is significant at the 1% level.

Chapter 8. Results of Interviews

The results from the interviews show that the Baltic stock market does not display typical investor behavior. The majority of market participants have changed from individual investors to institutional investors, which indicates that the level of market wide herding should vary over time. Initially, when the stock market was opened in the Baltics, there were many retail investors as people received certificates that they could exchange for shares. However, many market participants, that hold a small proportion of shares, sold them to larger investors. Even if there still is a diverse investor composition, the market is now largely driven by institutional investors. For example, the stock market in Riga has only around 100 active private investors, who follow the market activity on a daily basis. In any case, the retail investors often do not have a power to change the market direction and instead they tend to follow institutional investors. The institutional investors trading activities have a large impact on stock prices. Due to this reason retail investors tend to follow the movements of the institutional investors. That means that individual investors are more likely to exhibit group mentality. Overall, at the moment there are two distinct groups of investors in this area: ones who buy and hold shares, and ones who engage in active trading. Thus, the first mentioned does not engage in herding activities as their portfolio composition remains constant over time.

Each countries individual market is comparatively small and split in main lists and secondary lists according to market capitalization. Overall, the secondary lists compared to the main lists, are more illiquid in all Baltic countries and the trading activities occurs more seldom and without any noticeable and logical pattern. Therefore, no considerable patterns or technical movements can be observed in the secondary lists. In other words, individuals who invest in the secondary list do not follow market consensus. Notably, some speculations and inside trading have been observed where some market participants abuse the illiquidity for personal gain. For example, management team that sells shares before announcing results, which do not match forecasts. Generally, in the cases where illiquidity is high, herd behavior may not be apparent as speculation affects only few stocks. This will not be reflected as market wide herding. However, when considering the main drivers of stock prices it has been observed that in the short run stock prices tend to be driven by supply and demand, while in the long run, fundamental values appear to have a larger impact. It means that investors consider their investment carefully and do not base it on fads.

During the financial crisis in 2008 the market showed an increase in trading activity, mainly because institutional investor wanted to get out of their positions and they were fighting for better selling opportunities, clearly signaling willingness to herd under market down days. Surprisingly, there was no major damage in the stock market. The herding was limited since investors had difficulties to sell shares. This happened due to the small size of the market. Interestingly, the trading activity has decreased over time, but it does not necessarily imply that group mentality has also decreased. It has been observed that during large drops or rises trading activities can be very high, which can be seen as a signal of investors making similar decisions. Moreover, it can be challenging to draw any general conclusions on the patterns of investors' behavior in the Baltic stock market as it is mainly driven by the activities of institutional investors. Due to this reason, forecasting becomes ambiguous when the market is experiencing large drops and rises. In general, it has been observed that increased trading activities may influence individual's investment behavior and raise panic in the market. However, it does not always induce market participants to engage in trading activity as trading is closely affected by supply and demand rules. Nevertheless, some institutional investors such as pension capital do not trade on regular basis, which further limits the possibility to detect market wide herd mentality. Also, currently more and more professional traders are entering the market in comparison to 2006, when there were more private investors. However, at the moment it is hard to estimate if professional investors will affect the level of herd behavior.

Further on, the stock exchange in the Baltics is working towards one marketplace. This would be beneficial for investors in the area, as they would have the possibility to invest in more diverse securities. The goal is to achieve harmonized regulations and practices. Currently, the stock markets in the Baltic States are considered as one marketplace, especially after the implementation of a common website and trading platform. Thus if investors are active in all three markets then the level of herding should be equal across the Baltics. Presently, the stock market consists mainly of investors from the three countries rather than foreign investors. Hence, the behavior observed in the stock market can be linked to the local cultural traits. However, the

Baltic markets are working towards attracting more foreign investors. For example, the alignment with the Nordic market is increased, especially as it is included in the NASDAQ OMX group. The goal is to achieve higher participation from retail investor in the Baltics. That would proportionally decrease the level of institutional investors and perhaps show some new behavior trends, as retail investors would have a higher power to influence the market. However, there is some struggle with the legal aspects associated with an increase in foreign-trading activity in the Baltics.

In addition, the markets in the Baltics are becoming more integrated with global stock markets and investors hold shares abroad. The investors are active in, for example, Scandinavia, Central Europe and the US. This implies that they have an interest in global events. The investors are observed to react mostly to market movements in the EU and the US. In most of the cases the investment decisions are influenced by economic news in countries close by, such as Russia, Germany, and Sweden. The reflection of news is more observable in the index rather in specific stock prices because each individual investing in certain security responds differently to macroeconomic events. One of the possible explanations could be that the media do not have a considerable focus on the stock markets in the Baltics or internationally. The investors instead tend to exchange their views in local Internet portals and forums. Thus, they form their opinions in a segregate way. As a result, some stocks in the market reflect value that is close to their fundamental one. However, it is often not the case, especially for illiquid stocks and in volatile market conditions. One of main factors influencing the valuation of stock is the free float. Moreover, it can be concluded that some investors may have a tendency to react in a similar manner. However, it is not reflected in overall investment decisions.

Chapter 9. Conclusion

This study examines the presence of market wide herd behavior in the Baltic stock market by using daily price data. The purpose of this study was to analyze if the Baltic countries exhibit market wide herd behavior over the time period 2006-2014. The models used in this study capture human behavior traits by measuring the return dispersion (CSAD) in relation to the market return. It is assumed that herd behavior is present if negative and significant non-linear relationship exists between CSAD and the market index. Herd behavior models allow determining if group mentality is driving the investors' financial decisions.

Overall, it was expected that herd behavior would be more present in the Baltics. Surprisingly, our results showed that no certain herding pattern could be identified. A possible explanation of these findings could be the high presence of institutional investors, as indicated by the interviews. In addition, countries show different herding activities. Overall, Vilnius show the least herd oriented investor behavior; it leads to assume that stock market participants in this market base their decisions on their own information rather than on collective actions. Furthermore, when sub-periods were analyzed no herd behavior was found during extreme market movements as in 2007 and 2008. An explanation for the obtained results in the Baltics as revealed by one of the interviews could be that investors had difficulties to sell shares as the market downturn induced an unwillingness to purchase shares. The time period 2009-2014 showed more statistically significant results of herding activities as the market recovered after the financial crisis in 2008. Furthermore, herding asymmetries were tested during different market conditions. As our results indicated, an asymmetric pattern was observed under up and down market days as well as substantial days, with the most significant results in Tallinn and Riga.

This study further investigated the impact of the US stock market on the investors in the Baltic stock market. More specifically, we tested if the Baltic stock market herds around the US market. Remarkably, our findings showed that the Baltic investors do not herd around US, even though they are influenced by the US stock market. Similarly, when considering volatile market conditions no relationship between the US and the Baltics was found. As a further extension of our study we also considered investors' sentiment. We provide evidence that there is a relationship between investors' sentiment and herd behavior only in Riga and Tallinn. Thus, we can conclude that the herd behavior in these two markets is more apparent when investors are anxious about future market conditions. However, no such relationship was found during substantial up and down days. This means that investment behavior is not affected by expectations of future market conditions during volatile periods.

Our findings have imperative practical implications. The findings indicate that investors in the Baltics are more rational than expected when making their investment decisions, which can be valuable when modeling movements in stock prices. Moreover, the absence of herding activities in the three Baltic countries provide support for policymakers to be less concerned about large market movements in the stock markets of these countries. Also, one of the interviews revealed that some speculation and insider trading is occurring, although rarely. Notably the findings for all three countries are coherent, insinuating that investors in these markets are equally informed and hence a smooth transition of information occurs between markets. It is also in accordance with the interviews; that investors in the Baltic countries view the stock market as a whole and trade stocks across borders. We can conclude that there are diversification possibilities for the investors in Vilnius, as limited herd behavior was apparent in this market overall and during large market movements.

As no previous studies have focused on market wide herding in the Baltics, this study contributed to the herd behavior field with an additional geographical specification. Further on, future studies could bring additional input on herd behavior in the Baltics. Since our study is limited by only considering the influence of the US market, future research could test if the Baltics herd around other countries and regions. For example, an interesting comparison could be made by considering the influence of the EU and Russia. Especially, as Maneschiöld (2006) in an international stock market co-integration analysis claims that Latvian stock market has a long run relationship with the European markets, where the German market is the dominant one. In addition, a different methodology, for example, the one proposed by Hwang and Salmon (2004) could be applied to the Baltics in order to compare the results with our study. Finally, herding on an industry level could be studied. As no herding was identified in Vilnius, a further study could reveal if the market herds around particular industries in this market.

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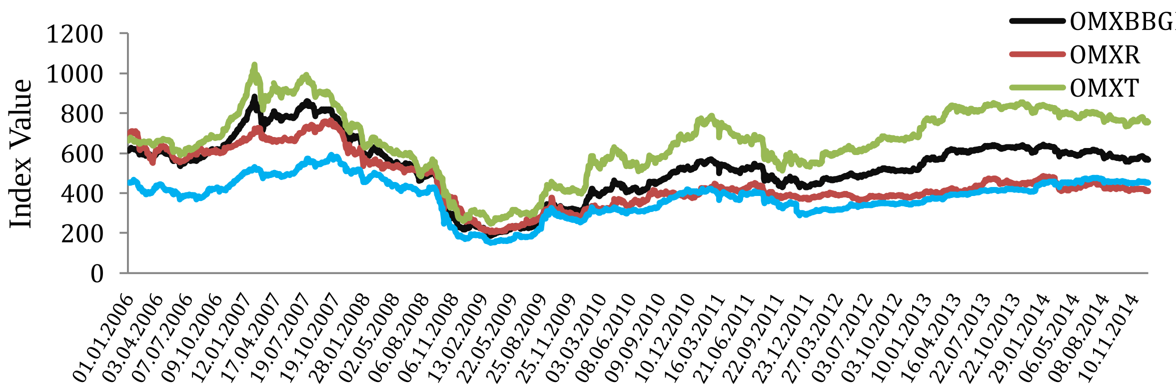
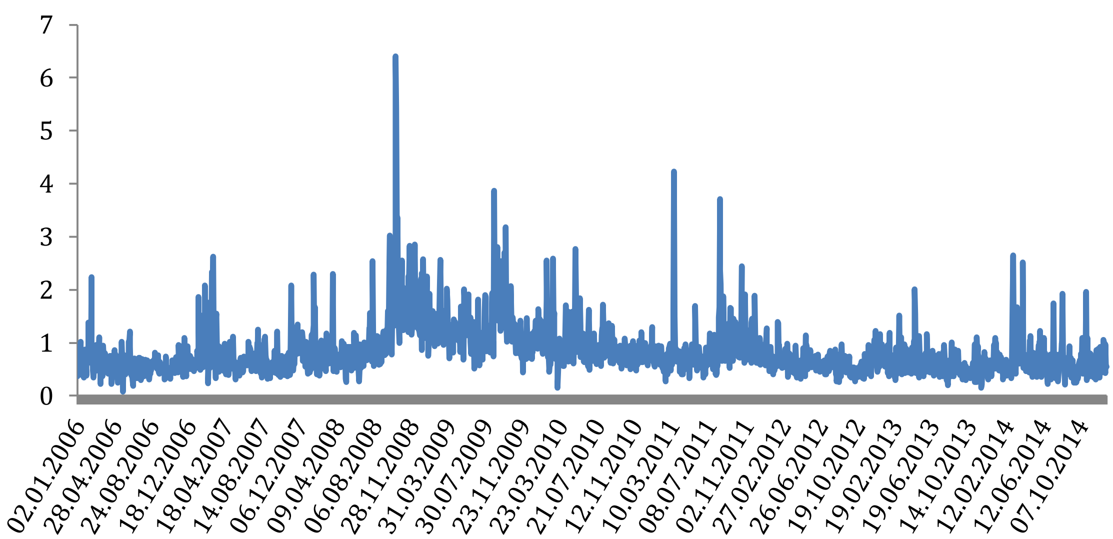
APPENDIX

Figure A1 Stock market indices development in the Baltics.



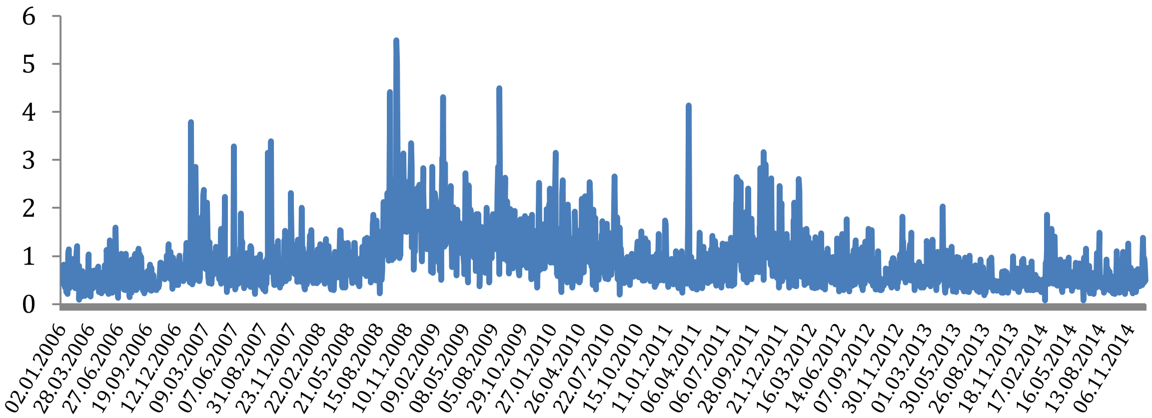
Notes: This figure reports four indices over the sample period 2006-2014.

Figure A2 Cross Sectional Absolute Deviation (CSAD) for the Baltics market.



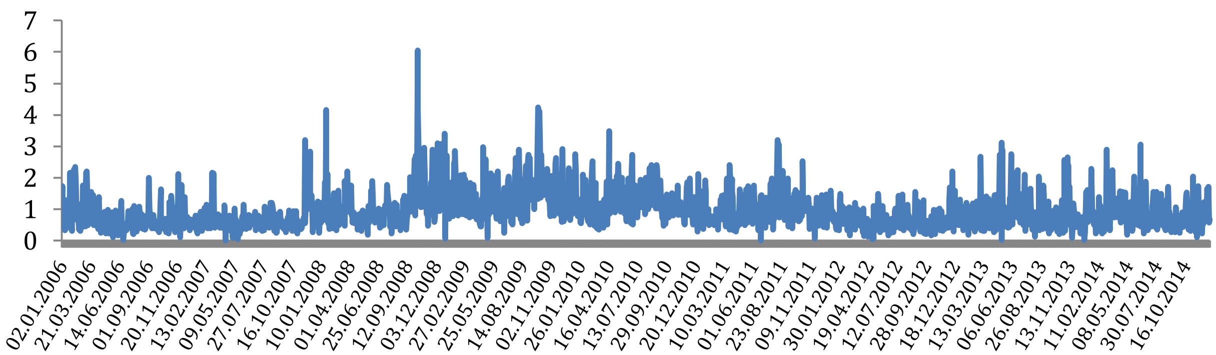
Notes: This figure reports CSAD over the sample period 2006-2014. Calculations of CSAD are given by Eq. (1).

Figure A3 Cross Sectional Absolute Deviation (CSAD) for Tallinn market.



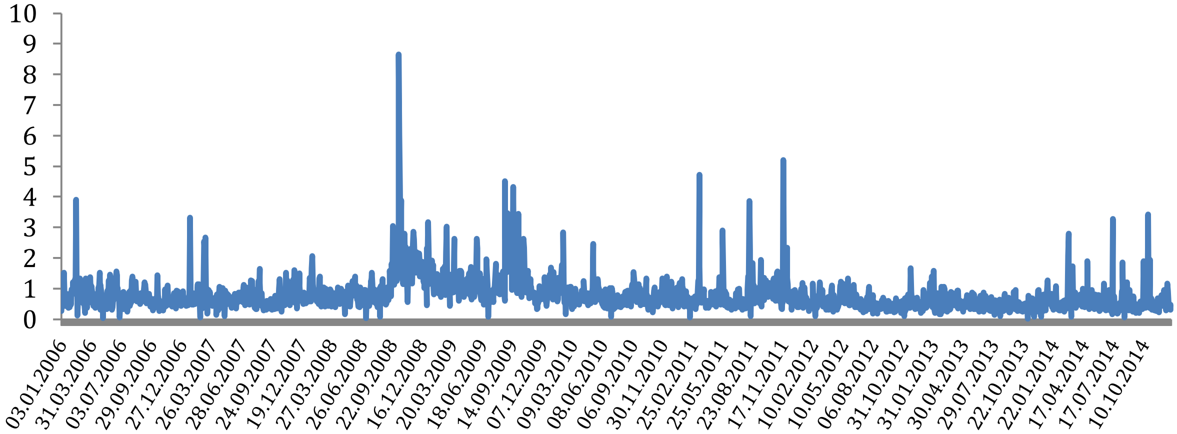
Notes: This figure reports CSAD over the sample period 2006-2014. Calculations of CSAD are given by Eq. (1).

Figure A4 Cross Sectional Absolute Deviation (CSAD) for Riga market.



Notes: This figure reports CSAD over the sample period 2006-2014. Calculations of CSAD are given by Eq. (1).

Figure A5 Cross Sectional Absolute Deviation (CSAD) for Vilnius market.



Notes: This figure reports CSAD over the sample period 2006-2014. Calculations of CSAD are given by Eq. (1).

Interview questions

1. What is your position at NASDAQ OMX Baltic?

2. What changes or patterns regarding the investor behavior have you noticed in time period 2006-2014? Is there any difference between the main or in the secondary list regarding investor behavior? Or between institutional and retail investors?

3. Was there an increased trading activity during the financial crisis in 2008?

4. Have you observed an increase in trading activity during periods when the market experiences large drops and rises? If yes, do the majority of investors react in the same way and do they tend to follow each other's behavior?

5. Is there a cooperation among the Baltic stock markets? Do investors tend to invest in the local market or over the Baltics, or abroad, for instance, US?

6. Do market conditions and news in the US influence investors' behavior in the NASDAQ OMX Baltic?

7. What is your view on the local stock market? Is there any clear patterns regarding stock price movements?

8. What do you think is the main drive of a stock value: fundamental reasons, speculation or anything else?

Table A1 OMXBBGI composition on 13 April, 2015.

Instrument in index:		Market capitalization
APG1L	Apranga	164 217 121,20
BLT1T	Baltika	15 909 991,50
CTS1L	City Service	55 317 500,00
GRD1R	Grindeks	54 155 250,00
HAE1T	Harju Elekter	52 548 000,00
KNF1L	Klaipėdos nafta	146 913 987,02
LNA1L	Linas Agro Group	109 827 815,02
LSC1R	Latvijas kuģniecība	77 600 000,00
MRK1T	Merko Ehitus	172 575 000,00
NCN1T	Nordecon	35 289 276,47
OEG1T	Olympic Entertainment Group	299 028 675,82
OLF1R	Olainfarm	94 229 171,82
PRO	Pro Kapital Grupp	134 725 371,75
PRF1T	PRFoods	25 143 859,00
PTR1L	Panevėžio statybos trestas	16 840 500,00
PZV1L	Pieno žvaigždės	79 911 414,59
RSU1L	Rokiškio sūris	50 215 158,00
SAB1L	Šiaulių bankas	83 274 480,00
SAF1R	SAF Tehnika	6 415 588,80
SFGAT	Silvano Fashion Group	59 280 000,00
TAL1T	Tallink Grupp	547 139 436,48
TEO1L	TEO LT	640 874 451,80
TKM1T	Tallinna Kaubamaja	243 560 616,00
TVEAT	Tallinna Vesi	296 000 000,00
VSS1R	Valmieras stikla šķiedra	88 202 826,45
ZMP1L	Žemaitijos pienas	33 620 625,00
	Sum	3 582 816 116,72
	Baltic regulated market total	6 520 471 435,85
	Index as a percentage	54,95%

Notes: This table reports the composition of the market index that is applied when the Baltic market is considered on an aggregate level.

Table A2 List of liquid stocks.

NASDAQ OMX Tallinn		
Main list	BLT1T	Baltika
	HAE1T	Harju Elekter
	SFGAT	Silvano Fashion Group
	TKM1T	Tallinna Kaubamaja
	VNU1T	Viisnurk
	ARC1T	Arco Vara
	EEG1T	Ekspress Grupp
	NCN1T	Nordecon
	MRK1T	Merko Ehitus
	OEG1T	Olympic Entertainment Group
	PRF1T	PRFoods
	VSN1T	Skano Group AS
	TAL1T	Tallink Grupp
	TVEAT	Tallinna Vesi
	ETLAT	Eesti Telekom
	LTR1T	Luterma
	NRM1T	Norma
	SKU1T	Saku Õlletehas
	SMN1T	Starman
	TAL3T	Tallink Grupp
Secondary list	PTAAT	PTA Grupp AS
	PKG1T	Pro Kapital Grupp
	JRV1T	Järvevana
	KLV1T	Kalev
	RLK1T	Rakvere Lihakombinaat
	TPD1T	Trigon Property Development
NASDAQ OMX Riga		
Main list	GZE1R	Latvijas Gāze
	GRD1R	Grindeks
	OLF1R	Olainfarm
	RKBV	Rīgas kuģu būvētava
	VNFT	Ventspils nafta
	LSC1R	Latvijas kuģniecība
	SAF1R	SAF Tehnika
Secondary list	BALZ	Latvijas balzams
	DPKR	Ditton pievadķēžu rūpnīca
	GRDX	Grindeks
	LTT1R	Latvijas tilti
	OLFA	Olainfarm
	VSS1R	Valmieras stikla šķiedra

	LKB1R	Latvijas Krājbanka
	LMET	Liepājas metalurgs
NASDAQ OMX Vilnius		
Main list	APG1L	Apranga
	GRG1L	Grigiškės
	IVL1L	Invalda LT
	LDJ1L	Lietuvos dujos
	PTR1L	Panevėžio statybos trestas
	PZV1L	Pieno žvaigždės
	RSU1L	Rokiškio sūris
	SAB1L	Šiaulių bankas
	SNG1L	Snaigė
	UTR1L	Utenos trikotažas
	AVG1L	Agrowill Group
	CTS1L	City Service
	LES1L	LESTO
	LNA1L	Linas Agro Group
	LNR1L	Lietuvos energijos gamyba, AB
	TEO1L	TEO LT
	VBL1L	Vilniaus baldai
	VLP1L	Vilkyškių pieninė
	EKR1L	Ekranas
	RST1L	Rytų skirstomieji tinklai
	SAN1L	Sanitas
	SRS1L	Snoras
	UKB1L	Ūkio bankas
	VNG1L	Vilniaus Vingis
Secondary list	LNS1L	Linas
	ZMP1L	Žemaitijos pienas
	AMG1L	Amber Grid
	INL1L	INVL Baltic Farmland
	KNF1L	Klaipėdos nafta
	LGD1L	LITGRID
	LJL1L	Lietuvos jūrų laivininkystė
	ALT1L	ALT investicijos
	ATK1L	Alytaus tekstilė
	KJK1L	Klaipėdos jūrų krovinių kompanija
	KTK1L	Kauno tiekimas
	LBS1L	DFDS LISCO
	LEL1L	Lietuvos elektrinė
	LEN1L	Lietuvos energijos gamyba
	LFO1L	Lifosa

	LLK1L	Limarko laivininkystės kompanija
	MNF1L	Mažeikių nafta
	NDL1L	DNB bankas
	SRS2L	Snoras
	STU1L	Stumbras
	VST1L	VST

Notes: This table reports the stocks that are included in the study.

Table A3 List of illiquid stocks.

NASDAQ OMX Tallinn		
Secondary list	TFA1T	Tallinna Farmaatsiatehas
NASDAQ OMX Riga		
Main list	RTFL	Rīgas Transporta flote
Secondary list	FRM1R	Rīgas farmaceitiskā fabrika
	GRZ1R	Grobiņa
	KA11R	Kurzemes atslēga 1
	LAP1R	Liepājas autobusu parks
	LJMC	Latvijas Jūras medicīnas centrs
	RAR1R	Rīgas autoelektroaparātu rūpnīca
	RJR1R	Rīgas juvelierizstrādājumu rūpnīca
	RRR1R	VEF Radiotehnika RRR
	SCM1R	Siguldas CMAS
	SMA1R	Saldus mežrūpniecība
	TMA1R	Talsu mezrupnieciba
	BRV1R	Brīvais Vilnis
	KCM1R	Kurzemes CMAS
	LOK1R	Daugavpils Lokomotīvju remonta rūpnīca
	NKA1R	Nordeka
	RER1R	Rīgas elektromašīnbūves rūpnīca
	TKB1R	Tosmares kuģubūvētava
	VEF1R	VEF
	BLZ1R	Baloži
	KVDR	Kvadra Pak
	LKB2R	Latvijas Krājbanka
	LMA1R	Laima
	LODE	Lode
	PLKB	DNB Banka
	OLK1R	Olaines kūdra
	RMS1R	Rigas Miesnieks
	RRA1R	Rīgas raugs
	RSA1R	Rīgas starptautiskā autoosta
	SMR1R	Strenču MRS

	STR1R	Staburadze
	TUK1R	Tukuma mezrupniecibas saimnieciba
	ZOV1R	Latvijas Zoovetapgāde
NASDAQ OMX Vilnius		
Secondary list	ANK1L	Anykščių vynas
	DKR1L	Dvarčionių keramika
	GUB1L	Gubernija
	AGP1L	Įmonių grupė ALITA
	INC1L	INVL Technology
	INR1L	INVL Baltic Real Estate
	KNR1L	Kauno energija
	VDG1L	Vilniaus degtinė
	KBL1L	Klaipėdos baldai
	MZE1L	Mažeikių elektrinė
	PRM1L	Pramprojektas

Notes: This table reports the stocks that are excluded from the study because they did not meet the liquidity requirement.

Table A4 Estimates of herd behavior using the baseline model for NASDAQ OMX Baltic.

Year	All market				Main list				Secondary list			
	Constant	$\lvert R_{m,t}\rvert$	$R_{m,t}^2$	$\overline{R^2}$	Constant	$\lvert R_{m,t}\rvert$	$R_{m,t}^2$	$\overline{R^2}$	Constant	$\lvert R_{m,t}\rvert$	$R_{m,t}^2$	$\overline{R^2}$
2006-2014	0,574***	0,796***	0,027	0,464	0,507***	0,835***	0,008	0,434	0,689***	0,721***	0,059	0,361
	(40,214)	(13,277)	(0,683)		(33,380)	(14,137)	(0,228)		(37,154)	(9,268)	(1,103)	
2006	0,505***	0,538***	-0,044	0,122	0,439***	0,433**	-0,024	0,054	0,588***	0,685***	-0,089	0,116
	(17,095)	(3,043)	(-0,194)		(10,938)	(2,108)	(-0,109)		(18,099)	(2,771)	(-0,246)	
2007	0,537***	0,569***	0,028	0,353	0,489***	0,509***	0,071	0,266	0,606***	0,646***	-0,030	0,326
	(16,366)	(3,352)	(0,294)		(12,008)	(2,830)	(0,712)		(19,017)	(3,740)	(-0,318)	
2008	0,665***	0,847***	0,017	0,573	0,606***	0,865***	-0,009	0,544	0,738***	0,789***	0,069	0,600
	(13,684)	(5,803)	(0,219)		(12,272)	(5,741)	(-0,129)		(15,266)	(5,323)	(0,873)	
2009	1,053***	0,459***	0,054*	0,326	1,025***	0,459***	0,063**	0,310	1,097***	0,457***	0,040	0,253
	(22,622)	(5,543)	(1,900)		(21,149)	(5,363)	(2,079)		(20,446)	(4,386)	(1,279)	
2010	0,764***	0,288*	0,212*	0,382	0,713***	0,310	0,213	0,304	0,856***	0,249	0,209*	0,272
	(18,092)	(1,683)	(1,812)		(13,196)	(1,504)	(1,581)		(18,301)	(1,537)	(1,947)	
2011	0,633***	0,596***	0,112	0,473	0,546***	0,639***	0,118	0,463	0,810***	0,509***	0,100	0,297
	(17,363)	(3,304)	(0,906)		(14,641)	(3,136)	(0,869)		(15,906)	(2,888)	(0,902)	
2012	0,506***	0,536***	0,103	0,309	0,453***	0,547***	0,044	0,291	0,639***	0,502*	0,257	0,101
	(23,185)	(4,639)	(1,069)		(24,295)	(4,638)	(0,440)		(12,316)	(1,677)	(0,990)	
2013	0,523***	0,430**	0,152	0,118	0,403***	0,633***	0,007	0,312	0,780***	-0,075	0,616	0,002
	(19,450)	(2,416)	(0,644)		(23,424)	(4,695)	(0,039)		(11,712)	(-0,180)	(1,218)	
2014	0,535***	0,534**	0,179	0,154	0,496***	0,568**	0,119	0,156	0,532***	0,855***	0,029	0,157
	(13,322)	(2,086)	(0,873)		(11,874)	(2,145)	(0,549)		(14,546)	(3,360)	(0,129)	

Notes: This table reports the regression results of CSAD based on Eq. (2).The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.

* The coefficient is significant at the 10% level.

** The coefficient is significant at the 5% level.

*** The coefficient is significant at the 1% level.

Table A5 Estimates of herd behavior using the baseline model for NASDAQ OMX Tallinn.

Year	All market				Main list				Secondary list			
	Constant	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$\overline{R^2}$	Constant	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$\overline{R^2}$	Constant	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$\overline{R^2}$
2006-2014	0,568***	0,914***	-0,040*	0,355	0,542***	0,855***	-0,023	0,383	0,658***	1,132***	-0,102***	0,189
	(32,152)	(17,889)	(-1,927)		(33,096)	(17,393)	(-1,204)		(23,989)	(15,302)	(-2,978)	
2006	0,512***	0,243	0,208	0,098	0,472***	0,240	0,260	0,150	0,609***	0,336	-0,001	0,018
	(15,019)	(1,045)	(0,756)		(14,631)	(1,064)	(0,903)		(11,654)	(0,938)	(-0,003)	
2007	0,655***	0,491***	0,033	0,136	0,604***	0,430***	0,079	0,182	0,763***	0,576***	-0,042	0,103
	(13,512)	(3,397)	(0,461)		(12,229)	(2,752)	(1,065)		(14,461)	(3,542)	(-0,471)	
2008	0,710***	0,979***	-0,020	0,467	0,662***	0,939***	-0,024	0,482	0,953***	0,975***	0,053	0,287
	(12,567)	(5,115)	(-0,189)		(12,992)	(5,280)	(-0,252)		(9,551)	(3,284)	(0,329)	
2009	1,164***	0,469***	0,029*	0,218	1,125***	0,416***	0,045***	0,242	1,340***	0,678***	-0,036	0,074
	(19,381)	(5,150)	(1,696)		(18,853)	(4,623)	(2,709)		(12,994)	(3,591)	(-1,089)	
2010	0,707***	0,717***	-0,081	0,285	0,669***	0,640***	-0,043	0,308	0,870***	1,064***	-0,252**	0,119
	(14,514)	(4,154)	(-0,931)		(14,548)	(3,638)	(-0,459)		(9,194)	(4,153)	(-2,404)	
2011	0,651***	0,630***	0,053	0,338	0,611***	0,583***	0,086	0,403	0,737***	0,938***	-0,174	0,080
	(11,435)	(3,333)	(0,560)		(11,603)	(3,094)	(0,898)		(8,326)	(3,758)	(-1,554)	
2012	0,583***	0,613***	0,128	0,245	0,552***	0,688***	0,011	0,281	0,751***	0,067	0,750***	0,112
	(13,856)	(3,296)	(1,494)		(15,700)	(3,835)	(0,133)		(7,847)	(0,178)	(4,400)	
2013	0,423***	0,764***	-0,135	0,220	0,417***	0,639***	0,020	0,265	0,443***	1,201***	-0,679*	0,073
	(15,281)	(4,170)	(-0,626)		(17,196)	(3,930)	(0,098)		(7,822)	(3,376)	(-1,816)	
2014	0,436***	0,603**	0,058	0,157	0,440***	0,569**	0,025	0,156	0,421***	0,761*	0,128	0,089
	(15,416)	(2,115)	(0,158)		(15,435)	(2,056)	(0,070)		(9,027)	(1,655)	(0,215)	

Notes: This table reports the regression results of CSAD based on Eq. (2). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.

* The coefficient is significant at the 10% level.

** The coefficient is significant at the 5% level.

*** The coefficient is significant at the 1% level.

Table A6 Estimates of herd behavior using the baseline model for NASDAQ OMX Riga.

	All market				Main list				Secondary list			
Year	Constant	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$\overline{R^2}$	Constant	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$\overline{R^2}$	Constant	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	$\overline{R^2}$
2006-2014	0,613***	0,906***	-0,054	0,364	0,550***	0,946***	-0,074*	0,328	0,662***	0,847***	-0,027	0,261
	(30,658)	(13,645)	(-1,261)		(27,555)	(13,300)	(-1,820)		(26,278)	(11,462)	(-0,583)	
2006	0,473***	0,736***	-0,023	0,297	0,373***	0,688***	-0,035	0,318	0,560***	0,778***	-0,012	0,185
	(11,645)	(5,888)	(-0,463)		(10,311)	(6,453)	(-0,837)		(9,902)	(4,197)	(-0,171)	
2007	0,457***	0,553**	0,275	0,362	0,438***	0,423	0,477	0,335	0,487***	0,607***	0,058	0,266
	(13,237)	(2,209)	(1,080)		(11,109)	(1,386)	(1,417)		(12,455)	(2,662)	(0,268)	
2008	0,688***	0,682***	0,048	0,520	0,583***	0,741***	0,028	0,461	0,779***	0,630***	0,065	0,453
	(13,920)	(4,419)	(0,653)		(10,646)	(4,277)	(0,384)		(12,834)	(3,852)	(0,824)	
2009	1,060***	0,650***	-0,064*	0,212	1,095***	0,614***	-0,066*	0,132	1,038***	0,643***	-0,052	0,192
	(10,983)	(4,378)	(-1,673)		(10,544)	(3,858)	(-1,781)		(9,764)	(3,977)	(-1,167)	
2010	0,933***	0,485***	0,102*	0,354	0,822***	0,697***	-0,005	0,274	1,034***	0,269*	0,209***	0,213
	(17,666)	(4,524)	(1,885)		(13,460)	(4,640)	(-0,057)		(13,247)	(1,932)	(4,008)	
2011	0,754***	0,771***	-0,016	0,294	0,691***	0,565**	0,133	0,236	0,820***	0,956***	-0,154	0,185
	(14,846)	(4,152)	(-0,128)		(11,063)	(2,235)	(0,696)		(14,196)	(4,324)	(-1,246)	
2012	0,556***	0,279	0,701*	0,169	0,561***	0,367	0,499	0,158	0,550***	0,192	0,904	0,079
	(12,403)	(0,942)	(1,654)		(12,416)	(1,170)	(1,167)		(7,536)	(0,379)	(1,170)	
2013	0,679***	0,587	0,001	0,058	0,458***	0,932***	-0,195*	0,221	0,821***	0,145	0,316	0,015
	(8,227)	(1,602)	(0,003)		(12,957)	(5,391)	(-1,757)		(7,091)	(0,324)	(1,100)	
2014	0,622***	0,748***	0,035	0,252	0,688***	0,620***	0,007	0,119	0,574***	0,681***	0,153*	0,189
	(14,631)	(5,278)	(0,558)		(12,681)	(3,783)	(0,101)		(10,848)	(3,652)	(1,846)	

Notes: This table reports the regression results of CSAD based on Eq. (2). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-Statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.

* The coefficient is significant at the 10% level.

** The coefficient is significant at the 5% level.

*** The coefficient is significant at the 1% level.

Table A7 Estimates of herd behavior using the baseline model for NASDAQ OMX Vilnius.

	All market				Main list				Secondary list			
Year	Constant	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$\overline{R^2}$	Constant	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$\overline{R^2}$	Constant	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$\overline{R^2}$
2006-2014	0,522***	0,770***	0,042	0,468	0,454***	0,778***	0,040	0,452	0,639***	0,716***	0,053	0,348
	(35,051)	(13,000)	(1,216)		(29,157)	(13,189)	(1,241)		(34,636)	(10,682)	(1,423)	
2006	0,507***	0,656***	-0,029	0,303	0,427***	0,499***	0,082	0,412	0,632***	0,515***	0,036	0,222
	(15,021)	(3,468)	(-0,243)		(15,484)	(4,303)	(0,896)		(13,381)	(2,803)	(0,310)	
2007	0,503***	0,638***	0,058	0,267	0,384***	0,722***	0,030	0,365	0,586***	0,660***	0,028	0,253
	(12,976)	(3,540)	(0,425)		(14,271)	(4,195)	(0,213)		(13,396)	(3,247)	(0,182)	
2008	0,728***	0,556***	0,109	0,560	0,739***	0,476**	0,121	0,483	0,715***	0,659***	0,094	0,576
	(11,227)	(3,367)	(1,416)		(9,867)	(2,601)	(1,539)		(11,497)	(3,822)	(1,200)	
2009	0,922***	0,617***	0,014	0,358	0,911***	0,566***	0,035	0,291	0,936***	0,682***	-0,013	0,358
	(15,385)	(4,774)	(0,467)		(13,768)	(3,724)	(1,046)		(15,498)	(5,599)	(-0,472)	
2010	0,596***	0,506**	0,068	0,275	0,554***	0,543**	0,032	0,221	0,663***	0,466**	0,116	0,183
	(16,239)	(2,544)	(0,429)		(12,881)	(2,337)	(0,180)		(12,883)	(2,149)	(0,737)	
2011	0,525***	0,710***	0,047*	0,597	0,451***	0,746***	0,040	0,571	0,671***	0,643***	0,060**	0,437
	(14,240)	(5,194)	(1,804)		(12,044)	(5,115)	(1,465)		(12,576)	(4,612)	(2,172)	
2012	0,449***	0,406*	0,398	0,167	0,397***	0,170	0,672*	0,177	0,658***	0,675	0,040	0,024
	(16,580)	(1,680)	(1,107)		(13,224)	(0,704)	(1,889)		(9,962)	(1,156)	(0,046)	
2013	0,420***	0,649***	-0,097	0,123	0,335***	0,754***	-0,159	0,219	0,618***	0,623	-0,189	0,007
	(17,145)	(3,563)	(-0,370)		(17,625)	(4,669)	(-0,654)		(9,346)	(1,115)	(-0,248)	
2014	0,443***	0,835***	-0,039	0,155	0,350***	0,911***	-0,059	0,311	0,476***	1,186***	-0,273	0,158
	(11,270)	(3,920)	(-0,231)		(13,133)	(4,745)	(-0,335)		(10,750)	(4,080)	(-1,068)	

Notes: This table reports the regression results of CSAD based on Eq. (2). The date range from 2006-01-02 to 2014-12-30. $\overline{R^2}$ is the adjusted $\overline{R^2}$. t-statistics are given in parentheses, calculated using Newey-West heteroscedasticity and autocorrelation consistent standard errors.

* The coefficient is significant at the 10% level.

** The coefficient is significant at the 5% level.

*** The coefficient is significant at the 1% level.