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Responsibility for any remaining errors lies with the author alone.

ABSTRACT

The purpose of this master thesis is to report the findings of an investigation into the historical returns of the Baltic stock market and to determine if the market has reached the weak form of efficiency.

To detect anomalies and to determine the form of market efficiency, the author of this thesis chose three econometric models: Autoregressive model (AR) linking current returns to past ones, Autoregressive Distributed Lag model (ADL), linking current returns of one index to the past returns of another index and utilizing Dummy Variable Approach to help find day-of-the-week effects. The author analyzed daily, weekly, and monthly data from 13 indices over a 14-year time period from January 2000 to August 2014. In addition to this, a separate 4 year period from 2010-2014 has been analyzed to look at the development after the financial crisis of 2008.

The author found significant predictive power on future returns in historical data for the entire 14-year period. This trend has remained significant during the last four years, as well. These results indicate the possibility of forecasting future returns by looking at past returns. The author also found evidence of Granger causality in the stock exchanges of the three Baltic countries when analyzing the entire 14-year time period. The Lithuanian stock market Granger caused both the Estonian and Latvian stock markets, the Estonian stock market Granger caused both the Lithuanian and Latvian stock markets, and the Latvian stock market Granger caused the Estonian stock market. The period of the last four years was different in terms of this relationship, with only the Estonian stock market Granger causing the Latvian stock market. The author also found a significant "Monday effect" in the Baltic stock market. From this information the author has concluded that the Baltic stock market does not have a weak form of efficiency.

Keywords: Efficient Market Hypothesis, Day-of-the-week effects, Autoregressive models, Granger causality, Baltics.

SAMMENDRAG

Hensikten med denne oppgaven er å se på resultatene av en dataanalyse gjort på de historiske avkastningene for det Baltiske aksjemarkedet, samt å finne ut om markedet har nådd en svak form av effisiens.

For å påvise avvik og bestemme graden av markedseffisiens har tre økonometriske modeller blitt valgt for å teste dataene. Autoregressive modell (AR) som linker de nåværende avkastningene til historiske avkastninger; Autoregressive Distributed Lag modell (ADL) som linker de nåværende avkastningene i ett marked til historske avkastninger i et annet marked, samt Dummy Variable Approch som skal hjelpe til med å finne ut om det er en påvisabar dag-i-uken effekter. Daglige, ukentlige og månedlige data fra 13 indekser over en tidsperiode på 14 år fra 2000-2014, samt en separat fireårsperiode fra Januar 2010-August 2014 har blitt analysert for å se på utviklingen i etterkant av finanskrisen i 2008.

Forfatteren av denne oppgaven har funnet ut at det er en signifikant effekt av å analysere historiske data for å kunne forutse fremtidige prisutviklinger i aksjemarkedet. Signifikansen har blitt noe svekket de siste fire årene, men analyse av historiske data for å estimere fremtidig pris har fortsatt en signifikant positiv effekt. Det har også blitt avdekket bevis for Granger kausalitet på aksjebørsene for de tre baltiske statene under hele tidsperioden.

Det litauske aksjemarkedet hadde Granger kausalitet mot både det estiske og latviske markedet, the estiske aksjemarkedet hadde Granger kausalitet mot både det latviske og litauske markedet og det latviske aksjemarkedet hadde Granger kausalitet mot det estiske aksjemarkedet. I tidsperioden fra 2010 til 2014 var forholdene mellom markedene noe annerledes en tidligere. Her var det kun det Estiske aksjemarkedet som hadde Granger kausalitet mot det latviske aksjemarkedet. Forfatteren har også funnet en signifikant «mandagseffekt» i de baltiske aksjemarkedene. Ut fra funnene gjort i denne oppgaven har forfatteren konkludert med at det Baltiske aksjemarkedet ikke har en svak form av effisiens.

Nøkkelord: Effisient Markedshypotese, Dag-i-uken effekter, Autoregressive modeller, Granger kausalitet, Baltikum

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ABBREVIATIONS

EMH – Efficient Market Hypothesis

CCE – Central and Eastern Europe

VSE – Vilnius Stock Exchange

RSE – Riga Stock Exchange

TSE – Tallinn Stock Exchange

MEUR – Million Euros

AR – Autoregressive model

ADL – Autoregressive Distributed Lag model

OLS - Ordinary Least Squares

1. INTRODUCTION

Globalization of the world economy has made a huge impact on the public financial markets and made it easy for money to move from one country to another. The equity market has become a very important part of every country's economy, attracting investors and contributing to economic growth. One of the signs an investor may look for before investing is market efficiency.

An efficient market means that relevant information is incorporated into the prevailing asset price and that there are no possibilities to make abnormal returns from an active investment strategy. Fama (1970) developed the Efficient Market Hypothesis (EMH), which has become a very important element of finance, and many financial researchers are paying close attention to it. However, many researchers, including Shiller (2003), severely criticized the EMH for being unrealistic and too theoretical. Over the years, repeated criticism has refined the EMH theory and made it more realistic. The determination of market efficiency is one of the tools used to evaluate an investment environment, describe the equity market, and determine how developed the market is. Knowing the efficiency level of a market is even more important for the smaller markets in their development phase due to their nature of changing more rapidly, as is the case with the Baltic markets in this study. The EMH theory provides valuable insights for investors, and it ought to be important in deciding whether to invest in a market or not.

The Baltic stock market is an emerging market with low market liquidity, low trading volumes, and possibly slow absorption of information. Previous research has shown that the Baltic stock market is possibly inefficient (Smith, 2012). Inefficiency makes it difficult to forecast future developments in the market and to make an investment decision by using classical investment management techniques, such as applying risk management or forecasting future earnings. Possible reasons for market inefficiency include the lack of investment vehicles, the market could be inflexible, insufficient experience about the market participants, and limited financial power among investors.

Much research has been conducted in the area of efficiency in different countries, mostly in the United States and Western European markets. The Baltic Equity market is not covered by analysts as well as the developed markets, but research results indicate that the situation in the market environment regarding market efficiency is getting better (Degutis and Novickytė, 2014). The Baltic Equity market is experiencing rapid change and needs to be researched and analyzed continuously.

The originality of this thesis comes from the fact that the author combined econometrical methods and research on seasonality to obtain a picture of the weak form of efficiency in the Baltic equity market. Within the thesis, the author included industry indices to determine if there are significant differences in different industry sectors in terms of market anomalies. Most of the previous research in this field has been conducted by evaluating the main benchmark index, the main Baltic country indices, or single stocks. The author of this thesis also included the OMXB10, which contains the 10 most liquid stocks and is the only index which is tradable in the Baltic stock market. According to Chordia et al. (2008) and Chung and Hrazdil (2010), liquidity plays an important role in market efficiency and the author of this thesis expected this index to be important when evaluating Baltic market efficiency.

The objective of this thesis was to analyze the Baltic stock market on the basis of the EMH theory. The author of this thesis attempted to determine if the Baltic equity market had reached a weak form of efficiency. To achieve this goal, the author asked the following research questions:

- What is the present market efficiency in the Baltic exchanges?
- Does the market have clear day-of-the-week effects?
- Is the Granger causality present in the Baltic exchanges?

To achieve the research objective and answer the research questions, the author investigated the efficiency of the Baltic market during the period from January 2000 to August 2014 by applying generally-accepted quantitative methods, including econometrical tests such as the Autoregressive model (AR) and the Autoregressive Distributed Lag model (ADL), and the Dummy Variable Approach. The author applied the AR and the ADL models on daily, weekly, and monthly indices data, and studied calendar effects by using the Dummy Variable Approach. The author used the 13 Baltic indices: the Baltic benchmark index, the country indices for Vilnius stock exchange (VSE), Riga stock exchange (RSE) and Tallinn stock exchange (TSE), the index of the 10 most liquid stocks, and the indices of the eight main industry sectors in the Baltics.

The first chapter of this thesis is the introduction. In the second chapter, the author presents general theories on market efficiency. In the third chapter, the author gives a review of the previous research on the Baltic stock market. In the fourth chapter, the author provides background information on the Baltic equity market, its history, and development. In the fifth chapter, the author presents the data choice and data problems, as well as statistical information. Finally, in the sixth chapter, the author presents the methodology used to test for market efficiency and the results of this thesis.

2. WHAT IS AN EFFICIENT STOCK MARKET AND WHAT DOES (IN)EFFICIENCY IMPLY?

In this chapter, the author discusses the theoretical aspect of the efficient market, defines market efficiency, and discusses the EMH and its implications. The author also discusses questions regarding mechanisms that drive markets toward efficiency and discusses the consequences of market inefficiency. Finally, the author analyzes various research articles in which the researchers expressed different points of view, and discusses criticisms of the EMH.

The first extended studies in stock market efficiency were conducted in the 1950s, although the first attempts were already made in 1900 (Bodie et al., 2011). Kendall and Hill (1953) examined 19 British stocks and American spot prices for cotton and spot prices for wheat. They found that there was no pattern in stock prices that could be predictable. Roberts (1959) conducted a similar study on American stock data. Roberts obtained the same results: that stock prices were following random patterns.(Shiller 1981, Jaffe et al. 1989, Jegadeesh and Titman 1993) concluded the opposite about stock market efficiency.

Fama (1965) took the research further and formalized the argument that the stock prices were following a random walk where he also defined the efficient market: "In an efficient market, at any point in time, the actual price of a security will be a good estimate of its intrinsic value" (Fama 1965). Fama (1970) developed the EMH, which became widely accepted, with many scientists conducting research on this topic in several markets around the world, employing various techniques. According to the EMH, the prices already contain past information and in the event of new information, the price quickly adjusts so that at any time, the security price will be equal to its real value. Bodie et al. (2011) called the EMH an implication of the no-free-lunch proposition.

Sollis (2012) noted that the EMH has practical value for investors. If the market is informationally inefficient, then it is possible to earn abnormal returns and consistently beat the market by applying an active investment strategy. The stock market is the place where the seller meets the buyer to exchange publicly traded shares, and the most important goal for the seller and the buyer is to make a profit. When the money is put into the stock market, the goal is to generate a return on the capital invested. Many investors try to not only make a profitable return, but to also outperform the market by predicting future prices and that competition among the investors will drive speculative profits to zero in a marketplace for publicly traded assets. This is the strongest underlying principle driving the EMH.

An efficient market does not mean that there are no price movements, but it does mean that the movements must be random or unpredictable. According to Heakal (2014), both fundamental and technical factors affect price movements. The fundamental factors include **e**arnings per share (EPS) and the price-earnings ratio (P/E). The technical factors include inflation, demographics, economic strength of the market, substitutes, incidental transactions, trends, and liquidity. Shiller (1990) claimed that dividends are the reason for most stock price movements. The information carrying these factors which are affecting the stock market is found in financial news, research, political, economic, and social events. In an efficient market, all this information should already be reflected in the stock price and no one should have an informational advantage in predicting stock prices to achieve higher returns than the market average (Bodie et al., 2011).

A major implication of market efficiency is that in an efficient market, the market price is an unbiased estimate of the true value of the investment and speculative trading is unprofitable. It does not mean that the market price will be a true value all the time. It means that it will be random and not correlate with any observable variable. This means that no investor will be able to consistently find the mispriced securities relative to a risk-adjusted benchmark. The chances to find mispriced stocks and beat the market using any investment strategy should be 50/50, meaning that none of that kind of activity would be profitable and portfolio managers would not be able to add value. The best strategy in that kind of market would be a buy-and-hold strategy, with trading reduced to a minimum or a passive indexing strategy which tracks the market.

The efficient market does not imply that the stock prices cannot deviate from the true value. The only requirement is that the deviation from the true value should be random. The efficient market also does not imply that no investor could earn abnormal returns at any point in time. It would be possible for an investor to beat the market about 50% of the time, but no one would consistently beat the market. Over a longer time period, profits would also be consistent with the risk-expected returns.

Fama (1970) stated that the assumptions for the efficient market should be no transaction costs, all available information should be free and available to everyone, and that all investors should agree on the implications of the current information for current price and distributions of future prices for each security. The most recent expressions of the EMH in academic research recognize the existence of market friction, information costs, agency, and capital structure constraints (Ang et al., 2009). Assumptions stated by Fama (1970) have been adjusted over time and the current assumptions are that transaction costs should be lower than the expected returns and that the investor must have money available to trade all discovered opportunities until the inefficiency has been fully taken advantage of and fades out.

To make the market efficient, there must be investors who believe that the market is inefficient and that it is possible to earn abnormal returns. The more investors trying to beat the market, the more efficient the market becomes. Strategies to benefit from market inefficiency make it efficient. Grossman (1976) researched this self-driven market efficiency mechanism and showed that the competitive markets can be "over-informationally” efficient. If competitive prices reveal too much information, then traders may not be able to earn a return on their investment in information. In the Grossman (1976) model, traders who invested in research earned profits and their trading activity pushed the prices toward their real value. Other traders who invested nothing in information could observe the market price movements and were able to achieve a utility as high as traders who paid for the information. That is informationally-efficient price systems aggregate diverse information, but while doing this, the price system eliminates the private incentive for collecting the information. Then many individuals attempt to earn a return on information collection, the equilibrium price is affected, and it perfectly aggregates their information. This provides an incentive for individuals to stop collecting information (Grossman, 1976).

Market efficiency cannot be said to be either efficient or inefficient. There are several levels of market efficiency. Fama (1970) stated that market efficiency can be ranked on one of three levels:

- Weak Form of market efficiency, which means that current stock prices reflect all information from market transactional data. Technical analysis on past prices or econometrical tests on returns will not help to achieve abnormal returns. Fundamental analysis, on the other hand, might help to achieve abnormal returns.
- Semi-Strong Form of market efficiency means that the current stock prices not only reflect all of the information like historical prices, but also all of the information that is

publicly available. It means that neither technical nor fundamental analysis would help to achieve abnormal returns. If the market has semi-strong efficiency, then fundamental analysis will not generate abnormal returns. Economic profits may accrue to managers with competitive advantages in value-relevant information.

- Strong Form of market efficiency assumes that a stock price reflects all the information, whether it is public or private. It means that no one can earn money from inside information. If the market has strong efficiency, then no analysis will generate abnormal returns and active portfolio management has little potential to add to performance.

One should consider not just the different levels of efficiency, but also how different the market is in its form of efficiency to different investors. It is unlikely that all markets are equally efficient to all investors, but the largest and most liquid markets might be efficient for the average investor. This is the consequence of differential tax rates and transaction costs.

There is much evidence of market inefficiency which would help investors to recognize it:

- There is a possibility to predict future prices accurately in more than 50% of the cases.
- Asset prices do not react quickly to new information and it is possible to benefit from them.
- Investors can outperform the market in more than 50% of the cases in the long-term.
- Market has seasonality or calendar effects.
- Stock market crashes because of asset or credit bubbles.

In understanding the process by which markets become efficient, one must consider liquidity as one factors which is closely related to efficiency. Empirical evidence from academic research has shown that more liquid markets are more informationally efficient and active trading is driving the markets toward efficiency (Ang et al., 2009). Chordia et al. (2008) analyzed a continuous series of short-horizon returns of all New York Stock Exchange (NYSE) stocks that traded every day for a 10-year period, and found that higher liquidity might impact market efficiency by facilitating arbitrage trading. Chordia et al. (2008) concluded that more liquid markets should exhibit less return predictability from past order flows and can be interpreted as an indicator of market efficiency. Chung and Hrazdil (2010) extended the Chordia et al. (2008) study, confirmed the results of Chordia et al. (2008), and further documented a positive correlation between liquidity and market efficiency. The greater the liquidity, the higher degree of market efficiency.

The driving question in financial economics since the inception of the EMH is whether the theory is correct or not. Tests of the theory on stock returns concluded with inefficiency, suggesting that the EMH may not hold for all markets all the time (Ang et al., 2009). The most recent debates has focused on if the anomalies on stock returns should suggest inefficiency, or the inability of researchers to identify and specify the risk factors which is relevant to the market (Ang et al., 2011).

Criticism of market efficiency points out the fact that the market can never be totally efficient because it is impossible for inside information to be available for everyone. It is also quite unlikely that the market will reach total semi-efficiency because if it is impossible to make a profit from the market no matter what strategy, technique, or analysis an investor would use, then investors would stop searching for opportunities in that market, which would again lead to market inefficiency. It could work if one thinks about the efficient market as a self-regulating mechanism where the market becomes efficient by itself immediately after the inefficiency occurs, but that would again let some investors or strategies take advantage of these kinds of inefficiencies and profit from them to beat the market.

Shiller (1981) was one of the greatest critics of EMH. By employing econometrical tests and analyzing studies done by other researchers and himself, Shiller showed that the prices are too volatile to possibly be efficient. Shiller (1990) claimed that the weight of evidence against EMH remains in the direction of substantial excess volatility. Shiller stated that the information about the popular models themselves will allow more adequate theorizing about human behavior in speculative markets. Investors who are employing speculative strategies are not capable of using all models, but rather, are choosing one of the models and believing in it. Investors do respond to news and information, and they know the behavior models, but they simply will not be able to pursue a theoretical analysis of the evidence for all these competing models, and would not be able to choose the right model at the right time. Shiller (2003) suggested that behavioral finance, which was developed in the 1990s, is one of the most important contradictions to the EMH. Shiller claimed that EMH might lead to incorrect interpretation of events such as stock market bubbles.

Behaviorists are criticizing the EMH and stating that investors are human beings full of biases and it would not be possible for everyone to react rationally, and, thus, make the market completely efficient. LaPorta et al. (1997) paid a lot of attention to the behavioral finance. LaPorta et al. studied stock price reactions around earnings announcements and examined a hypothesis that the abnormal return of value stocks is the result of expectation errors made by investors. The evidence suggested that behavioral factors about future earnings prospects play an important role in the superior return to value stocks.

The EMH also states that abnormal earnings from the market are nothing but luck, although in the real world, we have plenty of examples of investors or investment managers who managed to outperform the market consistently over an extended period of time. Jegadeesh and Titman (1993) provided strong evidence of market inefficiency. Jegadeesh and Titman (1993) documented that momentum strategies of buying stocks that have performed well and selling stocks that have performed poorly over the same period of time generated significant positive returns over 3- to 12-month holding periods. Some scientists have argued that the returns from these strategies are either compensation for risk, or, alternatively, the product of data mining. Jegadeesh and Titman (2001) conducted an extended study and found that momentum strategies continue to be profitable and that past winners outperform past losers by approximately the same magnitude as in the previous period. This evidence provides some assurance that the momentum of profits are not entirely due to data snooping biases. Moreover, Jegadeesh and Titman (2001) results suggest that market participants have not altered their investment strategies in a way that would eliminate this source of return predictability.

Fama (1998) explained his point of view more precisely and criticized some studies conducted after the EMH was developed. Fama stated that some of the previous studies on efficiency involved analyzing long-term return anomalies which might suffer from data-mining, explaining that market overreaction is as frequent as underreaction and this is consistent with market efficiency. Research on long-term return anomalies are sensitive to methodology and might not be so accurate. Nevertheless, most long-term return anomalies can reasonably be explained as simple chance. Researchers who study long-term returns usually state the market efficiency as the null hypothesis and market inefficiency as the alternative hypothesis. According to Fama (1998), this is unacceptable and market efficiency can only be replaced by a more specific model of price formation. Fama (1998) concluded that the existence of any reliable patterns is unproven and the paradigm of market informational efficiency should be maintained. Fama and French (2008) argued that researchers who interpreted average return anomalies as evidence of market inefficiency were wrong. Fama and French claimed that the evidence for variables that predict future cash flows also predict returns, and does not by itself help to determine how much variation in expected returns is caused by risk and how much is caused by mispricing.

By continuously responding to criticism over the past several decades, supporters of the EMH have improved the hypothesis to reflect realism in the market place, including information, transactions, financing, and agency costs, and other real-world frictions (Ang et al., 2011). The most recent expressions of the EMH even allow a role for arbitrageurs in the market who may profit from their advantages like specialized knowledge, lower trading costs, low management fees or agency costs, and a financing structure that allows the arbitrageur to undertake trades with long verification periods (Ang et al., 2009).

The economic consequences might be that many investors would not be willing to invest in such a market because of the uncertainty. It is hard to use well-known investment strategies or predict future returns in an inefficient market. It also generates higher amounts of risk, which would not be acceptable for the majority of investors. If the market is inefficient because of bad liquidity, then it would be difficult to use an active trading strategy because an investor might struggle to even buy or sell the wanted amount of assets at any given time. Inefficient markets might also suffer from financial bubbles which lead to difficulties in pricing the assets. The Baltic markets are small markets with low liquidity which might lead to inefficiency. There is a special group of investors who choose to trade in developing markets. It is investors who are willing to tolerate a higher level of risks for a possibility to get greater returns.

3. PREVIOUS RESEARCH ON MARKET EFFICIENCY IN THE BALTIC STOCK MARKET

Within this chapter, the author included a discussion of all the chosen articles and other research on the topic of market efficiency in the Baltic stock market. In Table 3.1, the author presents a summary of these articles. The first two articles about the efficiency of the Baltic Equity market were both published in 1998, one by Butkutė and Moščinskas (1998), Klimašauskienė and Moščinskienė (1998). The authors of both articles found the weak form of efficiency in the Baltics. Similar studies in which researchers studied the general statistical parameters, however, found opposite results (Kvedaras et al., 2002, Januškevičius, 2003, Smith, 2012). Januškevičius (2003), Dikanskis and Kiselovs (2006), and Maniusis and Urba (2007) analyzed trading strategies. Some researchers, including Laidroo (2008, 2012) chose event-study analysis. Sakalauskas and Kriksciuniene (2007a, 2008a, 2009a, 2012) covered the calendar effects. Further in this chapter, the author discusses the articles listed in Table 3.1.

Table 3.1. Summary of research on the efficiency of the Baltic stock market.

Author	Year	Country	Results
Klimašauskienė and Moščinskienė	1998	Lithuania	Efficient (weak form)
Butkutė and Moščinskas	1998	Baltics	Efficient (weak form)
Kvedaras et al.	2002	Baltics	Inefficient (weak form)
Januškevičius	2003	Lithuania	Inefficient (weak form)
Kiete and Uloza	2005	Lithuania + Latvia	Partly efficient (semi-strong)
Dikanskis and Kiselovs	2006	Baltics	Inefficient (weak form)
Maniusis and Urba	2007	Baltics	Inefficient (weak form)
Avdejev and Kvekšas	2007	Baltics	Inefficient (weak form)
Laidroo	2008	Baltics	Inefficient (semi-strong)
Sakalauskas and Kriksciuniene	2007a,b 2008a,b,c 2009a,b	Lithuania	Inefficient (weak form)
	2011, 2012, 2013	Baltics	
Jazepčikaitė	2008	Baltics	Inefficient (semi-strong)
Stasiulis	2009	Baltics + CEE	Inefficient (semi-strong)
Macijauskas	2010	Lithuania	Inefficient (weak form)
Laidroo and Grigaliuniene	2012	Baltics	Inefficient (semi-strong)
Smith	2012	Baltics + Europe	Inefficient (weak form)

Source: Compiled by the author.

The first two studies were conducted by analyzing general statistical parameters and applying historical return-based predictability tests. Klimašauskienė and Moščinskienė (1998) conducted a full-sample fixed-parameter analysis. These researchers tested for weak form efficiency by using unit root tests, white noise test, and autocorrelation plots in the Lithuanian stock market returns for five stocks which were traded actively. Klimašauskienė and Moščinskienė (1998) concluded that the market was following weak form efficiency. Butkutė and Moščinskas (1998) duplicated the Klimašauskienė and Moščinskienė (1998) study with the same type of research on all three Baltic countries' stock markets. Butkutė and Moščinskas (1998) analyzed returns for seven stocks from Lithuania, six from Latvia, and 12 from Estonia in the period from the first trading day in 1996 to the beginning of 1998. Butkutė and Moščinskas (1998) concluded that the Lithuanian stock market was partly following weak form of efficiency. The Latvian stock market had a weak form of efficiency. The Estonian stock market appeared to be least efficient of these three countries. Sakalauskas and Kriksciuniene (2011) also conducted full-sample fixed-parameter analysis, but Sakalauskas and Kriksciuniene captured long memory in the Baltic stock market by applying the Hurst exponent (H) characteristic and Shannon's entropy measure for symbolized time series on data from the beginning of 2007 to the end of 2010. The results indicated that the market efficiency value for the Baltic market stock indices was very low when compared to the developed market efficiency. The efficiency of the Baltic stock market has similar value as the other emerging markets, such as Czech Republic, Russia, Egypt, and Slovenia. Sakalauskas and Kriksciuniene (2013) conducted an extended study employing the same research methods and confirmed that the efficiency of the Baltic market strongly falls behind the developed countries. Kvedaras et al. (2002) conducted full-sample time-varying parameter analysis employing variance ratio robust and the Kalman filter technique to track the changing degree of weak-form efficiency in VSE, RSE and TSE over the period from 1997 to 2002. Kvedaras et al. (2002) found evidence of inefficiency in all three markets, but noticed the movement toward weak-form efficiency in the Estonian and Lithuanian markets. Smith (2012) conducted rolling estimation windows analysis with fixed parameter on 18 European stock markets, including Lithuania, Latvia, and Estonia by using rolling-window variance ratio tests including bootstrapping techniques to measure the persistence of deviations from random walk of daily data for the time period from the beginning of 2000 to the end of 2009. Smith (2012) found that efficiency varies widely, with the highest efficiency in the Turkish, United Kingdom (UK), Hungarian, and Polish markets, and the lowest efficiency in the Ukrainian, Maltese, and Estonian stock markets. The global financial market crisis of 2007–2008 coincided with return predictability in the Croatian, Hungarian, Polish, Portuguese, Slovakian, and UK stock markets, while Greece, Latvia, Romania, Russia, and Turkey experienced low effect. Smith (2012) ranked the markets in terms of relative efficiency, with Lithuania ranked as number 13, Latvia as number 7, and Estonia as number 16. None of the markets were efficient in absolute terms.

The next important topic in determing market efficiency involves using active trading strategies to determine if it is possible to outperform the buy-and-hold strategy by emloying active portfolio management. Januškevičius (2003) tested the weak-form of efficiency for Lithuania by using a trading simulation based on predicted values of two Lithuanian indices over the period from 1999 to 2002, yielding 15.180 predicted values in total. The majority of the buy-and-hold strategies were outperformed with statistically-significant returns, indicating inefficiency of the market. Dikanskis and Kiselovs (2006) tested for weak-form efficiency in the three Baltic Stock markets by using a moving average and the head-and-shoulders pattern for the period from January 2000 to January 2006. Dikanskis and Kiselovs (2006) showed that active portfolio management outperformed the passive strategy and concluded that the Baltic stock market was inefficient. Maniusis and Urba (2007) used the same methodology as Jegadeesh and Titman (1993) and discussed the short-run momentum effect and stock efficiency across the Baltic stock exchanges using the time period from 2000 to 2007. Maniusis and Urba (2007) formed portfolios of stocks looking at their past performance and going long in the best stocks, while shorting the worst ones. Maniusis and Urba (2007) was the first attempt to carry out such research in the Baltic equity market. The results indicated that the short-run momentum effect is present in the Baltic stock exchanges and that there is a possibility for stock market participants to earn excess returns using trading strategies based on the phenomenon.

Another important area of market efficiency is event-study analysis. Kiete and Uloza (2005) tested for semi-strong information efficiency in Lithuania and Latvia by conducting an event study on the earnings announcements in the period from 2001-2004. Kiete and Uloza used Patell's standardized residual test, sub-samples which were constructed based on naïve assumptions, and by simulating possible trading strategies. The researchers found it impossible to earn abnormal returns by investing on day one and selling on any other day in the event window, and, therefore, concluded that a semi-strong form of market efficiency held in Lithuania, but found it inefficient for downward price movements. The Latvian market seemed to provide many earning opportunities. Kiete and Uloza's primary conclusion was that the markets were very different from each other. The findings in Lithuania seem to be explainable and can be compared with previous studies. Findings in the Latvian market were unexpected and difficult to interpret, making the authors question if the other forms of market efficiency could be distinguished. Kiete and Uloza (2005) concluded that both markets were partly efficient. Stasiulis (2009) conducted a follow-up study of the Kiete and Uloza (2005) study by using the same methodology. Stasiulis (2009) investigated the semi-strong form of efficiency in the Central and Eastern Europe (CEE) stock markets, including the Baltics, in the period from 2005-2008. Stasiulis applied the event-study methodology to look at the earnings announcements. Stasiulis used Patell's standardized test to determine if the announcements had any information of value. Stasiulis used several other tests, including the generalized sign test, Patell's *Z*-test, and cross-sectional tests to determine if there were inefficiencies toward the good or bad news, or both. Stasiulis (2009) confirmed the results of Kiete and Uloza (2005), and showed that earnings announcements did give information to investors and that it was possible to utilize this to make substantial returns, especially in Slovenia. In other countries, such as Latvia, it was not possible, due to the illegality of short-selling. Laidroo (2008) conducted an event-study, using a theme-based content analysis of public announcements on Tallinn, Riga, and Vilnius Stock Exchanges during the period 2000-2005, looking for semi-strong efficiency. Laidroo analyzed 68 companies and 6.601 public announcements, and concluded that there were clear signs of inside trading. Laidroo (2008) suggested that the improvements in disclosure regulations concerned public announcements, especially pointing out the problem for disclosure of comments on financial results. According to Laidroo (2008), this could be especially beneficial for small investors, who are the last to receive this kind of information. Laidroo and Grigaliuniene (2012) wrote an article about asymmetries in price reactions to quarterly earnings announcements on the Tallinn, Riga, and Vilnius Stock Exchanges during 2000–2009. Laidroo and Grigaliuniene investigated asymmetries in price reactions to quarterly earnings announcements on Tallinn, Riga, and Vilnius Stock Exchanges during 2000-2009. Laidroo and Grigaliuniene investigated asymmetries by focusing on the tone of the news, the state of the economy, and by combining the impact of the tone of the news and the state of the economy. There was weak evidence that the reaction to negative earnings news was lower than to positive news. Jazepčikaitė (2008) employed event-study methodology to look for semi-strong efficiency in the Baltic stock markets for the daily data in the period from 2001 to 2008. Jazepčikaitė (2008) investigated abnormal returns surrounding the corporate news announcements and concluded that there were opportunities to earn abnormal returns by exploiting market inefficiency. Jazepčikaitė (2008) also found a clear sign of insider trading.

Another important topic involved in the detection of anomalies in the market is seasonality. Avdejev and Kvekšas (2007) analyzed calendar effects in the Baltic Stock market in the period from 2000 until the end of 2006. Using GARCH and EGARCH models' specifications, Avdejev and Kvekšas (2007) presented convincing evidence for the existence of day-of-the-week and month-of-the-year effects in stock market indices returns. Avdejev and Kvekšas (2007) found that the three markets were strongly integrated with each other, and all three were positive in January and negative on Monday. They found positive Tuesday and Friday effects for TSE; positive Tuesday, Thursday, and Friday effects for RSE; and positive Wednesday and Friday and negative Monday effects for VSE. Macijauskas (2010) also researched seasonality of the Lithuanian stock market. Macijauskas used monthly, weekly, and daily data from the period of 2000 to 2010. The results indicated that seasonal anomalies existed in the Lithuanian stock market. August had the lowest returns and October had the highest standard deviation. January had a clear positive trend.

Sakalauskas and Kriksciuniene conducted several studies of seasonality by applying different methods and analyzing the concept from different points of view. Sakalauskas and Kriksciuniene (2007a) conducted a Kolmogorov-Smirnov test to examine the impact of daily trade turnover on the day-of-the-week effect in the Vilnius stock exchange using return data from the beginning of 2003 to the end of 2006. They concluded that the day-of-the-week effect in emerging stock markets has a similar tendency to vanish, as was found in research on developed markets. Sakalauskas and Kriksciuniene (2009a) also used the Kolmogorov-Smirnov test to study the calendar effects on particular days of the month—the last five days of the month and the first half of the month—for the Vilnius stock exchange. They found no significant difference in returns, but a strong relationship between risk level and these periods of the month. Sakalauskas and Kriksciuniene (2009a) concluded that the stocks with low trading volume had higher volatility the last five days of the month, and stocks with large trading volumes had high volatility during the first days of the month.

Sakalauskas and Kriksciuniene also studied neural networks methodology. Sakalauskas and Kriksciuniene (2008c) analyzed the impact of trading taxes on intra-week stock return seasonality by constructing a trading strategy based on the changing content of a stock portfolio during particular days of the week on the Vilnius stock exchange. This was achieved using return data from the beginning of 2003 to the end of 2006. Significant seasonality was found in 20 of 24 stocks. The Sakalauskas and Kriksciuniene (2008c) results validated the use of neural network methodology. Sakalauskas and Kriksciuniene (2007b, 2008b, 2009b) confirmed the effectiveness of artificial neural network model in comparison with the traditional linear statistical methods in identifying anomalies in the Vilnius stock exchange. Sakalauskas and Kriksciuniene (2008a) analyzed the impact of trading commissions on the day of the week effect in the Lithuanian stock market by approaching trading activities only on particular days of the week. Sakalauskas and Kriksciuniene (2008a) found significant intra-week stock return seasonality for 17 of 24 stocks. Data used were from 2003 to 2008. Sakalauskas and Kriksciuniene (2012) investigated the day-of-the-week effect in the Baltic stock market by applying the Hurst exponent measure for the period from 2004 to 2012. They concluded that the Tallinn stock exchange was the most developed market, while Riga had the worst results of all three Baltic States.

Another important area of research giving insight into efficient markets is the relationship between the markets. Brännäsa et al. (2007, 2012) analyzed simultaneity and asymmetry of returns and volatilities in the Baltic stock exchanges and in Moscow, Russia, using the advanced vector ARasMA - asQGARCH model. Brännäsa et al. found compelling evidence for simultaneous effects regarding both return and volatility. They concluded that Riga and Tallinn were both dependent on one or both of the other Baltic countries, whereas Vilnius remained uninfluenced by the other two markets. Dubinskas and Stunguriene (2010) used the Dickey-Fuller and Johansen methods to determine co-integration level and Granger causality methodology to test the similarity of the general trends in the Baltics and Russia during three time periods—pre-crisis (01.02.2008 – 31.08.2008), during the crisis (01.09.2008 – 30.05.2009), and post-crisis (01.06.2009 – 31.12.2009). The markets were found to be co-integrated during all three periods, but the strongest co-integration was observed in the crisis period, and the weakest was after the crisis. During the first period, VSE was mostly influenced by the RSE and Moscow stock exchanges, while no causality was established between the RSE and TSE. Kazukauskas (2011) investigated long-run relationships and short-run dynamic linkages between the Baltic and Swedish markets during the period from 2000-2011. Kazukauskas (2011) found that VSE Granger causes TSE, whereas TSE does not Granger cause VSE and there was no causality between TSE-RSE or RSE-VSE. Hegerty

(2012) analyzed economic integration between the markets of the Baltic Sea Region by using Granger causality tests, including block exogeneity and impulse-response functions, and found that Estonia influenced Lithuania and that Scandinavia had a stronger influence on the Baltics than the Eurozone.

Other researchers conducted empirical literature surveys for the Baltics. Lim and Brooks (2011) included the Baltics in their empirical literature survey about weak-form market efficiency. They categorized emerging markets based on non-overlapping sub-period analysis, time-varying parameter model, and rolling estimation window. Lim and Brooks (2011) found that the financial crisis negatively affected the improvement of market efficiency. That is why it is important to research market efficiency continuously to be able to predict future market development. Degutis and Novickytė (2014) conducted a critical review of literature and methodology. Degutis and Novickytė reviewed articles from various countries, but focused primarily on the Baltic countries. Degutis and Novickytė (2014) concluded that there was not enough research about market efficiency in the Baltic equity markets.

4. THE BALTIC ECONOMIES AND STOCK MARKET DEVELOPMENT

To understand the Baltic Equity market and to answer questions regarding why it is functioning as it is, the author of this thesis further investigated the Baltic economies. In this chapter, the author presents an overview of macroeconomic rates of Lithuania, Latvia, and Estonia. The author also reviews the historical development of financial markets in these three countries and the plot of the current situation of the Baltic equity markets.

4.1. Basics on the Baltic economies

After being a part of the Russian Empire for centuries and 50 years as a part of the Soviet Union, Lithuania renewed their independence in 1990 followed by Latvia and Estonia in 1991. Right after the countries regained their independence, they began implementing their old national currencies Litas in Lithuania, Latas in Latvia, and Kroon in Estonia. In Table 4.1, the author presents some basic information on each of these countries' economies.

Table 4.1. Basic facts about the Baltic States.

	Lithuania	**Latvia**	**Estonia**
Population, thousands	2.972	2.165	1.258
GDP per capita (PPP), $, 2013	22.600	19.100	22.400
Major industries	Metal-cutting machine tools, electric motors, television sets, refrigerators and freezers, petroleum refining, shipbuilding (small ships), furniture, textiles, food processing, fertilizers, agricultural machinery, optical equipment, electronic components, computers and amber jewelry.	Processed foods, processed wood products, textiles, processed metals, pharmaceuticals, railroad cars, synthetic fibers, and electronics.	Engineering, electronics, wood and wood products, textiles; information technology and telecommunications.

Source: Compiled by the author based on data from CIA (2013) World Fact book

All three Baltic States are important transit countries between the east, north, and west. They are well located in the geographical centrum of Europe with a cost line to the Baltic see and the Scandinavian countries right across the sea. The region has an attractive investment environment known for political stability and economic freedom. It has a young, well-educated, and cheap workforce, in comparison with its western and northern neighbors (NASDAQ OMX, 2011).

In 2004, all three countries became members of NATO and the European Union (EU), and in 2007, they all joined the Schengen agreement. Since the inception of the EU, these three countries each wanted to be a part of the euro zone so as to become even closer to the west and to distance themselves from Russia. All three countries have now achieved this goal. The Euro was introduced in Estonia in 2011 and in Latvia in 2014, and it will be introduced in Lithuania in 2015. It took a while to meet the Maastricht criteria and to get to the point where the EU agreed to implement the Baltic States in the common currency because of their high inflation and lack of economic stability. Inflation in 2008 had reached 15,3% in Lithuania, 11,1% in Latvia, and 10,6% in Estonia. In the last five years, inflation has stabilized and was under five percent. In Figure 4.1, the author presents GDP growth information for all three Baltic countries compared with the EU average, which might explain the economic instability. The Baltics had high economic growth, one of the highest in Europe before 2008, and then fell dramatically and reached its lowest in 2009. The shrinkage of the economy was respectively -14,8% in Lithuania, -17,7% in Latvia, and -14,1% in Estonia.

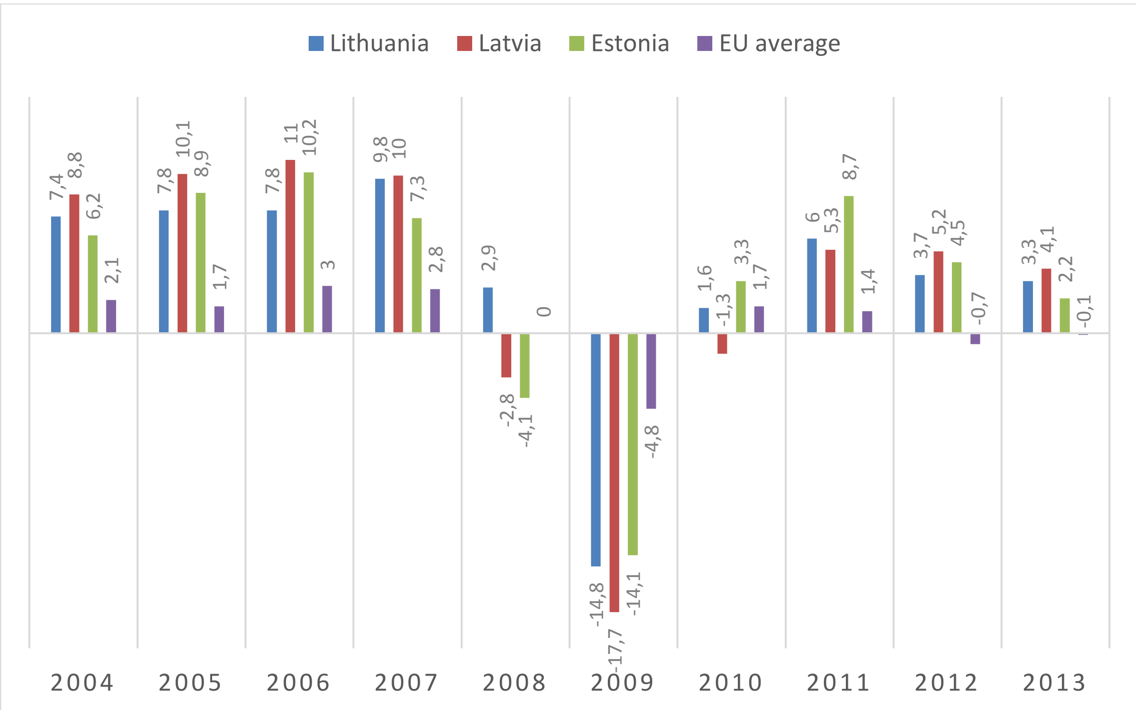

Figure 4.1. Real GDP growth rate (%)

Source: Compiled by the author based on data from Eurostat (2014)

One of the reasons why the credit crisis hit this region so hard might be lack of natural resources and a small industrial sector. The industry sector only accounts for 28,3% in Lithuania, 25,7% in Latvia, and 30,0% in Estonia. The service sector accounts for 68,0% in Lithuania, 69,4% in Latvia, and 66,2% in Estonia. According to the World Bank Data (2013), all three countries had a negative trade balance for the past 15 years despite having one of the fastest growing export growths in Europe (Vanags, 2013). The economies were suffering from the market bubble, which was driven by consumers spending and lending that burst dramatically in 2008 after the US housing bubble burst, which revealed many bad loans in the banking sector. Luckily, in 2010, these three countries stabilized their economies, and Lithuania and Estonia even reached positive GDP growth. In 2011, all three countries were back on track with positive GDP growth: 6,0% for Lithuania, 5,3% for Latvia, and 8,7% for Estonia. This growth slowed in 2012 and 2013, as can be seen in Figure 4.1.

The secret of the rapid recovery was strong budget cuts on wages and public expenditures, and austerity measures. Åslund (2011) gave great feedback about the crisis resolution in all three countries. Åslund stated that the Baltics had proven that old wisdom, sometimes forgotten, still holds, and the Baltic countries, besides having huge difficulties defending themselves from such a dramatic event due to being small and open economies with a large output contraction, had done a great job of coping with the economic crisis. Bandow (2013) stated: “Instead of desperately seeking bail-outs to preserve bloated social programs, troubled nations need to rediscover what is affordable, revive private sector growth, and adopt tough reforms. We all should hope that the other EU nations learn the Baltic lessons before it is too late”.

Not everyone was so positive about how the Baltics handled the crisis. Kattel and Raudla (2013) criticized the Baltic governments for relying on funding from the EU (20% of the national budget in the case of Estonia). Kattel and Raudla also stated that there were geographical positions that helped the Baltics and not the decisions their governments made. During the boom, the Baltic States developed “enclave industries”—a few major companies tied very closely to larger capitalist states nearby, like Sweden and Finland. These have driven export growth after the crash, with exports now returning to pre-crisis levels. Trading with neighbors—especially Scandinavian countries that did not suffer from the crisis to the same extent—was crucial for the Baltics to recover, but this had little to do with austerity.

According to (Kattel and Raudla, 2013), austerity has, however, cost a high price for the Baltics. Wages fell by 15% on average during the crisis, the unemployment rate increased, and mass emigration began. The unemployment rate (see Figure 4.2) reached its peak in 2010, with 17,8% for Lithuania, 19,5% for Latvia, and 16,7% for Estonia. The same year, the unemployment rate among young people (see Figure 4.2) was also at its highest, with 35,7 % in Lithuania, 36,2 % in Latvia, and 32,9% in Estonia. At the same time, the EU average was 21,1%. In 2011, the unemployment rate was significantly higher in the Baltic States than in the EU, but in 2012 and 2013, Estonia managed to reduce the unemployment rate for people in total and for people younger than 25 years old. Lithuania and Latvia also reduced the unemployment rate for young people in 2013, even pushing below the EU average, but the unemployment rate in total was still 1% higher than the EU average.

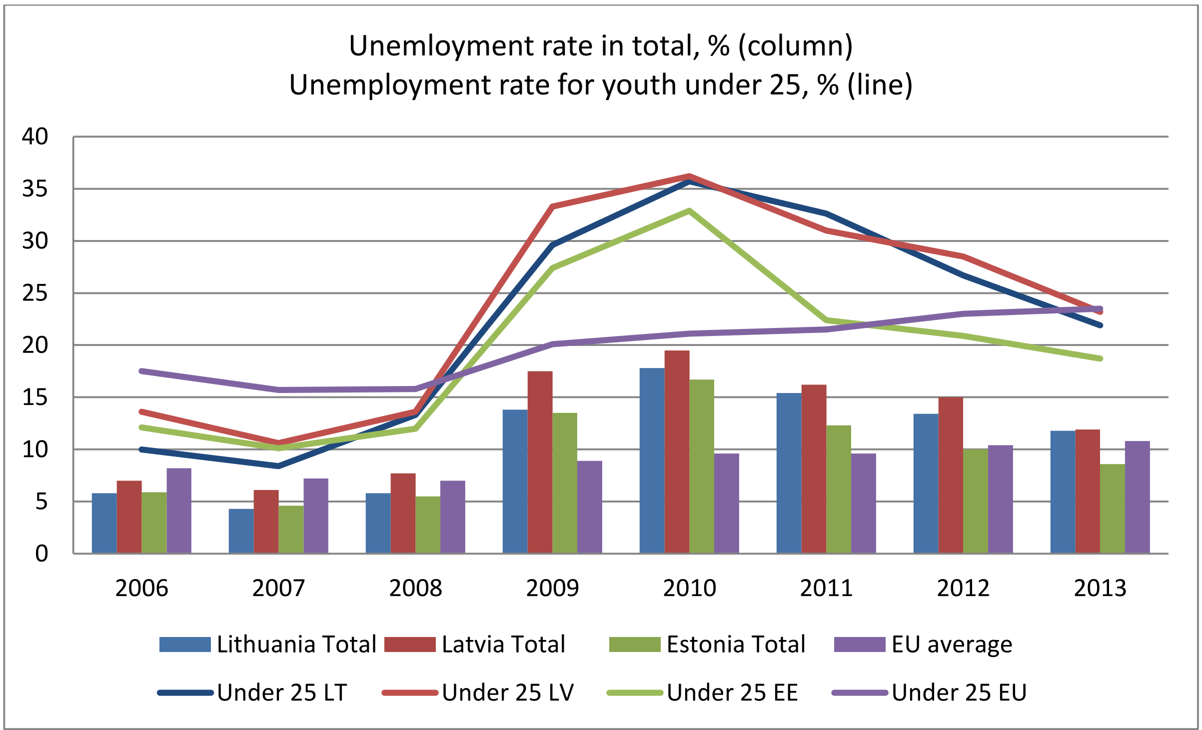

Figure 4.2. Unemployment rate in total and for youth under 25 years old

Source: Compiled by the author based on data from Eurostat (2014)

Hugh (2013) pointed out the same problem as Kattel and Raudla (2013) of the Baltic States: emigration. The problem is that the countries' populations are falling, along with their workforces, and young, educated people are continuing to leave, looking for a brighter future elsewhere, even if they now do so at a slower rate than they did during the height of the crisis (Blanchard et al., 2013). The region has lost approximately 20 % of its population since 1992, when the Baltic States had 8 million citizens, whereas in 2013, it had reduced to 6,5 million. There has not been a single year with population growth in that period (Adomanis, 2013). According to Statistics of Lithuania (2014), in Lithuania alone, the population dropped dramatically from 3,5 million in 2001 to 3 million in 2011.

Despite of the good geographical location, “free economic zones” and tax discounts, which are described on internet pages Invest Lithuania (2014) and the Investment and development agency of Latvia (n.d) Lithuania and Latvia did not do an impressive job of attracting investments, as can be seen in Figure 4.3. These two countries have not even reached the EU average in the past 10 years for foreign direct investments. Estonia has been more successful in attracting foreign investments, as can be seen in Figure 4.3. The most favorable tax discount that attracted investors to Estonia was that there was no corporate income tax on reinvested profits (Estonian Export Directory, n.d) Their direct investment flows reached 8% of GDP in 2007 and 2009, which was much better than the EU average, but in 2011, direct investment flows went down by 6,4%. Negative values of direct investment flows show that the value of disinvestment by foreign investors was more than the value of capital newly invested in the reporting economy.

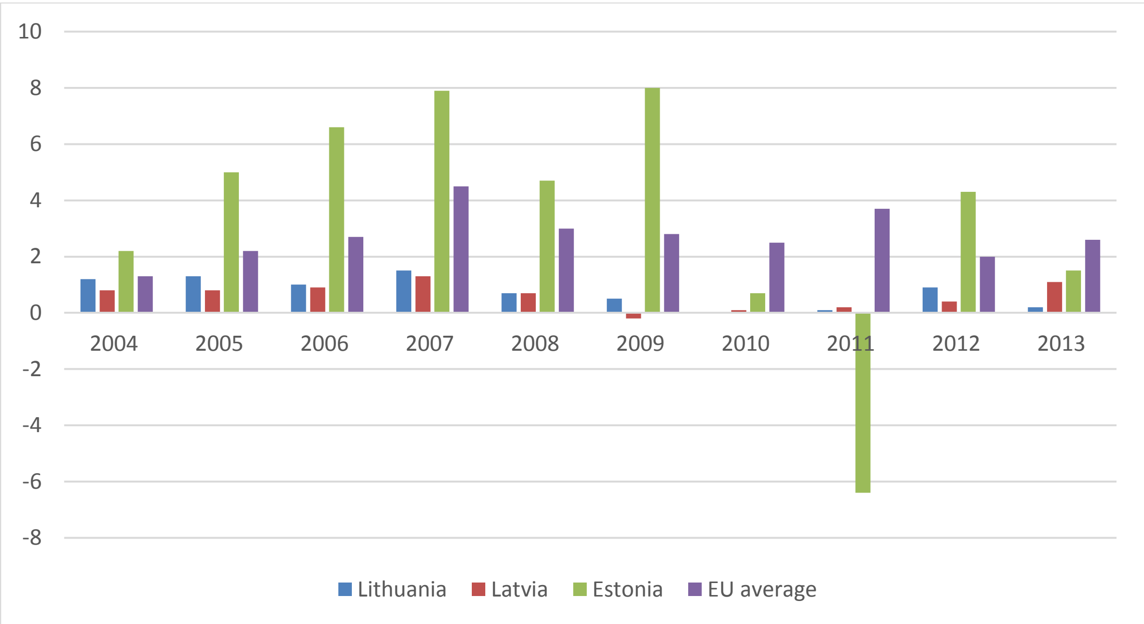

Figure 4.3. Direct investment flows (% of GDP)

Source: Compiled by the author based on data from Eurostat (2014)

The future forecast for the three economies does not promise very high growth. Because of the Ukrainian crisis, the Baltic countries are exposed to Russian pressure. It is worth mentioning that 30% of Estonians and 34% of Latvians are native Russian speakers. In Lithuania, this number is just 8% according to CIA (2013). The Baltic States will pay a high price for the economic sanctions against Russia, which is Lithuania's largest trading partner, accounting for 25% of the total trade. Latvia and Estonia trade with Russia, however, their trade with Russia only accounts for approximately 10% of the total trade, including agriculture, food processing, ports, transport, and logistics (Economist, 2014). Latvia and Estonia are still dependent on Russian gas, while Lithuania has managed to free itself from the Russian gas monopoly (Seputyte, 2014), and now have their own offshore gas terminal and are obtaining gas supplies from Norway. It will be enough to cover the gas needs for the entire population, as well as supply Latvia and Estonia in the future (Adomaitis, 2014). On the bright side, the Baltic economies may make changes, adapt to challenges, and find new and more stable trading partners. The 2014 index of economic freedom ranked Estonia as number 4 in the region and number 11 in the world. Lithuania was ranked 11 in the region and 21 in the world. Latvia was ranked 19 in the region 42 in the world. This shows the progress and confirms that the Baltics are moving in the right direction.

4.2. The development of the Baltic stock markets since 1990

After the restoration of independence in the 1990s, all three countries began to create a securities market from the ground up. Every business was state property and the first step all three countries were taking was to begin mass privatization and creation of an entirely new legal basis.

In 1993, Vilnius Stock exchange was opened and the first securities were traded. At first, they were open twice a week, but in 1996, stocks began to be traded daily. In 1995, Riga Stock exchange was launched. Trading took place once a week as a single price auction. In 1995, Tallinn Stock Exchange was established, but was not opened for trading until 1996.

In 2000, the Lithuanian, Latvian and Estonian stock markets began a history of cooperation. A joint list of securities listed on the Baltic Stock Exchanges—the Baltic List—was announced and all three countries joined the Nordic Alliance NOREX.

In 2001, HEX Group from Finland acquired ownership in the Tallinn Stock Exchange Group. In 2002, HEX Group became the main shareholder of the Riga stock exchange. In 2003, HEX Group announced a merger with the Swedish market operator OM Group and become OMX. In 2004, the new Nordic-Baltic trading platform was used by seven exchanges: Sweden, Denmark, Iceland, Finland, Estonia, Latvia and Lithuania. The same year, the joint Baltic market was created with the introduction of the Baltic list—Baltic Index—and a new market information web-site.

In 2007, the Baltic exchanges introduced single Baltic membership, and gave members the right to trade equities and fixed income products in all three Baltic markets through the exchanges in Tallinn, Riga, and Vilnius via single access point to all three exchanges.

In 2008, NASDAQ Stock Market completed the merger with the Baltic and Nordic stock exchange group OMX. As a result of the merger, the largest publicly-traded company in the world was created: NASDAQ OMX Group.

NASDAQ OMX Baltic is a part of the NASDAQ OMX Group, the world's largest exchange company that delivers trading, exchange technology, and public company services across six continents over 70 exchanges in 50 countries. In 2010, NASDAQ OMX Nordic and Baltic exchanges introduced a new trading system for equity trading—INET—the most advanced securities trading technology in the world. As a result, all NASDAQ OMX equity markets across the world trade on the same global trading platform.

The official trading, clearing, and settlement currency of NASDAQ Baltic market is the euro. It became the euro in 2011 on the Tallinn and Vilnius stock exchanges. Riga Stock exchange began trading in euros later. The goal was to make the Baltic region more accessible to local and international investors. For foreign investors, a common currency reduces transaction costs through savings in conversion costs, allows for smoother management of cross-border portfolios, and diminishes trading-related risk. As a result, the efficiency and attractiveness of the Baltic securities market significantly increased and larger flows of portfolio investments were captured, which is the basis for bringing new investments to the Baltic region.

The Baltic Stock Exchange is divided into two main segments: the Baltic regulated market and First North Baltic. NASDAQ OMX First North is an alternative marketplace. It involves higher risk and has lower regulatory demands and admission requirements. It does not have the legal status as an EU-regulated market. Companies at First North are subject to the rules of First North and not the legal requirements for admission to trading on a regulated market. In October 2014, only two companies were on this list.

The Baltic regulated market contains the Baltic Equity List, the Baltic Bond List, and the Baltic Funds List. The Baltic Equity List consists of the Baltic Main List, which, in the first half of the year in 2014, included 34 blue-chip companies, and the Baltic Secondary List, which included 47 companies that did not meet quantitative admission requirements. In total, it had a market cap of approximately EUR 6 billion as can be seen in table 4.2. The Baltic Bond List contains 75 bonds, including Latvian and Lithuanian government bonds, and corporate and mortgage bonds of different maturities which had a market cap of approximately EUR 4,2 billion in October 2014. The Baltic Funds List had 112 funds listed in October 2014. In Table 4.2, the author of this thesis presents stock market statistics for the past 10 years.

Table 4.2. Major statistics of the Baltic stock market.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014H1
Market CAP MEUR	11.645	13.893	13.096	5.177	6.386	6.846	5.206	5.603	5.731	6.043
Market turnover MEUR	2.596	2.457	2.382	978	495	488	401	282	302	124
Number of companies	103	100	99	94	89	87	80	80	79	81

Source: Compiled by the author based on data from NASDAQ OMX Baltic (2014) and World Bank Data (2013)

As can be seen in Table 4.2, the market cap for the stocks fell dramatically in 2008 and still has not reached its pre-crisis values. In Figure 4.4, it can be seen the market cap in percentage of GDP for the Baltic States. They lag behind the average of the EU by a substantial percentage. In 2012, market capitalization of Vilnius stock exchange was 9,4% of GDP, Riga had only 3,9%, and Tallinn 10,4%, while the average in the EU was 62,5% of GDP. The Baltics had far higher numbers before 2008. Then the Vilnius and Tallinn stock exchanges had a market capitalization of approximately 30% and Riga market cap was approximately 15% of Latvian GDP. The crisis in 2008 had a very large impact on the Baltic markets.

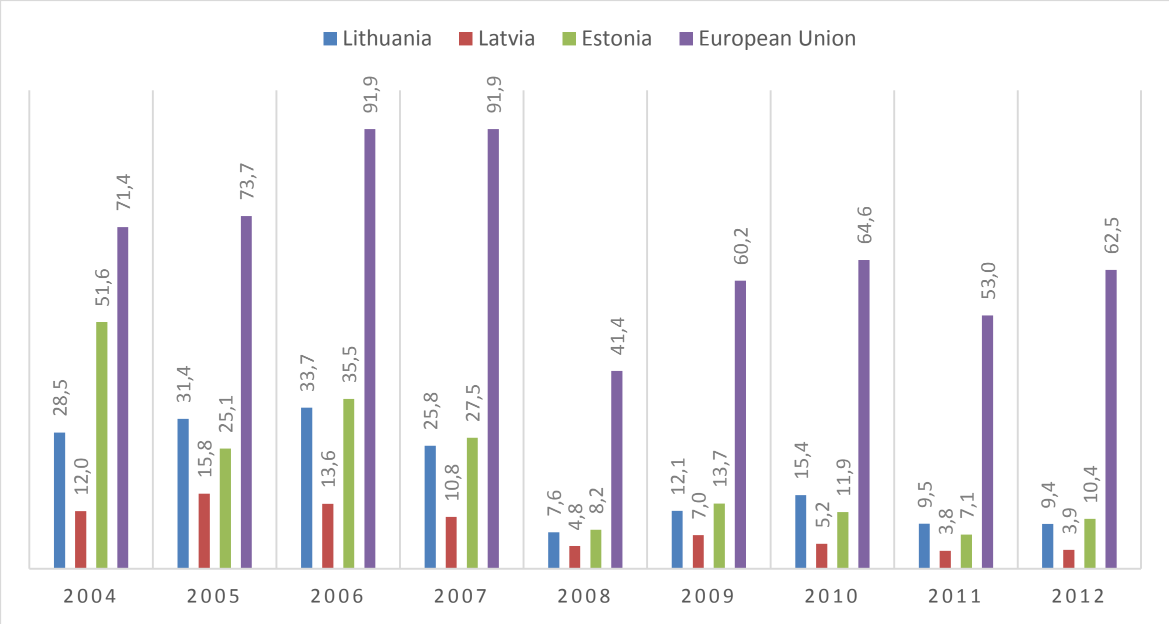

Figure 4.4. Market capitalization of listed companies (% of GDP)

Source: Compiled by the author based on data from World Bank Data (2013)

The Baltic States lag behind in value of stocks traded. According to World Bank data (2013) the total value of stocks traded were 0,4% of GDP in Lithuania, Latvia was at 0,11% of GDP value traded, and Latvia was at 0,8% of GDP value traded, while the EU average was 48,2%. This shows that all three exchanges have extremely low liquidity, low trading volumes, and limited financial power. Liquidity is a huge problem. It deters investors because it might be difficult to have an active trading strategy. In the next chapter the author is going to review the development and basic statistics of the Baltic indices as well as historical excess returns for different periods to see what theoretical earning opportunities the Baltic investors had. "Theoretical" because there are possible profits to earn, but without liquidity, it is a huge risk and no guarantee that it will be possible to buy or sell the needed quantity of particular stock at any given moment.

5. DATA AND BASIC STATISTICS

In this chapter, the author will look further into the market environment discussed in the previous chapter and include single indices. The author will present the data which has been analyzed for this thesis and also give insight into price development, statistical analysis and the weaknesses of the data.

5.1. Data selection and data problems

In this thesis, the author used 13 Baltic indices: Benchmark index, all-share indices of Lithuania, Latvia, and Estonia, index of the most liquid stocks, and eight main industries' indices, which were collected from the NASDAQ OMX Baltic internet site. The list of indices used in this thesis are presented in Table 5.1. The period of data used in this thesis was from January 2000 until August 2014, including three sub-periods: one before the financial crisis from 2000 to 2006, one during the financial crisis from 2007 to 2009, and the last period from 2010 until August 2014. The author used daily data, weekly average data, and monthly average data. The author calculated returns by using the logarithmic returns methodology.

Table 5.1. Explanation of the indices used in the thesis.

INDEX CODE	NAME
OMXBBGI	Baltic Benchmark - largest and most traded shares from all sectors
OMXT	All-Share index of Tallinn.
OMXR	All-Share index of Riga.
OMXV	All-Share index of Vilnius.
OMXB10	10 Most liquid stocks of Baltics.
B1000GI	Basic Materials sector of Baltics
B2000GI	Industrials sector of Baltics
B3000GI	Consumer Goods sector of Baltics
B4000GI	Health Care sector of Baltics
B5000GI	Consumer Services sector of Baltics
B6000GI	Telecommunications sector of Baltics
B7000GI	Utilities sector of Baltics
B8000GI	Financials sector of Baltics

Source: Compiled by the author based on data from NASDAQ OMX Baltic (2014)

OMX Baltic Benchmark GI index (OMXBBGI) consists of a portfolio of the largest capitalization and most traded shares in Lithuania, Latvia, and Estonia, representing all sectors available on the NASDAQ OMX Baltic Market. The index serves as an indicator of the overall trend in the market. The index is revised two times a year. The weight of the stocks, which is included into the index, is based on the market value adjusted by the free float.

OMX Tallinn (OMXT), OMX Riga (OMXR), and OMX Vilnius (OMXV) include all the shares listed on both the Main and Secondary lists. The indexes reflect the current status of the market in these three countries.

OMX Baltic 10 (OMXB10) consists of the 10 most actively traded stocks on the NASDAQ OMX Baltic Market. The weight of the constituent stocks is based on the market value adjusted by the free float. The composition of the index is revised two times a year.

Sector indexes (B1000GI-B8000GI) are developed by the FTSE Group based on the Industry Classification Benchmark (ICB). Sector indexes show the trend of a specific industry and enable peer comparison between companies engaged in the same industry. They include shares listed on the Main and Secondary lists of the NASDAQ OMX Baltic exchanges. The author did not cover neither the Energy sector index (B0001GI) or the IT sector index (B9000GI) in this thesis because of the entire years missing in the index trading data. Gross type of indices (GI) is used in this thesis because of reflecting the true performance of the market by reinvesting dividends. In Figure 5.1 we can see the sector indices divided by the share of market cap.

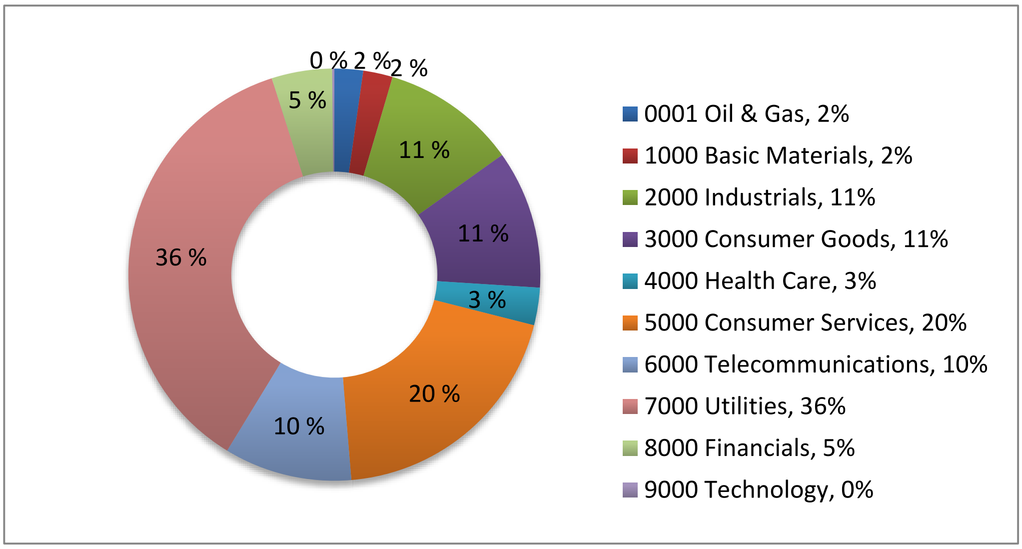

Figure 5.1. Baltic companies by sector according to market cap 2014 H1 (%)

Source: Compiled by the author based on data from NASDAQ OMX Baltic (2014)

As can be seen in Figure 5.1, the utilities sector has the highest market share with its 36%. The consumer services sector is the second highest with 20%. Consumer goods, industrials, and telecommunications are next and share third place with its 10-11% of the market cap. Next are basic materials, healthcare, and financials, with market shares of 2%, 3%, and 5%, respectively. In Figures 5.2, 5.3, 5.4, and 5.5, one can see the prices development of the main indices (Figures 5.2 and 5.3) and sector indices (Figures 5.4 and 5.5).

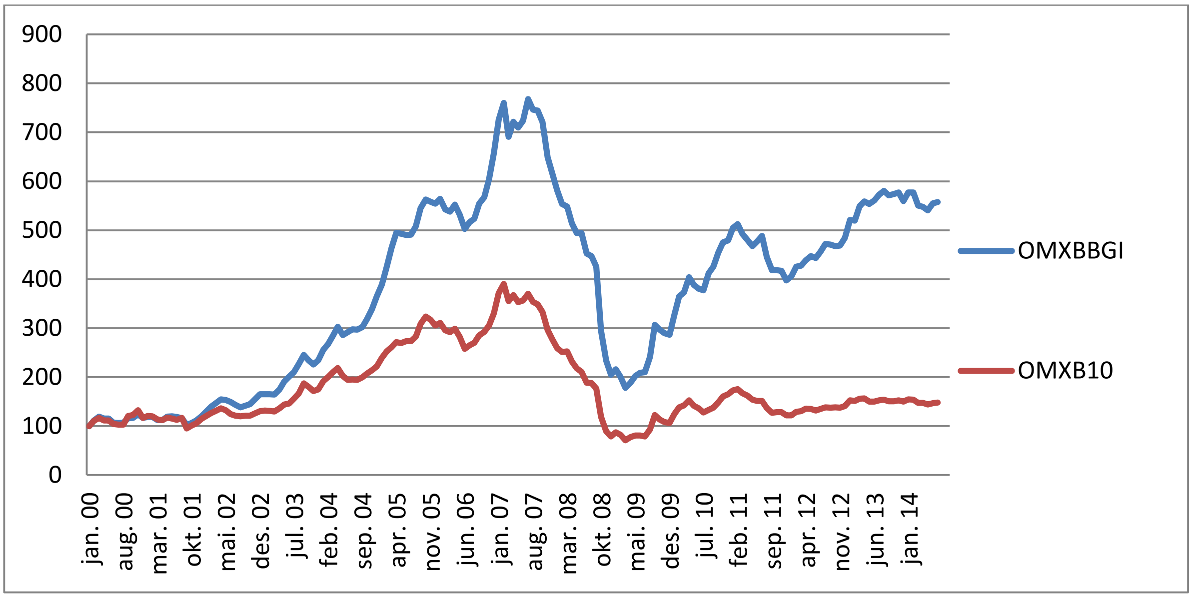

Figure 5.2. Historical overview of the OMXBBGI and OMXB10 indices, 2000-2014 (rebased January 2000 = 100, monthly observations)

Source: Compiled by the author based on data from NASDAQ OMX Baltic (2014)

In Figure 5.2, one can see the development of the Baltic benchmark index, which represents the biggest and most traded companies from all sectors and the OMXB10 index, which represents the 10 most liquid traded companies in the Baltic stock market. One can see a difference in development of these indices. OMXB10 is the only tradable index in the Baltic market and the only index which has had future contracts on it since 2007. One can also see that development of the tradable index was much smoother and did not have such a large difference between highs and lows as the Baltic benchmark index.

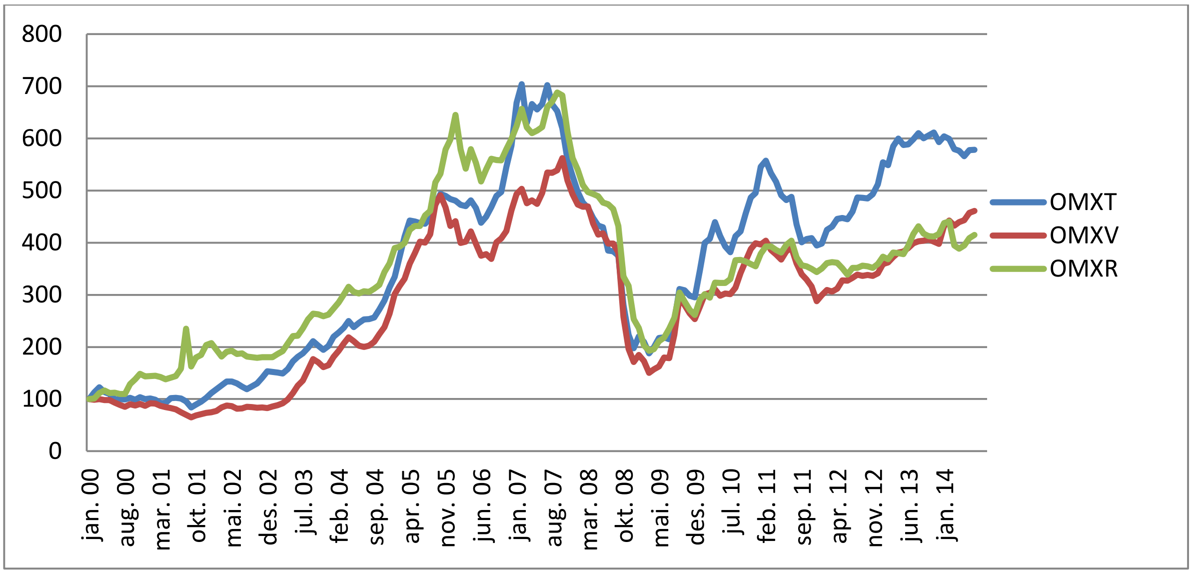

Figure 5.3. Historical overview of the country indices, 2000-2014 (rebased January 2000 = 100, monthly observations)

Source: Compiled by the author based on data from NASDAQ OMX Baltic (2014)

In Figure 5.3, one can see the development of the main indices of each country. These are all-share indices fully representing the three markets. As can also be seen from Figure 5.3, the markets are highly integrated and moving in the same direction, showing very similar patterns. This can also be confirmed by Table A.1 in Appendix A on page 64 which shows the correlation between these three country indices and the main indices seen in Table 5.2. All three countries are highly correlated, especially in the period of the financial crisis from 2007-2009 and most recently from 2010 to 2014.

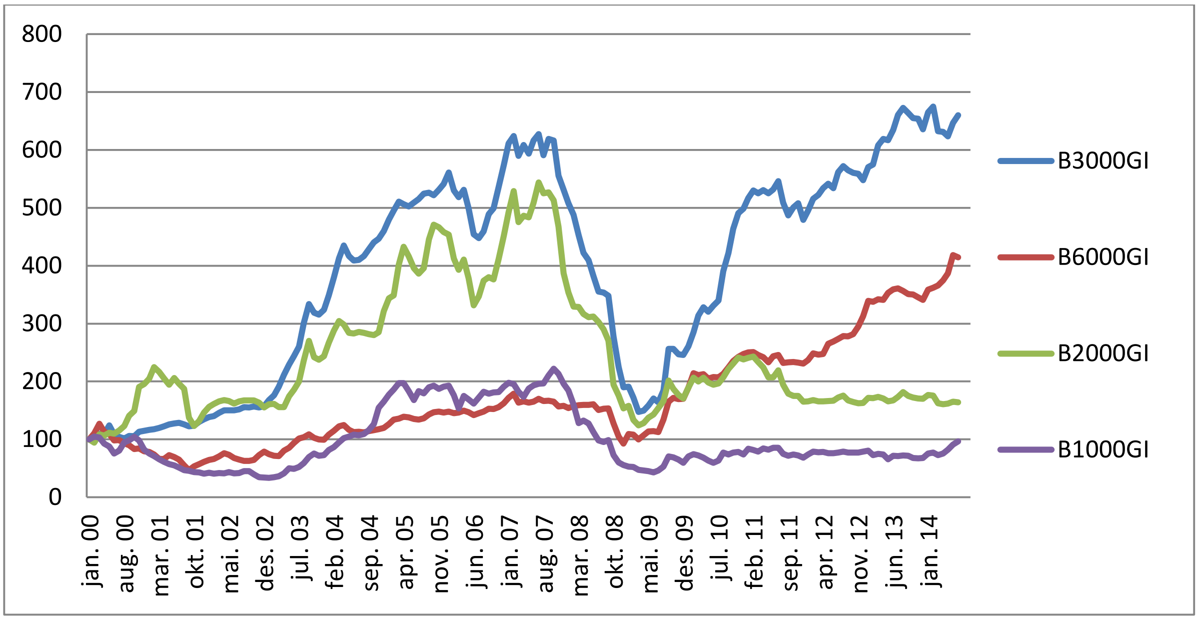

Figure 5.4. Historical overview of the industry indices, 2000-2014 (rebased January 2000 = 100, monthly observations)

Source: Compiled by the author based on data from NASDAQ OMX Baltic (2014)

In Figure 5.4, one can see the indices that contain Consumer Goods (B3000GI), Telecommunications (B6000GI), Industrials (B2000GI), and Basic Materials (B1000GI) from top to bottom, respectively. It appears that all four indices had a completely different development. The most stable development belongs to materials and at the same time, it has a tendency to go down. Industrials had been growing up until 2007, when it was reduced dramatically, and then became stable, while consumer goods had a similar development since the beginning. After the crisis, however, it began to increase very fast again and reach new highs, even larger than during the pre-crisis period. Telecommunications were slowly, but surely, growing without facing big ups and downs.

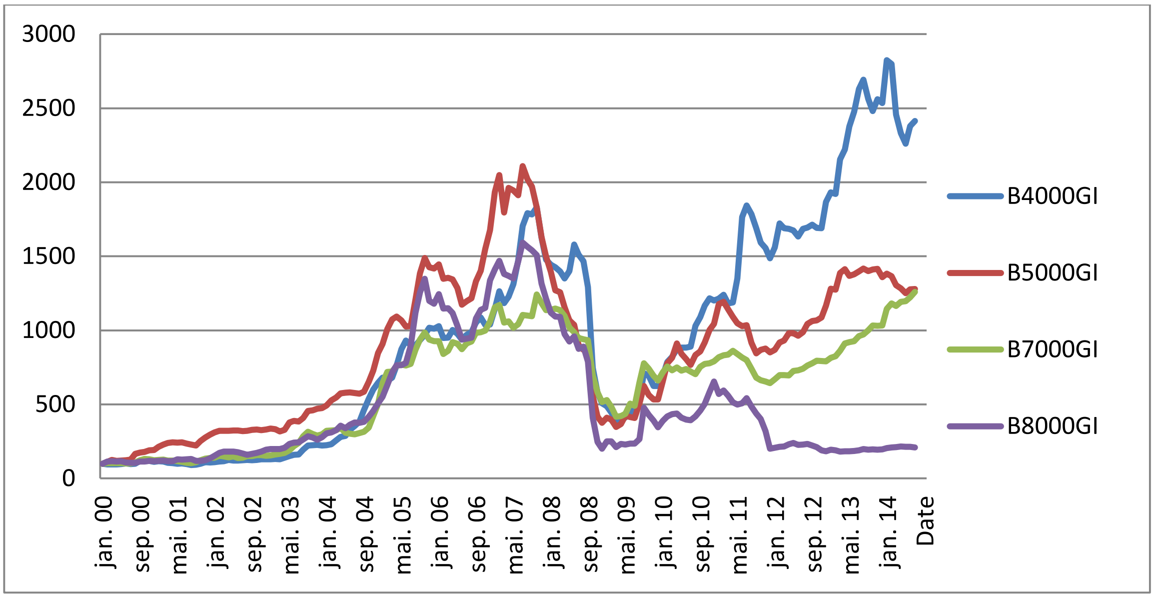

Figure 5.5. Historical overview of the industry indices, 2000-2014 (rebased January 2000 = 100, monthly observations)

Source: Compiled by the author based on data from NASDAQ OMX Baltic (2014)

In Figure 5.5, one can see the development of sector indices which had more extreme development than the indices in Figure 5.4. As can be seen in Figure 5.5, the indices have been trending in several different directions. The development before 2010 was quite similar but since 2011, all four indices have gone in separate directions. The sectors in this figure stand for Health Care (B4000GI), Consumer Services (B5000GI), Utilities (B7000GI), and Financials (B8000GI). Health care has increased by a few hundred percent since 2009. Consumer services and utilities have grown, but the financials index went straight down. It might be the consequences of two big Lithuanian banks—Snoras and Ukio Bankas—which went into bankruptcy in 2011 and 2013, respectively.

There are some limitations in the analysis. In this thesis, the author analyzed stock market indices, but did not include other market vehicles like fixed income securities, funds or single stocks. The data were from 2000 to 2014, which is not a very long period of time, but the author needed to keep in mind that the stock exchanges of the Baltic countries were opened in 1993 and 1996, with regular trading beginning in 1998. The indices only began to be calculated in 2000. Fourteen years is not an optimal time period for a quantitative analysis, but the author analyzed the longest possible time period. Indices are reviewed on a semi-annual basis, which might also explain some inconsistencies in the data.

5.2. Descriptive statistics

In this section of the thesis, the author presents the statistical results of the indices. The author used annualized returns on weekly prices to present the data. Daily data would contain too much noise and monthly data would miss some of the valuable information, therefore, weekly data were most appropriate in this context. In Table 5.2, one can see the annualized returns and standard deviation of all indices for different periods of time.

Table 5.2. Annualized returns and standard deviation of weekly data for different periods.

Index name	2000-2014		2000-2006		2007-2009		2010-2014	
	Annual returns %	Annual σ %	Annual returns %	Annual σ %	Annual returns %	Annual σ %	Annual returns %	Annual σ %
OMXBBGI	11,9	17,0	27,8	13,9	-28,9	25,5	14,4	13,0
OMXT	11,9	18,7	25,9	15,7	-24,8	26,0	14,8	16,4
OMXR	9,8	21,8	26,1	25,1	-28,6	23,6	10,2	12,7
OMXV	10,6	17,9	22,6	14,7	-21,4	27,6	13,1	12,9
OMXB10	2,9	19,9	18,2	16,1	-39,1	30,1	7,1	15,6
B1000GI	0,1	26,9	10,0	23,7	-37,8	35,6	10,0	24,2
B2000GI	2,8	20,8	20,7	21,3	-33,8	26,9	-0,5	13,5
B3000GI	12,9	15,4	25,4	12,3	-29,3	23,1	21,6	12,1
B4000GI	21,6	23,5	33,7	19,0	-18,3	33,8	29,4	20,7
B5000GI	17,5	24,8	41,7	19,5	-41,3	36,3	19,1	21,2
B6000GI	9,4	18,6	6,8	19,6	0,5	24,1	19,1	11,7
B7000GI	17,4	20,4	34,5	20,4	-17,5	28,2	14,4	12,1
B8000GI	5,6	31,2	38,2	19,3	-45,2	47,2	-10,6	31,5

Source: Compiled by the author

As can be seen in Table 5.2, there was some diversity in returns. All of the indices have generated positive average returns over the last 14 years. The pre-crisis period was years for high highs, where all returns were extremely high compared to other periods. In the period of the crisis, all returns were negative, except telecommunications (B6000GI), which had 0,5 growth. After the crisis, all indices managed to recover, except industrials (B2000GI) and financials (B8000GI). The standard deviation was quite high in all fourth periods, but the last period seems to be least volatile. In Table 5,3, the author presents the ratio between risk and returns by using Sharpe ratio methodology and finding out excess returns per amount of risk. As a risk-free rate, the author is using the Lithuanian government 10-year bond which according to the central bank of Lithuania gave a 3,1% return over the last year.

Table 5.3. Values of the Sharpe ratio of weekly indices' returns for different periods.

Index	2000-2014	2000-2006	2007-2009	2010-2014
OMXBBGI	**0,52**	**1,78**	-1,25	**0,87**
OMXT	0,48	1,46	-1,08	0,71
OMXR	0,31	0,92	-1,34	0,56
OMXV	0,42	1,33	**-0,89**	0,78
OMXB10	-0,01	0,94	-1,40	0,26
B1000GI (Basic Materials)	-0,11	0,29	-1,15	0,29
B2000GI (Industrials)	-0,01	0,83	-1,37	-0,26
B3000GI (Consumer Goods)	**0,64**	**1,81**	-1,40	**1,53**
B4000GI (Health Care)	**0,79**	**1,61**	**-0,63**	**1,27**
B5000GI (Consumer Services)	**0,58**	**1,99**	-1,22	0,76
B6000GI (Telecommunications)	0,34	0,19	**-0,11**	**1,37**
B7000GI (Utilities)	**0,70**	1,54	**-0,73**	**0,94**
B8000GI (Financials)	0,08	**1,82**	**-1,02**	-0,43

Source: Compiled by the author

The higher the Sharpe ratio, the better the results. The Sharpe ratio was negative for all the indices during the crisis, meaning that it was more profitable to invest in safe government bonds than in any Baltic country or industry. The whole 14-year period and another two sub-periods in general had positive Sharpe ratios, indicating the good profitability of the Baltic Stock market. The Baltic benchmark index and consumer goods were among the most profitable in all periods, except the crisis, during which these indices had the greatest fall. Health Care had the best results: one of the lowest downfalls during the financial crisis and one of the greatest returns during all other periods. Those indices which had their best results during the financial crisis also did well in the period after the crisis, except for the financials industry, which remained with a high negative Sharpe ratio, also after the crisis, which might be explained, as mentioned earlier, by the bankruptcy of the two main Banks of Lithuania in 2011 and 2013.

We can see that the Baltic stock market provided good opportunities but also higher risk for the Baltic investors. The history of the Baltic stock market is short and provides little information for investors on what they might expect to earn from their investments. In the next chapter we are going to discuss how to find anomalies in the market, and also if it is possible for Baltic investors to profit from these anomalies.

6. TESTING FOR EFFICIENCY

In this chapter the author will present the null hypothesis as well as the alternative hypotheses and the methodology and models used to conduct the research. We will also have a look at the estimation techniques used as well as the theory behind them and critiques of the models. In the second part of this chapter, the author applies these models and discusses the empirical results on the data presented in the previous chapter.

6.1. Methodology

To discuss the main research question of this thesis, "is the Baltic stock market efficient" the author states the null hypothesis:

H_0: The Baltic stock market has a weak form of efficiency

To support or reject the null hypothesis, the author tested the three following alternative hypotheses:

Hypothesis 1: It is possible to predict future returns from the historical data.

Hypothesis 2: The Granger causality is present in the VSE, RSE and TSE markets.

Hypothesis 3: The markets do have day-of-the-week anomalies.

The author is using an Autoregressive (AR) model, Distributed Lag model (ADL) and Dummy Variable Approach to either confirm or reject the stated hypotheses. When estimating the models, the author is using returns, calculated by applying logarithmic return methodology:

$$r_t = \ln (p_t/p_{t-1}) \tag{1}$$

where r_t is log return, p_t is today's price and p_{t-1} is yesterday's price.

All three models used in this thesis were estimated using the Ordinary Least Squares (OLS) multiple linear regression model. OLS is the method that minimizes the sum of squared vertical distances between the observed responses in the dataset and the responses predicted by the linear approximation.

The assumptions of OLS are:

- Linear in Parameters. The equation must be linear in parameters.
- Homoscedasticity. The error terms all have the same variance and are not correlated with each other: var(ut) = σ2 (constant).
- No autocorrelation. Values of residuals must be random and not correlated with each other; Cov $(u_i, u_j) = 0$ for $i \neq j$.
- No multicollinearity. There is no exact linear relationship among the independent variables.
- Zero Conditional Mean. The mean of the error terms should be zero. $E(U_t) = 0$ or no specification error.

The results of the model estimations will be interpreted using t-test values

test statistic = $\frac{\beta - \beta*}{SE(\beta)}$ (2)

The author is going to reject the null hypothesis if the t-value will be significant at 95% confidence level.

6.1.1. An Autoregressive model AR(n).

The EMH claims that stock price indices are basically random and not serially correlated. This means that data should not have any "memory" and it should not be possible to forecast the future earnings based on past values. A simple and widely-used model for serial correlation is the Autoregressive model of order n, denoted as AR(n). An AR(n) is a representation of a type of random process. This model helps to determine if current value of a variable only depends on its own past values and if historical data are useful in predicting future data. An important property of the time series processes is stationarity, which is fulfilled because of the properties of returns which are stationary. The model AR(n) can be specified as:

$$r_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i r_{t-i} + \varepsilon_t \quad (3)$$

where r_t is the index return series; r_{t-i} is the lag of return series; α_0 is the intercept term and the α_i are unknown parameters; ε_t is a white noise disturbance term; and n is the number of lags in the model.

H_0: $\alpha_1=\alpha_2=\ldots\ \ldots=\alpha_N=0$; $\varepsilon_t \sim N(0,\sigma^2)$

The author calculated the model using the Ordinary Least Squares (OLS) method. To interpret the results of the estimated models, the author used coefficients and their t-test values, as well as adjusted R^2 to determine how well the model captures patterns. If the coefficient is significantly different from zero, then stock returns can be predicted from the past information.

There are some weaknesses in the model. According to DeFusco et al. (2007), an important issue to be aware of when using this model is the sample period in use. The estimates can change substantially across different sample periods and there is no clear techniques in the theory that determines how long of a sample period to use when estimating the model. Another weakness is that Autoregressive models are more restrictive than the theory of market efficiency requires, and, therefore, it is the reason why one cannot draw a clear conclusion from this model alone, but must employ other models, as well as get a wider picture.

6.1.2. Granger causality and an Autoregressive Distributed Lag model ADL(n,q).

Another model used to test market efficiency is based on predicting the present values on the basis of past values of other variables—in other words, if one of the Baltic stock exchanges can be helpful in predicting future values of other stock exchanges in the Baltics. This relationship is defined as Granger causality.

Granger causality is a term for a specific notion of causality in time-series analysis and its definition was developed by Granger (1969) and Sims (1972). Granger causality is not identical to causation. Causation describes a relationship in which one variable can be explained by another variable, while Granger causality refers to the correlation between the current value of one variable and the past values of others, and shows whether a movement in one variable can best be described by its own past or whether it can be better explained by the past movements of another variable. Granger causality claims to move beyond correlation to test for causation and is used to determine if one time series is useful in forecasting another, even though it does not cause it. The necessary conditions of Granger causality are that only past values of one variable can Granger cause another, and variables are independent if both fail to Granger cause the other.

Granger causality can be tested in an Autoregressive Distributed Lag model ADL(n,q) since returns of the financial assets are assumed to be stationary. This model combines distributed lag models and Autoregressive models to a very simple dynamic structure and parametric model that combines the dynamics of time series and the effect of explanatory variables. It consists of stochastic regression involving time series that includes the current and past values of the variable in study and explanatory variables including lags. This model uses the notation ADL(n,q), where n is for number of lags of the dependent variable and q is the number of lags of the independent variables (Kiviet and Dufour, 1997).

The ADL(n,q) model includes lagged values of both independent and dependent variables, and was chosen due to the fact that it is not so strict as geometric lag models, nor as finite as distributed lag models. It is a general form that can capture the current and lagged effects of an independent variable over the dependent.

ADL(n,q) model:

$$r_t = \alpha_0 + \sum_{i=1}^{n}\alpha_i r_{t-i} + \sum_{i=1}^{q}\beta_i r_{t-i} + \sum_{i=1}^{q}\gamma_i r_{t-i} + \varepsilon_t \tag{4}$$

where r_t is the index return series; r_{t-i} is the lag of return series; α_0 is the intercept term; $\alpha_{i;}$ β_i; γ_i are unknown parameters; ε_t is a white noise disturbance term; n is the number of lags of dependent variable in the model, q is the number of lags of independent variable in the model.

H_0: $\alpha i=0$; $\beta i=0$; $\gamma i=0\ldots\ \forall i > 1$

OLS regression analysis has been used to estimate this model. To discuss the results, the author is using the t-test to determine whether Granger causality is present at the 5% level of significance. If t-values of coefficients $\alpha_{i;}$ β_i; γ_i are statistically significant at the 95% confidence level, the author will conclude that the Granger causality is present.

Stern (2011) discussed the criticism towards Granger causality, citing Roberts and Nord (1985) and their findings that the functional form of the time series affected the sensitivity of Granger's tests. Roberts and Nord stated that logarithmic transformation, which tends to increase the stationarity and reduce heteroscedasticity, has caused the logarithmic transformation showing no sign of causality, while the untransformed data showed significant results. Chowdhury (as cited in Stern, 2011) supported the critique of Granger causality, finding that prices and returns may be exogenous, but not in any meaningful philosophical or economic way. If one assumes that variable X Granger causes variable Y, then there might be still a third variable which drives both X and Y and appears that X drives Y, even though there is no actual causal mechanism directly linking the variables.

The model has a few weaknesses. The first problem is that it is not clear how many lags should be included in the ADL model. Another problem is related to OLS methodology, which is used to calculate the model. Finite distributed lag is difficult to estimate in practice, since lagged values of independent variables might be highly correlated and even if the autocorrelation is removed, the multicollinearity may still bias estimates of the variances. This may not be a problem for two lags, but can be misleading if the true relationship involves three or more variables.

6.1.3. Day-of-the-week effects and Dummy Variable Approach

One of the significant anomalies of the stock market and implication of the market inefficiency is the seasonal effects. The most common calendar effects found in the stock markets by previous studies are day-of-the week effects like Monday effect and Friday effect, as well as month of the year effects like January effect or holiday effects. Calendar effects have been found in both developed and emerging stock markets. This author attempted to test whether the day-of-the-week effect was present in the Baltic stock market. The author did not include month-of-the year effects in this study because there was not a long enough period of data available.

There is a large body of literature on the day-of-the-week effect of stock returns and previous studies strongly support the existence of the Monday effect. This effect refers to a phenomenon that the average return on Monday is significantly lower than the average return for the other days. The first to observe it was French (1980), who analyzed the Standard and Poor's portfolio daily returns during the period from 1953 to 1977 and concluded that average returns for Monday were significantly negative, while there were positive returns in other days. After that, there were plenty of researchers who confirmed this anomaly in different markets (Jaffe et al., 1989, Dubois and Louvet, 1996).

Most studies dealing with this anomaly use a simple Dummy Variable Approach (Gardeazabal and Regulez, 2004). According to Brooks (2008), a dummy variable is an important way to calculate day-of-the-week effects. The so called “Dummy Variable Approach” to the stock market seasonality is based on estimating a simple regression model, where each individual dummy variable accounts for the excess return for the particular day.

The original model used in the earlier studies of the day-of-the-week effect employing dummy variables was:

$$r_t = \alpha_0 + \alpha_1 D_{1t} + \alpha_2 D_{2t} + \alpha_3 D_{3t} + \alpha_4 D_{4t} + \alpha_5 D_{5t} + \varepsilon_t \quad (5)$$

where r_t is the index return series; α_0 is the intercept term; $\alpha_{1-}\alpha_4$ are unknown parameters; D_1= Monday; D_2=Tuesday; D_3=Wednesday; D_4=Thursday; D_5 =Friday; ε_t is a white noise disturbance term;

However, it is not possible to estimate the model in the above form because it contains too many dummy variables forming the perfect collinearity. The author will estimate the model with OLS methodology, and to avoid multicolinearity, the author has eliminated the fifth dummy variable representing Friday. $\alpha_{1-}\alpha_4$ are unknown parameters; represents the difference between Friday and other days.

In the first model employing dummy variables the author is using:

$$r_t=\alpha_0 + \alpha_1 D_{1t} + \alpha_2 D_{2t} + \alpha_3 D_{3t} + \alpha_4 D_{4t} + \varepsilon_t \quad (6)$$

H_0: $\alpha_1=\alpha_2= \alpha_3=\alpha_4=0$;

The second model is employing dummy variables and investigating Monday and Friday effects:

$$r_t = \alpha 0 + \alpha_1 r_{t-1} + \gamma_1^{Monday} + \gamma_2^{Friday} + \varepsilon t \quad (7)$$

Where γ_1^{Monday} = 1 if Monday; 0-otherwise; γ_2^{Friday} = 1 if Friday; 0-otherwise

H_0: $\alpha_1= \gamma_1^{Monday} = \gamma_2^{Friday} =0$;

The Dummy Variable Approach is based on estimating a simple regression model and the model is calculated based on the OLS. The t-values will be used to determine the significance of the coefficients.

There are quite a few weaknesses in the model. The main problem is again related to OLS because it ignores the time-varying volatility of returns. The author of this thesis eliminated one of the dummy variables to solve the perfect multicolinearity, but is left with the unidentified parameters of the model. Gardeazabal and Regulez (2004) claimed that the model based on the Dummy Variable Approach is unspecified, and leaves the risk factors out of the equation, while the OLS estimator of the parameters remains consistent. According to Gardeazabal and Regulez (2004), the model leaves too much variability of stock returns unexplained and the problem increases with sample frequency and inference on daily seasonality, which leads to weak or null evidence of seasonality.

6.2. Econometric results

In this section, the author of this thesis presents the empirical results from the models estimated, as well as confirms or rejects the thesis null hypothesis. The author chose to analyze two time periods in the first and second models. To obtain insight into the overall situation of the market, the author chose the entire period from 2000 to 2014 as the first period. The second period was the sub-period from 2010 to 2014, which the author analyzed to obtain a view of how the situation developed over the last few years.

6.2.1. An Autoregressive model AR(n).

The author applied an Autoregressive model of order n to determine if a non-zero significant relationship between the current return series and the past return series existed. In other words, by estimating this model, the author would attempt to determine if the historical returns could help with predicting future returns.

The author selected the amount of lags by the type of data. The author selected five lags on daily data, three lags on weekly data, and two lags on monthly data. In Table 6.1, one can see the AR(5) autoregressive model on daily data for the entire period from 2000 to 2014 and for the sub-period from 2010 to 2014. The AR(3) model on weekly data and AR(2) model on monthly data for both periods of time can be found in Table B.1 and B.2, respectively, in Appendix B. The AR(5) model equation:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_1 r_{t-2} + \alpha_1 r_{t-3} + \alpha_1 r_{t-4} + \alpha_n r_{t-5} + \varepsilon_t$$

H_0: $\alpha_1 = \alpha_2 = \ldots \ldots = \alpha_N = 0$; $\varepsilon_t \sim N(0, \sigma^2)$

The null hypothesis means that there are no "memory" in the data which leads us to the first alternative hypothesis for this thesis, implied that there was possible to predict future returns from looking at historical data. The estimation results of this model can be found in Table 6.1. The author used t-values to evaluate the results.

Table 6.1. Estimation results of the model AR(5) on daily data for different periods.

	2000-2014							2010-2014						
Index	α_0	α_1	α_2	α_3	α_4	α_5	R^2, %	α_0	α_1	α_2	α_3	α_4	α_5	R^2, %
OMXBBGI	0,00 **(2,03)**	0,15 **(8,96)**	0,04 **(2,13)**	0,03 **(1,78)**	0,03 **(1,90)**	0,02 (1,46)	2,81	0,00 **(1,83)**	0,07 **(2,31)**	0,03 (0,99)	0,04 (1,26)	0,01 (0,50)	0,00 (-0,13)	0,36
OMXT	0,00 **(1,91)**	0,14 **(8,49)**	0,03 **(2,07)**	0,02 (1,37)	0,01 (0,81)	0,02 (1,45)	2,32	0,00 (1,54)	0,09 **(2,98)**	0,02 (0,53)	0,01 (0,37)	0,00 (0,04)	0,00 (0,06)	0,41
OMXR	0,00 (1,50)	0,03 **(2,12)**	0,11 **(6,87)**	0,02 (1,20)	-0,09 **(-5,25)**	-0,02 (-1,51)	1,93	0,00 (1,42)	-0,17 **(-5,84)**	0,02 (0,56)	0,03 (0,84))	-0,01 (-0,38)	0,01 (0,43)	2,74
OMXV	0,00 **(1,78)**	0,13 **(7,91)**	0,04 **(2,34)**	0,03 **(2,07)**	0,03 **(2,03)**	-0,01 -(0,31)	2,24	0,00 **(1,66)**	0,05 **(1,82)**	0,04 (1,29)	0,03 (0,97)	0,01 (0,40)	-0,01 (-0,33)	0,16
OMXB10	0,00 (0,39)	0,15 **(9,34)**	0,04 **(2,30)**	0,04 **(2,34)**	0,00 (0,28)	0,02 (0,98)	2,91	0,00 (0,74)	0,12 **(4,16)**	0,01 (0,50)	0,02 (0,80)	-0,01 (-0,42)	0,00 (-0,07)	1,22
B1000GI	0,00 (0,05)	-0,11 **(-6,83)**	0,00 (0,17)	-0,04 **(-2,39)**	-0,02 (-1,31)	0,04 **(2,42)**	1,50	0,00 (0,88)	-0,23 **(-7,74)**	-0,08 **(-2,75)**	-0,12 **(-4,20)**	-0,13 **(-4,31)**	0,00 (0,12)	6,35
B2000GI	0,00 (0,43)	0,04 **(2,49)**	0,07 **(3,97)**	0,04 **(2,18)**	0,03 **(2,09)**	0,04 **(2,70)**	1,11	0,00 (-0,06)	-0,05 (-1,58)	0,06 **(2,16)**	-0,01 (-0,34)	0,03 (1,18)	0,00 (0,15)	0,40
B3000GI	0,00 **(2,39)**	0,08 **(4,63)**	0,00 (-0,27)	0,05 **(3,18)**	0,06 **3,75)**	0,04 **(2,22)**	1,41	0,00 **(2,95)**	0,04 (1,26)	-0,05 **(-1,69)**	0,02 (0,78)	0,00 (0,12)	0,04 (1,20)	0,10
B4000GI	0,00 **(2,83)**	-0,02 (-1,26)	0,00 (0,23)	0,01 (0,83)	0,00 (-0,07)	0,03 **(1,77)**	0,01	0,00 **(2,33)**	-0,06 **(-2,11)**	0,04 (1,47)	0,01 (0,49)	0,00 (0,04)	0,05 **(1,65)**	0,43
B5000GI	0,00 **(2,24)**	-0,07 **(-4,02)**	0,01 (0,78)	-0,02 (-0,99)	0,02 (0,99)	-0,01 (-0,42)	0,41	0,00 (1,52)	0,00 (-0,17)	-0,07 **(-2,50)**	0,04 (1,36)	-0,01 (-0,19)	0,04 (1,49)	0,43
B6000GI	0,00 **(1,55)**	0,05 **(3,12)**	0,05 **(3,19)**	0,01 (0,80)	0,02 (1,42)	0,01 (0,49)	0,56	0,00 **(2,68)**	0,09 **(2,98)**	-0,04 (-1,41)	0,03 (0,97)	0,04 (1,47)	-0,02 (-0,85)	0,77
B7000GI	0,00 **(2,79)**	0,01 (0,68)	0,04 **(2,19)**	0,03 (1,63)	-0,01 (-0,81)	-0,04 **(-2,39)**	0,24	0,00 **(2,23)**	-0,06 **(-1,92)**	0,00 (-0,10)	0,00 (-0,17)	-0,04 (-1,24)	-0,07 **(-2,25)**	0,40
B8000GI	0,00 (0,52)	0,08 **(4,96)**	0,03 **(1,81)**	0,03 (1,63)	0,05 **(3,08)**	0,01 (0,87)	1,14	0,00 (-0,62)	-0,01 (-0,19)	0,03 (1,11)	0,00 (-0,04)	0,04 (1,31)	0,02 (0,54)	- 0,14

Source: Compiled by the author
( ) = t-values
Bold types = Significant at 5% level

As can be seen in Table 6.1, in the first lag, the alphas were significant in 11 of 13 indices. In the second lag, eight of 13 coefficients were significant. In the third and fourth lags, six coefficients of the 13 indices remained significant. The situation in the sub-period from

January 2010 to August 2014 was slightly different, but still with a very high number of the significant coefficients. Nine of the 13 indices were significant in the first lag and four were significant in the second lag. This shows that the situation had slightly changed and the market had become less serial correlated over the last few years. R^2 was under 3% for the first period and between -0,14% and 6,3% for the second period, which was very low and meant that the nominator and denominator were close to each other and the model failed to capture patterns.

The results of the Autoregressive model of order 2, AR(2) for weekly data and order 3, AR(2) for monthly data, which can be found in Tables B.1 and B.2 respectively, in Appendix B on pages 66 and 67 shows overall significance for the 5% significance level for both models in both time periods. In the first lag, there were significant results in all coefficients for weekly and 12 of 13 for monthly returns data. The second lag had six significant coefficients in weekly data and two in monthly data. The overall results for the sub-period were significant, with 12 and 11 significant coefficients in weekly and monthly data, respectively. R^2 for the weekly and monthly data were much higher than those seen in monthly data, indicating greater explanatory power with less noise in the data.

The results between the main indices were quite similar to each other, with from 2 to 4 significant lags in the entire period, but only the first lag of the sub-period was significant. One interesting finding was that the t-values for the OMXBBGI and OMXB10 changed from positive in the first period to negative in the last lag of the second period in daily, weekly, and monthly data. The results of the industry indices varied from just one to all five lags being significant, and had a greater variation than the main indices.

Thus, the author could clearly reject the null hypothesis and confirm the alternative hypothesis, stating that it was possible to predict future returns from historical data. The results showed no evidence of the weak form of market efficiency in daily, weekly, or monthly data, or in the different time periods.

6.2.2. Granger Causality and an Autoregressive Distributed Lag model ADL(n,q).

As can be seen in Table A.1 in Appendix A on page 64, the countries are moderately or strongly correlated, but do they also Granger cause each other? To answer this question, the author employed the ADL(n,q) model to determine the granger causality between the Vilnius stock exchange (VSE), Riga stock exchange (RSE), and Tallinn stock exchange (TSE).

ADL(1,1) model on all-Share indices of VSE, TSE and RSE on daily, weekly and monthly data:

$r_t^{VSE}=\alpha_0+\alpha_1 r^{VSE}{}_{t-1}+\beta 1 r^{TSE}{}_{t-1}+\gamma 1 r^{RSE}{}_{t-1}+\varepsilon_t$

$r_t^{RSE}=\alpha_0+\alpha_1 r^{RSE}{}_{t-1}+\beta 1 r^{TSE}{}_{t-1}+\gamma 1 r^{VSE}{}_{t-1}+\varepsilon_t$

$r_t^{TSE}=\alpha_0+\alpha_1 r^{TSE}{}_{t-1}+\beta 1 r^{RSE}{}_{t-1}+\gamma 1 r^{VSE}{}_{t-1}+\varepsilon_t$

H_0: $\alpha i=0$; $\beta i=0$; $\gamma i=0\ldots\ \forall i > 1$

The null hypothesis means that there are no Granger causality, which leads to the second alternative hypothesis: there are Granger causality between the VSE, RSE, and TSE markets. The estimation results of this model can be found in Table 6.2. The author used t-values to evaluate the results.

Table 6.2. Estimation results of the model ADL(1,1) on daily, weekly and monthly indices' returns for the whole period.

	Data	**α_0**	**α_1 VSE**	**β_1 TSE**	**γ_1 RSE**	**R^2, %**
Vilnius Stock Exchange	**Daily**	0,00 **(1,89)**	0,10 **(5,36)**	0,09 **(4,96)**	0,00 (-0,10)	2,50
	Weekly	0,00 (1,29)	0,33 **(7,54)**	0,09 **(2,10)**	0,03 (1,13)	16,42
	Monthly	0,00 (1,02)	0,47 **(4,16)**	0,04 (0,31)	-0,05 (-0,62)	21,23
Riga Stock Exchange	**Data**	**α_0**	**α_1 RSE**	**β_1 TSE**	**γ_1 VSE**	**R^2, %**
	Daily	0,00 (1,28)	0,01 (0,85)	0,06 **(2,54)**	0,09 **(3,64)**	0,97
	Weekly	0,00 (1,11)	0,08 **(1,94)**	0,07 (1,27)	0,17 **(3,00)**	4,58
	Monthly	0,01 (1,10)	-0,14 (-1,55)	0,21 (1,56)	0,17 (1,35)	6,70
Tallinn Stock Exchange	**Data**	**α_0**	**α_1 TSE**	**β_1 RSE**	**γ_1 VSE**	**R^2, %**
	Daily	0,00 **(2,07)**	0,13 **(7,09)**	0,00 (-0,23)	0,04 **(2,21)**	2,22
	Weekly	0,00 (1,57)	0,26 **(5,97)**	0,01 (0,18)	0,15 **(3,24)**	13,46
	Monthly	0,01 (1,25)	0,32 **(2,80)**	-0,15 **(-2,02)**	0,22 **(2,01)**	19,36

Source: Compiled by the author
( ) = t-values
Bold types = Significant at 5% level

As can be seen in Table 6.2, the ADL(1,1) test resulted in Granger causality for Lithuanian and Estonian stock price indexes. Granger causality ran both ways and was significant at a 5% significance level. A single-direction relationship was common for Latvian and Lithuanian markets where RSE did not Granger cause VSE and VSE did Granger cause RSE. Apparently, the Lithuanian stock index has a strong influence on both Latvian and Estonian stock markets, whereas Latvian and Estonian stock market only has some influence on each other.

These results differ in the sub-period of the last four years (Table B.3 in Appendix B on page 68), where neither Lithuania nor Estonian stock markets Granger causes each other anymore. The relationship between Estonian and Latvian financial stock markets is significant during the period from 2000-2014, although in the second period the Latvian stock index does not Granger cause the Estonian stock index anymore.

The results can be compared with those of similar studies conducted to capture Granger causality. Dubinskas and Stunguriene (2010) found that VSE index was mostly influenced by RSE. No causality was established between the Latvian and Estonian capital markets. Kazukauskas (2011) found that VSE Granger causes TSE through a one-way relationship and no causality was found between the other two markets. Hegerty (2012) found that Estonia influenced Lithuania. One interesting element of these findings was that they were so different from each other. The current author’s findings were different from these three studies. However, they were similar in that in the second period, the current author also only found a one-way relationship in the data. However, when discussing the period from 2000 to 2014, De Gooijerb et al. (2007) found similar results and found that Riga and Tallinn were both dependent on one or more of the other Baltic countries, whereas Vilnius remained uninfluenced.

Despite the last years that depicted a very low Granger causality, it is still significant evidence for rejecting the null hypothesis and confirming alternative hypothesis that there are Granger causality in the VSE, RSE, and TSE markets. Brännäsa et al. (2007) discussed the reasons for this kind of relationship between the Baltic markets and pointed out that markets were closely related because of their geographical location, common institutional setup, and the same market markers.

6.2.3. Day-of-the-week effects and Dummy Variable Approach

In this section of the thesis, the author discusses the analysis of the day-of-the-week effect in the Baltic Stock market by using the Dummy Variable Approach and reviewing the results of the descriptive statistics for different days. In Table 6.3, one can find the descriptive statistics for the different weekdays of the main indices. In Figure 6.1, one can see the dynamics of the returns of the main indices.

Table 6.3. Descriptive statistics of main indices on days of the week for the whole time period**.**

Parameters		OMXBBGI	OMXT	OMXR	OMXV	OMXB10
Monday	Annual returs, %	-1,2	4,4	-23,6	-6,1	-16,4
	Annual σ, %	18,2	20,2	23,7	19,2	23,0
	Skewness	0,70	1,36	-0,98	-0,03	1,14
	Excess Kurtosis	14,06	17,20	12,20	23,04	28,71
Tuesday	Annual returs, %	12,7	7,8	9,6	2,8	-1,1
	Annualized σ, %	15,9	17,6	21,8	18,0	17,8
	Skewness	-0,52	-0,35	-0,06	0,47	-0,59
	Excess Kurtosis	6,66	4,26	8,82	11,06	7,57
Wednesday	Annual returs, %	18,2	22,1	15,6	14,7	12,1
	Annual σ, %	15,7	17,5	22,6	15,8	17,3
	Skewness	-0,58	0,14	-0,12	-0,66	-0,59
	Excess Kurtosis	10,71	5,10	12,39	9,48	10,99
Thursday	Annual returs, %	13,9	10,1	29,0	20,3	9,7
	Annual σ, %	15,5	17,9	24,3	17,3	17,8
	Skewness	0,08	-0,04	0,17	-0,25	0,34
	Excess Kurtosis	10,59	5,87	19,15	33,52	13,02
Friday	Annual returs, %	19,6	21,4	31,2	27,1	17,0
	Annual σ, %	15,1	17,8	23,7	15,1	16,7
	Skewness	-0,45	0,02	-0,26	-0,71	-0,57
	Excess Kurtosis	9,12	7,68	16,00	8,03	9,22

Source: Compiled by the author
N= approx. 740 weeks

As can be seen in Figure 6.1 and Table 6.3, almost all average returns were negative on Mondays, except for OMXT, which had 4,4% average return. OMXR had the lowest returns: minus 23,6%. Standard deviations were also higher on Mondays. As can be seen in Table 6.3, skewness was mainly positive on Mondays. This meant that the tail of the distribution was elongated to the right and there were more outliers to the right of the mean. Practically, it meant less risk in having a long position on Mondays than a short position. On other days, the skewness was negative, indicating that the risk for short positions was lower. In the data for this thesis, excess kurtosis was positive and significantly higher than zero on all weekdays, indicating leptokurtic distribution, meaning that there were more observations in the middle with a peak extended above the normal distribution and a greater percentage of both small and large deviations from the mean, leading to fatter and longer tails than with a normal distribution.

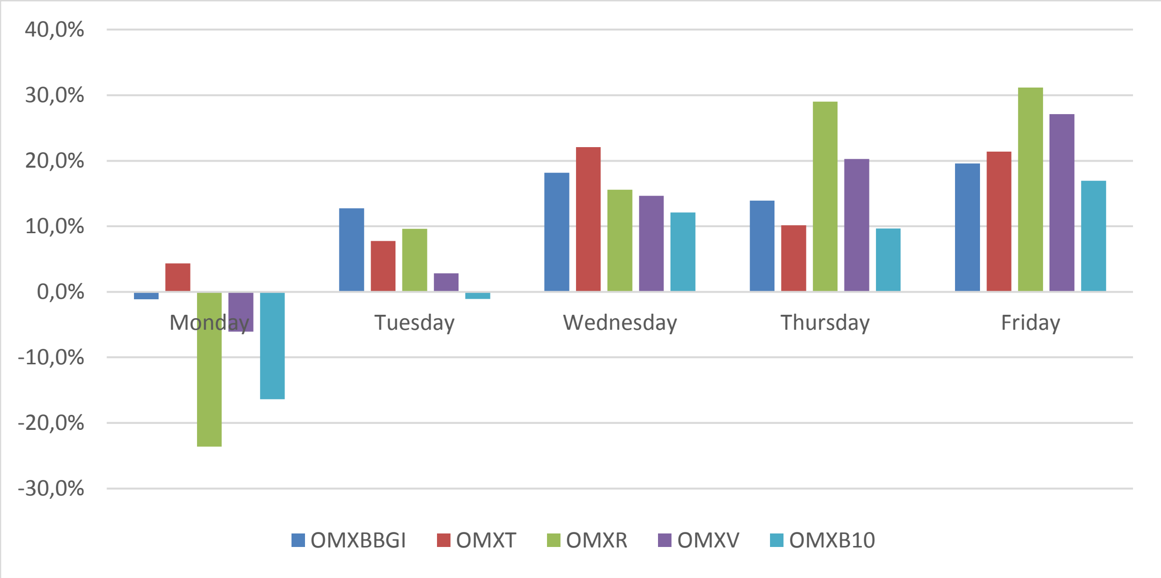

Figure 6.1. Annualized returns of main indices for the day of the week for the whole period (%)

Source: Compiled by the author

In Table A.2 in Appendix A on page 65 one can find the descriptive statistics for the different weekdays of industry indices. In Figure 6.2, one can see the dynamics of returns for the industry indices. As can be seen in the Table and in the graph, returns differed from those seen in the main indices presented in Table 6.3 and Figure 6.1. They became more extreme and did not follow the same clear pattern as in the main indices. Returns varied from minus 33,9% to plus 16,6% on Mondays and from 12,1% to 54,8% on Fridays. Standard deviations were quite stable during the weekdays and did not have a clear pattern. Interestingly, skewness was in the opposite direction. It was both positive and negative on Mondays, but mainly positive on other days. Excess kurtosis was also positive for all the indices on all days, but the levels of extremes varied from 2,7 to 175,25.

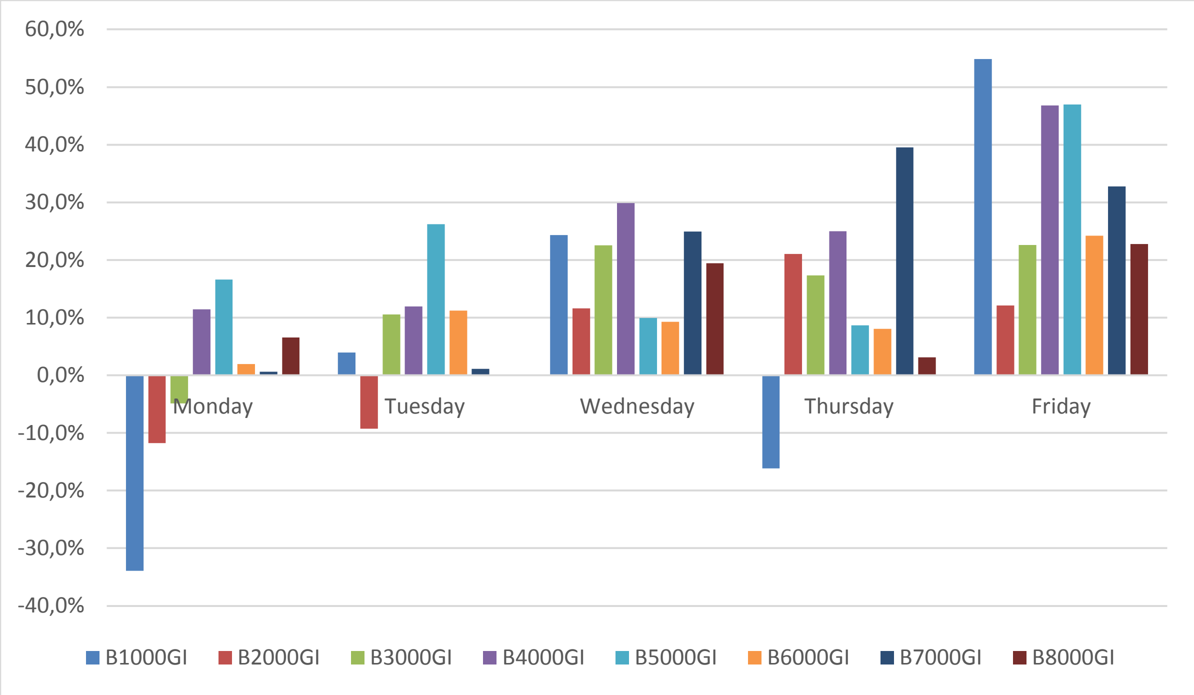

Figure 6.2. Annualized returns of industry indices for the day of the week for the whole period (%)

Source: Compiled by the author

The author later applied the models based on the Dummy Variable Approach. The first model focused on the Dummy Variable Approach on weekdays:

$$r_t = \alpha_0 + \alpha_1 D_{1t} + \alpha_2 D_{2t} + \alpha_3 D_{3t} + \alpha_4 D_{4t} + \varepsilon_t$$

where D_1= 1 if Monday; 0- otherwise; D_2= 1 if Tuesday; 0- otherwise; D_3= 1 if Wednesday; 0- otherwise; D_4= 1 if Thursday; 0- otherwise.

H_0: $\alpha_1=\alpha_2=\alpha_3=\alpha_4=0$;

Null hypothesis mean that returns are the same every day which represents the third alternative hypothesis for this thesis: there are day-of-the week effects in the data. Since the author eliminated the fifth dummy variable to avoid perfect collinearity, the returns of the other days were represented by Friday.

Table 6.4. Estimation results of the Dummy Variable Approach on day-of-the-week effects for the whole time period

Indices	α0	α1 (Monday)	α2 (Tuesday)	α3 (Wednesday)	α4 (Thursday)
OMXBBGI	0,0007 **(2,00)**	-0,0009 (-1,62)	-0,0003 (-0,54)	-0,0001 (-0,12)	-0,0002 (-0,44)
OMXT	0,0008 **(1,87)**	-0,0007 (-1,15)	-0,0005 (-0,90)	0,0000 (0,07)	-0,0004 (-0,74)
OMXR	0,0011 **(2,09)**	-0,0022 **(-2,86)**	-0,0008 (-1,09)	-0,0006 (-0,79)	-0,0001 (-0,11)
OMXV	0,0010 **(2,64)**	-0,0014 **(-2,42)**	-0,0010 **(-1,78)**	-0,0005 (-0,91)	-0,0003 (-0,52)
OMXB10	0,0006 (1,47)	-0,0014 **(-2,28)**	-0,0007 (-1,21)	-0,0002 (-0,34)	-0,0003 (-0,50)
B1000GI	0,0019 **(2,33)**	-0,0036 **(-3,05)**	-0,0020 **(-1,74)**	-0,0012 (-1,01)	-0,0028 **(-2,41)**
B2000GI	0,0004 (0,77)	-0,0009 (-1,36)	-0,0008 (-1,21)	0,0000 (0,01)	0,0004 (0,56)
B3000GI	0,0008 **(2,26)**	-0,0011 **(-2,07)**	-0,0005 (-0,87)	0,0000 (0,06)	-0,0002 (-0,34)
B4000GI	0,0017 **(2,67)**	-0,0014 (-1,54)	-0,0015 (-1,62)	-0,0007 (-0,73)	-0,0008 (-0,92)
B5000GI	0,0017 **(2,35)**	-0,0012 (-1,22)	-0,0008 (-0,79)	-0,0015 (-1,45)	-0,0015 (-1,50)
B6000GI	0,0009 **(1,97)**	-0,0009 (-1,44)	-0,0005 (-0,79)	-0,0006 (-0,93)	-0,0006 (-0,99)
B7000GI	0,0012 **(2,21)**	-0,0013 **(-1,66)**	-0,0013 **(-1,67)**	-0,0003 (-0,35)	0,0003 (0,42)
B8000GI	0,0008 (1,08)	-0,0007 (-0,68)	-0,0010 (-0,93)	-0,0002 (-0,16)	-0,0010 (-1,00)

Source: Compiled by the author
( ) = t-values
Bold types = Significant at 5% level

In Table 6.4, one can see the Monday effect with 6 of 13 significant coefficients on Mondays. The Monday effect continued on Tuesday, with 3 significant coefficients. Wednesday did not have any significant coefficients and Thursday had only one. In Table B.4 in Appendix B on page 69, one can find the empirical results of the model, which the author used to examine the Monday and Friday effects closer. There one can again see the Monday effect for 5 of 13 indices. The Friday effect did not seem to exist for this data.

When looking at indices separately in Table 6.4 and B.4 (Appendix B), one will find variation between the indices. The OMXBBGI index had no significant day-of-the-week effects in the first model, but showed significance on Monday in the second model. OMXT had no significant day-of-the-week effects. OMXR and OMXB10 were significant on Mondays in both models. OMXV had significant Monday and Tuesday effect in the first model and only for Mondays in the second model. The B1000GI index was significant on Mondays, Tuesdays, and Thursdays in the first model, and for Fridays in the second model. B2000GI, B4000GI, B5000GI, B6000GI, and B8000GI had no significant day-of-the-week effects in any of the tests. The B3000GI index had significant Monday effect in both models and the B7000GI index had significant Monday effect in the first model.

The results can be compared with similar studies on the Baltic market such as Avdejev and Kvekšas (2007), Macijauskas (2010), and Sakalauskas and Kriksciuniene (2012), which also detected the Monday effect in their studies. They have also detected Friday effect, which was not captured in this thesis.

Despite some indices not experiencing significant day-of-the-week effects in the data, the majority of indices experienced the Monday effect in the first or second model, providing the author with reason to reject the null hypothesis and confirm the alternative hypothesis that there are day-of-the-week effects in the data.

6.2.4. Results overview

We have now seen the results of all the models in the three sections above. In this section, the author compares the results of all models used in this thesis to obtain a clear picture of how the indices differed from each other. The results are presented in Table 6.5, below.

Table 6.5. Results overview in relation to the hypotheses

Index name	**H1**: "Memory" in the data?		**H2**: Granger caused?		**H3**: Day-of-the-week effect?	
	2000-2014	**2010-2014**	**2000-2014**	**2010-2014**	**Monday**	**Other day?**
OMXBBGI	**Yes**	**Yes**	-	-	**Yes**	No
OMXT	**Yes**	**Yes**	**Yes** by both	No	No	No
OMXR	**Yes**	**Yes**	**Yes** by both	**Yes** by VSE	**Yes**	No
OMXV	**Yes**	**Yes**	**Yes** by TSE	No	**Yes**	**Yes** T
OMXB10	**Yes**	**Yes**	-	-	**Yes**	No
B1000GI (Basic Materials)	**Yes**	**Yes**	-	-	**Yes**	**Yes** T TH F
B2000GI (Industrials)	**Yes**	**Yes**	-	-	No	No
B3000GI (Consumer Goods)	**Yes**	**Yes**	-	-	**Yes**	No
B4000GI (Health Care)	**Yes**	**Yes**	-	-	No	No
B5000GI (Consumer Services)	**Yes**	**Yes**	-	-	No	No
B6000GI (Telecommunications)	**Yes**	**Yes**	-	-	No	No
B7000GI (Utilities)	**Yes**	**Yes**	-	-	**Yes**	**Yes** T
B8000GI (Financials)	**Yes**	**Yes**	-	-	No	No

Source: Compiled by the author
T – Tuesday; TH-Thursday; F – Friday

As can be seen in Table 6.5, all the indices had "memory" in the data in both periods. Granger causality was much stronger in the first period than the second one. The three Baltic exchanges varied in their results. Tallinn stock exchange seemed to be the most efficient of the three Baltic countries, with no causality in the second period and no day-of-the-week effects. Vilnius stock exchange can be considered to be the second most efficient, with no causality in the second period and only caused by the TSE in the first period. Riga stock exchange had a significant Monday effect and was caused by both markets in the first period and caused by VSE in the second period.

The Benchmark index (OMXBBGI) and the index for the 10 most liquid stocks (OMXB10) had similar results with Monday effect in both indices. The author expected the tradable index to have better results than the other indices due to higher liquidity but this has proven not to be the case in this study. Among the industry indices, the greatest amount of anomalies were found in the indices for basic materials (B1000GI), consumer goods (B3000GI), and utilities (B7000GI).

Looking at the results from the research done in this thesis we can conclude that all three of the alternative hypotheses are confirmed. It is possible to predict future returns from looking at and analyzing historical data, Granger causality was and is still present in the stock exchanges for all three Baltic countries (VSE, RSE, TSE) and the markets do have clear day-of-the-week effects. All these confirmations leads to a rejection of the null hypothesis, and confirming that the Baltic markets does not have a weak form of efficiency.

CONCLUSIONS

EMH has become a very important part of finance. Many have tried to find anomalies in data that confirm or reject the theory, but the theory itself has become a great tool to help investors and portfolio managers find sound strategies in different types of markets. In the inception phase of the theory, it was criticized for being too theoretical, but over the past decades, a lot of work has been done to make the theory more practical in use. The purpose of this thesis was to analyze the Baltic stock market indices and determine if the market has reached the weak form of efficiency.

In this thesis, the author used daily, weekly and monthly returns of the 13 Baltic indices: Benchmark index, all-share indices of Lithuania, Latvia, and Estonia, index of the 10 most liquid stocks, and eight main industries' indices. The author chose the entire period from January 2000 to August 2014 to obtain insight into the overall situation of the market, and a sub-period from January 2010 to August 2014 to obtain a view of how the situation has developed over the last few years.

The author stated the null hypothesis "the Baltic stock market has a weak form of efficiency" and three alternative hypotheses in this thesis.

Hypothesis 1: It is possible to predict future returns from the historical data.

Hypothesis 2: The Granger causality is present in the Lithuanian, Latvian and Estonian markets.

Hypothesis 3: The Baltic market do have day-of-the-week effects.

To test the null hypothesis, the author chose three models to determine if there is evidence to reject or confirm this hypothesis. The three models used were the Autoregressive model (AR), the Autoregressive Distribution Lag model (ADL), and the Dummy Variable Approach. The AR model has been applied on all 13 indices to test for "memory" in the data. The ADL model has been used to test for Granger causality on the Lithuanian, Latvian, and Estonian stock markets. A Dummy Variable Approach method has been used to test for a day-of-the-week effect.

The author has found significant autoregressive behavior and “memory” in the data for the entire 14-year period, which has remained significant for the last four years as well. This led us to confirm the first alternative hypothesis.

The author also found evidence of Granger causality on all the three stock exchanges in the Baltics. In the entire period of 14 years, the Lithuanian stock market Granger causes both the Estonian and Latvian stock markets, the Estonian market Granger causes both the Latvian and Lithuanian stock markets, and the Latvian market Granger causes the Estonian stock market. The last four years have been totally different in terms of this relationship and only the Estonian stock market Granger caused the Latvian stock market in this time period. The second alternative hypothesis can therefore be confirmed.

The author also found clear Monday effect anomalies slightly continuing into Tuesday in the Baltic stock market, where seven of the 13 indices analyzed had significant coefficients on Mondays. The Friday effect was not confirmed. This means that the third alternative hypothesis could be confirmed.

The three stock exchanges in the Baltics had a similar market efficiency but Tallinn stock exchange seemed to be the most efficient of the three Baltic countries, Vilnius stock exchange came as the second one and Riga stock exchange was least efficient. The tradable index of the most liquid stocks had the same results as the Baltic benchmark index failing the authors’ expectations for this index to have better results due to higher liquidity.

In summary, all three of the alternative hypotheses have been confirmed in this thesis, and the null hypothesis stating that the Baltic stock market has reached the weak form of efficiency can definitely be rejected leading to the conclusion that the Baltic market is inefficient.

FURTHER RESEARCH

Efficiency in the Baltic markets still has several blank areas and should be further analyzed by researchers.

The Baltic bond market should be analyzed more, even though the trading activity in the bond market is still low. There are also research gaps regarding future contracts in the Baltics. There is only one index in the Baltics which is tradable and has future contracts on it, but it was not created until 2007. Because of late start and lack of information regarding returns, it has not been covered by analysts.

Other further research suggestions would be to expand the study by geography and do more econometric tests that could be used to capture more anomalies. The current author also found the lack of depth in studies whose authors analyzed the reasons for why markets are inefficient.

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APPENDICES

APPENDIX A. STATISTICS OF THE INDICES

Table A.1. Correlation between the main indices in different periods.

2000-2014	*OMXBBGI*	*OMXT*	*OMXR*	*OMXV*	*OMXB10*
OMXBBGI	1				
OMXT	**0,95**	1			
OMXR	**0,46**	0,34	1		
OMXV	**0,75**	**0,62**	0,36	1	
OMXB10	**0,92**	**0,86**	**0,49**	0,77	1
2000-2006	*OMXBBGI*	*OMXT*	*OMXR*	*OMXV*	*OMXB10*
OMXBBGI	1				
OMXT	**0,94**	1			
OMXR	0,33	0,19	1		
OMXV	**0,51**	0,38	0,21	1	
OMXB10	**0,85**	**0,72**	**0,51**	**0,63**	1
2007-2009	*OMXBBGI*	*OMXT*	*OMXR*	*OMXV*	*OMXB10*
OMXBBGI	1				
OMXT	**0,95**	1			
OMXR	**0,61**	**0,48**	1		
OMXV	**0,88**	**0,79**	**0,55**	1	
OMXB10	**0,97**	**0,94**	**0,50**	**0,86**	1
2010-2014	*OMXBBGI*	*OMXT*	*OMXR*	*OMXV*	*OMXB10*
OMXBBGI	1				
OMXT	**0,95**	1			
OMXR	**0,60**	**0,49**	1		
OMXV	**0,79**	**0,65**	**0,45**	1	
OMXB10	**0,94**	**0,94**	**0,49**	**0,74**	1

Source: Compiled by the author
Bold types = Strong and moderate correlation

Table A.2. Descriptive statistics of industry indices on days of the week for the whole time period.

Parameters		B1000GI	B2000GI	B3000GI	B4000GI	B5000GI	B6000GI	B7000GI	B8000GI
Monday	Annual returs %	-33,9	-11,8	-4,9	11,4	16,6	1,9	0,6	6,6
	Annual σ %	38,2	21,7	16,4	27,5	34,1	24,1	23,0	29,9
	Skewness	-1,93	-0,03	-0,14	-0,55	3,02	6,25	0,01	0,15
	Excess Kurtosis	27,63	4,67	10,64	6,07	37,83	103,34	7,78	11,25
Tuesday	Annual returs %	4,0	-9,3	10,6	11,9	26,2	11,2	1,1	0,0
	Annual σ %	36,8	21,2	15,5	35,4	29,7	18,1	25,0	29,5
	Skewness	1,03	0,21	0,70	5,86	0,54	0,03	0,73	-0,30
	Excess Kurtosis	9,80	4,31	7,56	105,96	6,25	5,52	14,30	8,82
Wednesday	Annual returs %	24,3	11,6	22,5	29,9	9,9	9,3	24,9	19,4
	Annual σ %	33,7	20,3	14,8	26,9	30,5	19,8	21,3	27,5
	Skewness	0,44	-0,30	0,41	-0,22	-0,04	0,56	0,44	-1,00
	Excess Kurtosis	4,47	7,65	4,72	5,07	6,40	7,45	4,60	11,69
Thursday	Annual returs %	-16,2	21,1	17,3	25,0	8,7	8,0	39,6	3,1
	Annual σ %	36,1	20,0	14,6	25,2	30,7	18,1	21,7	39,1
	Skewness	0,36	-0,03	-0,09	0,33	0,99	0,50	1,12	-8,79
	Excess Kurtosis	19,46	6,87	2,97	3,67	9,83	6,79	11,80	175,25
Friday	Annual returs %	54,8	12,1	22,6	46,8	47,0	24,2	32,8	22,8
	Annual σ %	34,4	22,3	18,1	25,4	30,3	18,3	24,8	22,8
	Skewness	1,30	-2,50	2,58	0,19	0,20	-0,72	2,60	1,06
	Excess Kurtosis	10,76	33,19	40,04	2,70	6,73	8,03	37,79	11,60

Source: Compiled by the author
N= approx. 740 weeks

APPENDIX B. ESTIMATION RESULTS

Table B.1. Estimation results of the model AR(3) on weekly data for different periods.

Index	2000-2014					2010-2014				
	α_0	α_1	α_2	α_3	R^2, %	α_0	α_1	α_2	α_3	R^2, %
OMXBBGI	0,00 (1,42)	0,34 **(9,43)**	0,09 **(2,42)**	0,05 (1,47)	16,41	0,00 **(1,72)**	0,32 **(4,94)**	0,07 (1,04)	-0,10 (-1,54)	10,75
OMXT	0,00 (1,52)	0,32 **(8,85)**	0,09 **(2,29)**	0,00 (0,05)	12,84	0,00 (1,43)	0,30 **(4,58)**	0,09 (1,40)	-0,11 **(-1,73)**	9,90
OMXR	0,00 (1,19)	0,12 **(3,34)**	0,19 **(5,16)**	-0,01 (-0,24)	5,17	0,00 (1,37)	0,30 **(4,66)**	-0,04 (-0,53)	-0,04 (-0,63)	7,69
OMXV	0,00 (1,11)	0,32 **(8,84)**	0,12 **(3,24)**	0,11 **(2,96)**	18,77	0,00 (1,61)	0,29 **(4,44)**	-0,02 (-0,37)	0,00 (-0,06)	6,83
OMXB10	0,00 (0,28)	0,31 **(8,55)**	0,11 **(3,03)**	0,02 (0,42)	13,59	0,00 (0,72)	0,29 **(4,52)**	0,06 (0,84)	-0,08 (-1,27)	8,61
B1000GI	0,00 (-0,03)	0,23 **(6,20)**	0,01 (0,18)	0,03 (0,71)	4,95	0,00 (0,80)	0,06 (0,96)	0,03 (0,54)	-0,01 (-0,14)	-0,73
B2000GI	0,00 (0,42)	0,39 **(10,62)**	-0,01 (-0,23)	0,08 **(2,20)**	16,02	0,00 (-0,09)	0,30 **(4,59)**	0,15 **(2,29)**	-0,15 **(-2,42)**	11,92
B3000GI	0,00 (1,57)	0,38 **(10,58)**	0,09 **(2,24)**	0,07 **(1,98)**	20,88	0,00 **(2,59)**	0,29 **(4,51)**	0,04 (0,55)	-0,03 (-0,41)	8,10
B4000GI	0,00 **(2,10)**	0,34 **(9,41)**	0,00 (-0,06)	0,10 **(2,68)**	13,19	0,00 **(2,18)**	0,35 **(5,36)**	-0,06 (-0,87)	0,01 (0,11)	10,06
B5000GI	0,00 **(1,75)**	0,26 **(7,28)**	0,00 (-0,02)	0,10 **(2,85)**	8,18	0,00 (1,55)	0,26 **(4,06)**	0,02 (0,35)	-0,09 (-1,31)	6,48
B6000GI	0,00 (1,44)	0,28 **(7,78)**	0,01 (0,38)	0,02 (0,60)	8,13	0,00 **(2,52)**	0,27 **(4,21)**	-0,06 (-0,89)	0,04 (0,68)	5,96
B7000GI	0,00 **(2,03)**	0,23 **(6,40)**	0,05 (1,36)	0,10 **(2,83)**	7,86	0,00 **(2,04)**	0,15 **(2,24)**	0,05 (0,80)	-0,02 (-0,27)	1,36
B8000GI	0,00 (0,35)	0,42 **(11,64)**	0,00 (0,05)	0,04 (1,22)	18,69	0,00 (-0,55)	0,36 **(5,52)**	-0,12 **(-1,84)**	0,09 (1,33)	10,58

Source: Compiled by the author
( ) = t-values
Bold types = Significant at 5% level

AR(3) model used in Table B.1:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_1 r_{t-2} + \alpha_1 r_{t-3} + \varepsilon_t$$

H_0: $\alpha_1=\alpha_2=\ldots\ \ldots=\alpha_N=0$; $\varepsilon_t \sim N(0,\sigma^2)$

Table B.2. Estimation results of the model AR(2) on monthly data for different periods.

Index	2000-2014				2010-2014			
	α_0	α_1	α_2	R^2, %	α_0	α_1	α_2	R^2, %
OMXBBGI	0,01 (1,16)	0,45 **(5,88)**	-0,03 (-0,43)	18,34	0,01 **(1,66)**	0,29 **(2,08)**	-0,07 (-0,48)	4,16
OMXT	0,01 (1,28)	0,46 **(5,99)**	-0,11 (-1,44)	17,09	**0,01** (1,31)	0,35 **(2,52)**	-0,07 (-0,51)	7,67
OMXR	0,01 (1,15)	0,04 (0,59)	0,14 **(1,90)**	1,21	0,01 **(1,84)**	0,11 (0,86)	-0,31 **(-2,46)**	7,57
OMXV	0,01 (1,09)	0,52 **(6,82)**	-0,10 (-1,33)	22,33	0,01 **(1,69)**	0,35 **(2,56)**	-0,14 (-1,05)	7,81
OMXB10	0,00 (0,18)	0,37 **(4,79)**	-0,06 (-0,81)	11,32	0,00 (0,72)	0,35 **(2,52)**	-0,06 (-0,47)	7,72
B1000GI	0,00 (-0,02)	0,35 **(4,62)**	-0,04 (-0,47)	10,79	0,01 (1,12)	-0,05 (-0,40)	-0,24 **(-1,79)**	2,36
B2000GI	0,00 (0,22)	0,37 **(4,95)**	0,01 (0,16)	13,67	0,00 (-0,18)	0,26 **(1,94)**	-0,23 **(-1,76)**	6,27
B3000GI	0,01 (1,39)	0,44 **(5,72)**	-0,01 (-0,15)	17,97	0,01 **(2,08)**	0,37 **(2,64)**	-0,02 (-0,14)	9,62
B4000GI	0,01 **(1,82)**	0,54 **(7,01)**	-0,09 (-1,18)	24,01	0,02 **(2,22)**	0,43 **(3,19)**	-0,24 **(-1,89)**	14,10
B5000GI	0,01 (1,49)	0,45 **(5,89)**	-0,09 (-1,17)	16,87	0,01 (1,33)	0,40 **(2,87)**	-0,06 (-0,44)	11,06
B6000GI	0,01 (1,24)	0,37 **(4,97)**	-0,16 **(-2,14)**	11,84	0,01 **(2,66)**	0,29 **(2,05)**	-0,15 (-1,08)	4,39
B7000GI	0,01 **(1,73)**	0,46 **(5,96)**	-0,03 (-0,36)	18,98	0,01 **(2,11)**	0,26 **(1,91)**	-0,11 (-0,81)	3,08
B8000GI	0,00 (0,29)	0,45 **(5,95)**	-0,11 (-1,51)	16,76	-0,01 (-0,50)	0,37 **(2,67)**	-0,07 (-0,52)	8,99

Source: Compiled by the author
( ) = t-values
Bold types = Significant at 5% level

AR(2) model used in Table B.2:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_1 r_{t-2} + \varepsilon_t$$

H_0: $\alpha_1=\alpha_2=\ldots\ \ldots=\alpha_N=0$; $\varepsilon_t \sim N(0,\sigma^2)$

Table B.3. Estimation results of the model ADL(1,1) on daily, weekly and monthly indices' returns (2010-2014)

	Data	α_0	α_1 VSE	β_1 TSE	γ_1 RSE	R^2, %
Vilnius Stock Exchange	**Daily**	0,00 **(1,75)**	0,03 (0,93)	0,02 (0,78)	0,04 (1,45)	0,34
	Weekly	0,00 (1,58)	0,27 **(3,25)**	0,02 (0,25)	-0,01 (-0,17)	6,80
	Monthly	0,01 (1,50)	0,25 (1,34)	0,03 (0,22)	0,03 (0,17)	4,28
Riga Stock Exchange	**Data**	**α_0**	**α_1 VSE**	**β_1 TSE**	**γ_1 VSE**	**R^2, %**
	Daily	0,00 (1,27)	-0,21 **-6,99)**	0,10 **(2,85)**	0,05 (1,24)	4,26
	Weekly	0,00 (1,07)	0,22 **(2,97)**	0,09 (1,31)	0,04 (0,51)	8,83
	Monthly	0,01 (1,61)	0,17 (0,94)	-0,03 (-0,17)	-0,13 (-0,67)	-3,43
Tallinn Stock Exchange	**Data**	**α_0**	**α_1 TSE**	**β_1 RSE**	**γ_1 VSE**	**R^2, %**
	Daily	0,00 (1,54)	0,06 **(1,75)**	0,02 (0,79)	0,05 (1,17)	0,73
	Weekly	0,00 (1,25)	0,23 **(2,71)**	0,07 (0,75)	0,10 (0,92)	9,07
	Monthly	0,01 (1,23)	0,39 **(1,87)**	-0,28 (-1,26)	0,15 (0,60)	8,56

Source: Compiled by the author

( ) = t-values

Bold types = Significant at 5% level

ADL(1,1) models on all-Share indices of Vilnius, Tallinn and Riga on daily, weekly and monthly data used in Table B.3.

$$r_t^{VSE}=\alpha_0+\alpha_1 r^{VSE}{}_{t-1}+\beta 1 r^{TSE}{}_{t-1}+\gamma 1 r^{RSE}{}_{t-1}+\varepsilon_t$$

$$r_t^{RSE}=\alpha_0+\alpha_1 r^{RSE}{}_{t-1}+\beta 1 r^{TSE}{}_{t-1}+\gamma 1 r^{VSE}{}_{t-1}+\varepsilon_t$$

$$r_t^{TSE}=\alpha_0+\alpha_1 r^{TSE}{}_{t-1}+\beta 1 r^{RSE}{}_{t-1}+\gamma 1 r^{VSE}{}_{t-1}+\varepsilon_t$$

H_0: $\alpha i=0$; $\beta i=0$; $\gamma i=0\ldots\ \forall i > 1$

Table B.4. Estimation results of the Dummy Variable Approach on Monday and Friday effects for the whole time period

	α0	α_1	γ_1^{Monday}	γ_2^{Friday}
	0,0005	0,1582	-0,0007	0,0002
OMXBBGI	**(2,35)**	**(9,78)**	**(-1,72)**	(0,39)
	0,0004	0,1474	-0,0004	0,0003
OMXT	**(1,72)**	**(9,10)**	(-0,89)	(0,69)
	0,0006	0,0417	-0,0017	0,0005
OMXR	**(1,95)**	**(2,55)**	**(-2,74)**	(0,78)
	0,0004	0,1394	-0,0009	0,0005
OMXV	**(1,89)**	**(8,59)**	**(-1,94)**	(1,12)
	0,0002	0,1639	-0,0011	0,0003
OMXB10	(0,98)	**(10,15)**	**(-2,22)**	(0,67)
	-0,0001	-0,1114	-0,0013	0,0020
B1000GI	(-0,25)	**(-6,84)**	(-1,39)	**(2,08)**
	0,0002	0,0523	-0,0008	0,0001
B2000GI	(0,86)	**(3,20)**	(-1,45)	(0,17)
	0,0006	0,0838	-0,0009	0,0002
B3000GI	**(2,85)**	**(5,14)**	**(-2,17)**	(0,44)
	0,0007	-0,0206	-0,0004	0,0010
B4000GI	**(1,97)**	(-1,26)	(-0,53)	(1,37)
	0,0005	-0,0665	0,0001	0,0012
B5000GI	(1,13)	**(-4,07)**	(0,10)	(1,50)
	0,0003	0,0566	-0,0004	0,0006
B6000GI	(1,13)	**(3,46)**	(-0,72)	(1,14)
	0,0008	0,0126	-0,0009	0,0004
B7000GI	**(2,48)**	(0,77)	(-1,39)	(0,66)
	0,0001	0,0881	-0,0001	0,0008
B8000GI	(0,14)	**(5,40)**	(-0,07)	(0,90)

Source: Compiled by the author
( ) = t-values
Bold types = Significant at 5% level

Dummy Variable Approach to test the Monday and Friday effect in Table B.4:

$r_t = \alpha 0 + \alpha_1 r_{t-1} + \gamma_1^{Monday} + \gamma_2^{Friday} + \varepsilon t$

γ_1^{Monday} = 1 if Monday; 0-otherwise

γ_2^{Friday} = 1 if Friday; 0-otherwise

H_0: $\alpha_1 = \gamma_1^{Monday} = \gamma_2^{Friday} = 0$;

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