RĪGAS EKONOMIKAS AUGSTSKOLA
STOCKHOLM SCHOOL OF ECONOMICS IN RIGA

SSE Riga Student Research Papers
2007:8 (95)

MONTHLY AND DAILY STOCK RETURN ANOMALIES – AN INVESTIGATION OF THE STOCK MARKETS IN THE BALTIC STATES

Authors: Aleksej Avdejev
Mindaugas Kvekšas

ISSN 1691-4643
ISBN 978-9984-822-07-5

March 2007
Riga

Strēlnieku iela 4a, Rīga, LV-1010, Latvija • Telefons: +371 6701 58 00 • Fakss: +371 6783 02 49 • E-pasts: office@sseriga.edu.lv • http://www.sseriga.edu.lv

Monthly and Daily Stock Return Anomalies – an Investigation of the Stock Markets in the Baltic States

Aleksej Avdejev

and

Mindaugas Kvekšas

Supervisor: Mārtiņš Kazāks

March 2007
Riga

Acknowledgements

The authors wish to express their deepest gratitude to their thesis supervisor Mārtiņš Kazāks for his valuable advice and support throughout the entire thesis writing process. Additionally, the authors would like to thank Kārlis Krēsliņš for coordination and providing guidelines to the writing process. Further thanks go to SSE Riga English Department team for their helpful comments on how to improve the quality of the paper.

We also thank our course mates for your fair critique and feedback, as well as friendship and faith. Last but not least, the authors are forever indebted to the Stockholm School of Economics in Riga for providing us with the means and knowledge to write this paper and for entrusting us with so much.

Abstract

This study explores the presence of persistent seasonal patterns in the three Baltic stock markets for the period from 2000 till the end of 2006. Using GARCH and EGARCH models' specifications the authors present convincing evidence for the existence of day-of-the-week and month-of-the-year effects in stock market indices returns, which is on par with previous research. When testing for comparable anomalies in the conditional volatility of the returns, the authors find that only Latvian stock market exhibits such trends of calendar seasonality. Furthermore, contrary to the authors' expectations, leverage effect was not noticed in any of the studied markets, which rejects the hypothesis for asymmetric market response to news. Lastly, the phenomenon of market interdependence was assessed and conclusion drawn that the three markets are indeed strongly integrated with each other.

Table of Contents

List of Tables

List of Figures

1 Introduction

According to Fama (1970) capital market is an efficient mechanism, under which all available information is reflected in asset prices. As to what type of information influences stock market prices there were definitions introduced for three types of efficiency. Numerous subsequent studies were done to demonstrate the proposed capital market efficiency.

More recent research, however, found that there are certain systematic calendar anomalies, which prompted debate about the validity of the efficient market hypothesis (EMH). Some of the most well known and well documented anomalies are the so called January effect, as well as Monday effect, which are often considered by investors to be the days of poor market performance. Another sufficiently documented seasonal market anomaly is the October effect, which is also associated with poor performance.

Jacobs and Levy (1988) tried to explain the Monday, also known as the weekend effect, by drawing lines between the tendencies of human nature to hide bad news, meaning that any bad information usually comes after the market closes to allow for calmer shock absorption over the weekend. Some logical explanations were as well presented regarding the January effect, for example, as a consequence of seasonal liquidity factors, as can be seen in Odgen (1990) or Gamble (1993); or as a consequence of tax based trading, which was analyzed by Brown *et al*. (1983), Berges *et al.* (1984) and others.

The existence of such trends contradicts the weak form of market efficiency hypothesis, which claims that historic performance and past prices are fully reflected in current stock prices and no future price movements can be predicted using this information. According to this hypothesis, stock returns should be time-invariant; therefore, no calendar properties should have any effect on the price. Thus, any evidence in favor of the existence of returns seasonality would have severe implications for investment strategies by invalidating the EMH.

Cross (1973), French (1980), Rogalski (1984) present convincing facts that, EMH is not true and stock returns are unevenly distributed across the different days of the week. Subsequently, Draper and Paudyal (1997), Pandey (2002), Lucey and Whelan (2004), and others present evidence of a monthly effect in stock returns.

In addition to differentiation in returns, Mandelbrot (1963) and Fama (1965) were among the first to present evidence that return volatility also has a deterministic pattern. They observed that return volatility exhibits “clustering”, i.e. periods of large movements and periods of relative tranquility exist in practice. Engle (1982) was the first to introduce a theoretical framework for analyzing financial time-series with time-varying volatility – ARCH model, which was later extended into generalized version by Bollerslev (1986), and others. The main idea behind it was its autoregressive property, which means that past observations are integrated into present, in other words, that risky times tend to follow risky times and calm times tend to follow calm times.

While the importance of seasonal trends in asset returns is not subject to debate, the existence of similar patterns in stock market volatility is very important for an investor as well. As Engle (1993) extensively argued in his later work, with the knowledge of calendar effects in the volatility of returns, risk-averse investors should shift their portfolio investments out of assets, whose volatility is expected to increase. Their portfolio performance should increase as a result. Other participants of the financial markets would find use for this information as well, for example with the knowledge of deterministic seasonal patterns in volatility they can place option bets. Thus, the examination of seasonal patterns in both the returns and volatility development over time is very useful.

1.1 The purpose of the research

The purpose of this work is to investigate the existence of such seasonal (day-of-the-week, month-of-the-year) patterns in the three Baltic stock markets (Lithuania, Latvia, and Estonia) for the period from January 1, 2000 till December 29, 2006. Relative to the amount of studies that have been conducted on the same issue for the US and developed European countries, very little research has been done on CEE and other developing countries. A rather low integration of capital markets might be the reason why developing financial markets received less attention from researchers. Another reason might be the relatively young age of these markets – for comparison, the Vilnius Stock Exchange started operating only in the early 1990s, while the famous Wall Street is older than a century.

Thus, the immediate difficulties we face in our research are, as already mentioned above, the rather young age and small size (small scope of operations) of the Baltic stock markets, which could cause our tests to provide inconclusive results. Unfortunately, we are constrained by the nature of the capital markets in question, thus we will have to accept them as they are. A positive feature of these markets is that they were relatively free of market shocks and crashes during the time period analyzed, which helps to remove unnecessary tension of extreme values in observations.

1.2 Formulation of the research question and hypotheses

This paper contributes to previous research by providing further evidence for the existence of calendar effects in the stock market behavior by looking at seasonal patterns in stock market indices returns and their volatility. The research question thus can be formulated as follows: "whether Baltic stock markets exhibit any trends of calendar seasonality in returns and volatility, and if yes, then which months or days have the highest impact on these capital markets, and whether the effects are positive or negative?" Close geographical proximity and other similarities suggest that markets could be tested for interdependence as well, in order to increase the explanatory value of the models. Finally, we also consider the probable existence of asymmetric response to different shocks in the markets. The latter, together with other research objectives, is more thoroughly discussed below.

Bollerslev's (1986) GARCH model was selected for our analysis to test for deterministic seasonal patterns. Furthermore, for reasons discussed later, we will additionally test for the presence of the same patterns by applying the exponential GARCH model, as first suggested by Nelson (1991).

The following hypotheses will be tested and analyzed:

1) Baltic stock markets exhibit calendar anomalies (day-of-the-week, month-of-the-year) in stock indices returns. The concern for the existence of persistent seasonal anomalies in stock market returns was first raised a few decades ago. Based on the pioneering work by Cross (1973), as well as on subsequent research of the topic (for example, French (1980), Rogalski (1984), and others) we believe it is logical to assume that similar (or vice versa - significantly different) movements will be observed in our study.

2) Volatility of returns on Baltic stock market indices follows seasonal trends. Common sense suggests that due to some specific news reaching markets at some particular dates (for example, bad news usually get published over the weekend, and dividends are usually paid out in April or May), the market participants' behavior might cause more volatile fluctuations in returns at some periods and less dramatic during the others. This phenomenon was first explained by Engle (1982). Many researchers followed (Nelson (1991), Franses and Paap (2000), and others), and confirmed that, similar to stock returns, persistent calendar trends can be observed in the returns volatility. In this paper we will test whether they occur in the Baltics. Consequently, based on preceding research, our expectation is to encounter them in our analysis.

3) There is a significant leverage effect in the Baltic stock markets. Leverage effect stands for asymmetric reaction to news by the stock market players. Black (1976) first noticed and documented this phenomenon; however, it was not until the invention of asymmetric ARCH-family models (such as Nelson's (1991) EGARCH) that deeper examination of the issue was made possible. Savva *et al.* (2004), for example, found evidence of a negative leverage effect in thirteen out of fifteen European stock markets analyzed, implying that negative shocks have a greater impact on the market performance. Based on this, we believe it is reasonable to expect to find a similar asymmetric news response (not necessarily negative) in our research.

4) Significant interdependence between the three stock exchanges is present. The concept of interdependence and contagion effect plays an important role in explaining stock markets trends around the world. As an indication of interdependence we propose to test for significant terms of lagged returns of neighboring countries predicting the returns in each of the analyzed states. The reasoning is based on the works of Pajuste (2000) and Scheicher (2001), who conclude that geographical proximity is the main contagion factor for two emerging markets. For a detailed discussion please refer to the corresponding section in literature review.

The rest of the paper is organized as follows. Section 2 consists of a thorough review of previous findings on the topic in question and related issues. Section 3 briefly describes the data and derives the models used for further analysis. Section 4 goes on with statistical data description and presents a preliminary analysis and discussion. Empirical findings follow in Section 5, where we present the results obtained after the application of the models, and examine the hypotheses. Section 6 continues the discussion of the empirical findings and their implications. Section 7 concludes with a summary and suggests the course for further research.

2 Literature review

Numerous studies have extensively analyzed and investigated the existence of seasonal patterns in stock returns. Among the first ones to present a convincing study for the presence of day-of-the-week effect was Cross (1973), as he found significant evidence of mean returns being higher on Friday than on Monday for the S&P 500 stock index for the period of 1953-1970. Further studies have confirmed the existence of a similar effect for the same market but over a larger time period, for example French (1980), when he presented his dummy variable approach, or Rogalski (1984).

Other markets were also analyzed for the presence of different seasonal variations in stock market returns. For instance, Balaban (1994) encountered day-of-the-week effects in the Turkish stock market and found significant evidence for the presence of such effects for the period of January 1988 – August 1994, and that they vary over time in direction as well as in magnitude. Gardeabazar and Regulez (2002) found statistically significant all-day-of-the-week effects, except for Tuesday, in the Spanish stock market for the period of 1998-2000. Interestingly, the authors document finding a positive Monday effect, as opposed to usually observed negative one.

Sarma (2004) presented undisputed results in favor of the existence of a strong day-of-the-week effect for the Indian market from January 1st 1996 to August 10th 2002, and by testing different day sets, found an unusually high positive return deviation from Monday to Friday, implying that consistent abnormal returns could be earned by buying on Monday and selling on Friday.

Lucey and Whelan (2004) examined the monthly and semi-annual patterns of the Irish market in the long term and found a strong and consistent January effect, as well as some April and semi-annual seasonalities over the period of 1934-2000. Draper and Paudyal (1997) found strong evidence of January and April effects in the UK equity market, and constructed a buy/sell strategy to profit from such market anomaly. Jarrett and Kyper (2005), however, made a remarkable contribution to research on the topic, when instead of testing for calendar patterns in stock indices, they investigated trends in prices of actual traded securities and also concluded that there are certain monthly anomalies in development of individual stock prices.

2.1 Subsequent model variations

The abovementioned studies concentrated mainly on seasonal patterns in stock market indices returns, and it was not until the revolutionary work by Engle (1982) when more researchers recognized the importance of investigating similar patterns in the volatility of returns. One of the pioneering papers in the field was published by Nelson (1991). More recently, Franses and Paap (2000) found proof for consistent day-of-the-week variations in the S&P 500 index returns volatility. Yakob *et al.* (2005) discovered significant day-of-the-week, month-of-the-year, monthly, and holiday effects in the conditional volatility in the East Asian and Pacific stock markets.

Throughout the investigation of systematic variations in stock market volatility some researchers encountered the issue of negative intercept coefficients for some days in volatility, “which implies negative unconditional variance for the corresponding days”

(Savva, *et al.*, 2004) and violates the rule of positive variance. This problem was encountered by Berument and Kyimaz (2001), as well as by Franses and Paap (2000), and others.

In order to prevent such accidental negative volatility, Bollerslev's GARCH model presents the variance as a linear combination of positive random variables with positive weights. Instead of imposing such restriction on the model, Nelson (1991) proposed to use a natural method of ensuring that the variance stays positive – namely to specify it in a logarithmic form.

Nelson criticized the GARCH model on some additional grounds. As it was first documented by Black (1976), stock returns are asymmetrically negatively correlated with changes in returns volatility, which means that volatility rises and responds more aggressively to negative information (when excess returns are lower than expected) than it falls with regard to positive information (when excess returns are higher than expected). The GARCH model assumes that only the magnitude of excess returns influences the conditional variance, and does not take into account the asymmetry due to different polarity. Nelson claimed that "a model in which variance responds asymmetrically to positive and negative residuals might be preferable for asset pricing applications."

Nelson's proposed Exponential GARCH model addresses both these drawbacks, by allowing asymmetric effects on the conditional variance, as well as removing unnecessary non-negativity related constraints.

Subsequently, multiple researchers have adopted EGARCH model for their financial data time-series analyses. For example, Savva *et al.* (2004) used periodic EGARCH specification to test for the presence of day-of-the-week trends in both the returns and the conditional variance of the returns of the majority of European stock market indices for the period from January 1st 1993 to April 30th 2005. They find that only Spain, Greece, Denmark, Netherlands, Finland and Norway have present day-of-the-week anomalies in the return equation, while almost all, except for UK, Portugal and France, exhibit day-of-the-week patterns in returns volatility. Additionally, as mentioned earlier, they confirm the asymmetry of shocks, i.e. that negative shocks have a much larger impact on volatility than positive.

Berg (2003) adopted several different specifications of the GARCH model for testing the existence of market anomalies in the Swedish market. To further facilitate the reliability of his tests he used EGARCH and TGARCH in addition to a simple generalized ARCH model, and all his tests showed significantly higher volatility for Monday, or any other normal trading day after a holiday.

In this paper we will conduct two series of tests. First, we will use the Generalized ARCH model of Bollerslev to test for the presence of calendar variations in Baltic stock market indices returns and their volatility. Then, similarly to Savva, *et al.* and Berg we will use the exponential GARCH model specification, to remove non-negative variance limitation and to account for shock asymmetry. This will allow us to investigate whether the results of both tests are significantly different from each other. Finally, the use of EGARCH model will also let us see whether the Baltic stock markets, similarly to other markets, respond stronger to negative information, i.e. whether volatility reacts asymmetrically to shocks.

2.2 Market interdependence

Contagion effect has become one of the most popular theories in explaining stock price movements worldwide. It is generally a well accepted fact that markets have influence on each other and, thus, any events in one market are bound to have a spillover effect on other economies. Dornbusch *et al.* (2000) presents such definition of contagion effect: "contagion, in general, is used to refer to the spread of market disturbances - mostly on the downside - from one country to the other, a process observed through co-movements in exchange rates, stock prices, sovereign spreads and capital flows".

Masson (1998) presents three types of contagion effects – monsoonal, spillovers and pure contagion. Monsoonal effects, as explained by him, are simple macroeconomic indicators from developing countries that trigger economic pressures in emerging markets. Spillovers usually occur between the countries of similar economic development, such as between two emerging economies, where devaluation in one currency might worsen the terms of trade for its neighbor. Lastly, pure contagion effect is anything that does not belong to the previous two, and might be caused by a simple market imperfection – for example misinterpretation of available information could make a bank run in one country to spread to its neighboring states in a self-fulfilling expectation. Similarly, a stock price shock in one county could lead investors to withdrawing their overseas investments as well, without digging into overseas economies fundamentals.

Thus, conceptually the causes of such propagation effects could be divided into two groups – fundamental and behavioral. Fundamental causes include anything that relates to normal interaction between economies, such as trade links, currency links, legal similarities, etc. Behavioral causes are contagion effects that cannot possibly be explained by fundamental macroeconomics and occur as irrational investor behavior – financial panic, herding, and loss of confidence. Individually, such behavior might be rational, but on an economy-wise scale it proves to be hazardous.

Stock markets nowadays are a cross-related system with many agents affecting each other. The degree of such impact depends on many factors, such as size of the economy, ratio of global integration, etc. When applied to emerging markets, however, these factors carry a limited weight on local stock market performance. Nowadays, many researchers agree that geographical proximity is one of the main driving factors of interrelation between two emerging economies. Scheicher (2001) in his studies of global and regional linkages in Poland, Hungary and the Czech Republic found only limited interaction – the returns exhibited a weak trend towards both regional and global shocks, while volatility showed a strictly regional convergence. Similarly, Tse *et al.* (2003) showed that there is absolutely no volatility spillover between the US and Polish stock markets, implying that emerging stock markets are not driven by a common long run trend in pace with developed economies.

Pajuste *et al.* (2000) in their research on predictability of stock returns in CEE countries concluded that stock markets of these economies are especially sensitive to stock price movements in their neighboring markets, and that geographical proximity can actually be a measure of financial integration.

With this in mind, we find it not only logical, but imperative to include the issue of correlation and interdependence between the Baltic States in our analysis of their stock markets.

3 Data and methodology

In this section we introduce the methods that are applied in our research. We start by identifying sources used to obtain the relevant data, and then continue with the description of the data sample. The explanation of adjustments performed in the sample is given. Another part of the discussion is dedicated to the formulation and presentation of econometric models based on which the empirical study is carried out.

3.1 Data description

The usage of the particular models was briefly justified at the literature review phase. To further assure credibility of the results we selected reliable information resources to collect the necessary data. Since our analysis covers all of the three Baltic stock markets – Lithuania, Latvia and Estonia, data sample comprises of three separate time series of stock market indices’ daily closing prices. The latter figures for the seven year period starting at January

1st, 2000 were retrieved from the website for the Baltic markets' branch of OMX Group. The explanation of the formula applied for calculating indices, which is the same for all three states, is presented there as well.[1]

Despite the fact that Vilnius, Riga and Tallinn have had operating stock markets since early 90s, however, the representative of OMX Lithuania confirmed that they could not provide any reliable records for these early years. And, although it is known to us that some other internet resources, e.g. Reuters database, in fact maintain older statistics, our decision was not to extend the sample obtained from OMX. While making such a choice we evaluated the fact that the financial markets in this region at that time were only emerging and considerably less developed than they have become in the recent years, therefore, back then they suffered from high levels of volatility and inadequate liquidity caused by low trading volumes. Moreover, the different methodology used in creating these indices would have had a significant negative impact on statistical analysis of the sample data.

Consequently, for each of the three countries our sample size equals to 1825 daily records (weekends excluded). It is, however, worth mentioning that no specific filtering was applied to the raw data set to avoid excluding any values. We base our decision on the fact that sample records are computer generated and extreme values could only occur due to peculiarities of trading activity in the markets. The abovementioned quantities are sufficient for performing statistically significant regressions which would allow testing for the presence of both month-of-the-year and day-of-the-week phenomena in the stock market indices' prices fluctuations.

3.2 Arranging the data set

The next thing to consider is modifying the data set so that to end up with the figures needed by the models we are going to employ. First of all, daily returns are calculated using the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100$$

Where:

R_t - the return on a stock market index during day *t*

P_t - the closing price of an index on day *t*

P_{t-1} - the closing price of an index on day *(t-1)*

[1] http://www.baltic.omxgroup.com/index.php?id=323433

In the equation the logarithmic stock returns are multiplied by 100 to approximate percentage changes and to avoid convergence problems. The issue of holidays to some extent has already been addressed in the original data set by entering either the closing price of the day before holidays or leaving the field empty. Hence, on these occasions in our calculations the daily return is set to zero. This was the approach also used by Savva et al. (2004); however, one has to take into account the fact that manually setting returns to zero would possibly affect the probability distribution of stock returns by worsening the kurtosis. Nevertheless, since in our case such adjusted values comprise a reasonably small part of the total sample, the analysis of the dataset filtered for “zeros” showed only minor changes in distribution characteristics.

Lastly, the new data array has to be updated by creating additional variables – five dummy variables for each day of the week when trading takes place and another twelve for every month.

3.3 Models specification

The choice of the models applied in the analysis was determined by their effectiveness tested and proved by other researchers. In general, financial time series have some certain characteristics which can only be captured with extensions of autoregressive conditional heteroskedasticity (ARCH) model. The Generalized ARCH (GARCH) model was mainly designed to address the following issues (The Mathworks, 2004):

1. Excess kurtosis. Probability distributions for asset returns often exhibit fatter tails than the standard normal, or Gaussian, distribution.
2. Volatility clustering (also known as conditional heteroskedasticity). The simple explanation of it states that some periods are more tranquil than others. Economic literature defines this in the following way: “volatility clustering can be thought of as clustering of the variance of the error term over time: if the regression error has small variance in one period, its variance tends to be small in the next period too. In other words, volatility clustering implies that the error exhibits time-varying heteroskedasticity.” (Stock and Watson, 2003, 563)
3. Leverage effects. “Evidence on asymmetry in stock returns behavior has been found by many researches, such that negative surprises seem to increase volatility more than positive surprises do. Since a lower stock price reduces the value of equity relative to corporate debt, a sharp decline in stock prices increases corporate leverage and could thus increase the risk of holding stocks”. (Hamilton, 1994, 668-9)

Accordingly, we selected GARCH(p,q) as a base model to be used in our study. This decision seems plausible taking into consideration all the arguments, which have been presented so far, in favor of employing it. However, due to the fact that our sample consists of daily data for a period of barely 7 years, we are using the two basic specifications of it, namely the more general and, in a sense, less constrained GARCH(2,2) and a specific GARCH(1,1), both of which incorporate only the most recent information (for further details see sub-section 3.3.1). Models using higher orders of ARCH and GARCH terms (i.e. higher *p* and *q* values), according to Engle, would be useful if applied to a longer time span, for example, several decades of daily observations. There is also another argument against employing higher order specifications – ARCH family models are infamous for difficulties in convergence of parameter estimates. Our experience confirmed the latter statement as no satisfactory results could be obtained when the order of ARCH and GARCH terms was increased to more than 2.

Nevertheless, of the three abovementioned financial time series characteristics, the last one is only captured by certain classes of asymmetric GARCH models. One of such is the EGARCH(p,q), which advantages over its predecessor were already covered in the literature review section. Hence, to make our study more complete, we include the specific EGARCH(1,1) model that also allows us to check for the existence of the leverage effect in the Baltic region.

To mitigate the issue of having autocorrelated errors, we take account of including lagged values of the return variable for the particular market into equations. Additionally, to test the hypothesis of existing interdependence between the Baltic stock markets, we also take the lagged values of the return variable from the other two stock exchanges. In our consideration we had taking up to four lags from each market. This seemed a plausible decision since stock markets are regarded as rapidly reacting to the new information. However, due to the complexity of the models, under some specifications, namely EGARCH(1,1) for both monthly and daily effects, we experience the problems of no convergence in parameter estimates; therefore, usage of the lags has been limited to including only the lags of returns for that particular country, hence, we will not be testing for the interdependence with this model.

In the following sub-sections we simultaneously present the methodology for estimating both, the day-of-the-week and month-of-the-year, effects in mean returns as well as in variation of volatility of the stock returns.

3.3.1 GARCH specification

The estimation of the day-of-the-week effect in return equation shall be performed based on the following expression:

$$R_t = a_M D_{M_t} + a_T D_{T_t} + a_W D_{W_t} + a_{TH} D_{TH_t} + a_F D_{F_t} + \sum_{i=1}^{n} t_i R_{t-i} + \sum_{i=1}^{n} r_i R_{t-i} + \sum_{i=1}^{n} v_i R_{t-i} + \varepsilon_t \qquad \text{(1a)}$$

For the purpose of easier reference and, more importantly, to maintain the model less complex, so that parameters could be estimated and no problems of no convergence occurred, the same equation for the estimation of the month-of-the-year effect can be rewritten as:

$$R_t = a_1 D_{1_t} + a_2 D_{2_t} + ... + a_{12} D_{12_t} + \sum_{i=1}^{n} t_i R_{t-i} + \sum_{i=1}^{n} r_i R_{t-i} + \sum_{i=1}^{n} v_i R_{t-i} + \varepsilon_t \qquad \text{(1b)}$$

Where R_t is the daily return on the stock market index; $D_M, D_T, D_W, D_{TH}, D_F$ are the dummy variables for weekdays, while D_1 to D_{12} are the monthly dummies at time *t*; and in both equations ε_t is an error term. In addition, the *t*, *r* and *v* are the coefficients for some particular lagged values of return variables in Tallinn (t), Riga (r), and Vilnius (v) stock markets. However, as it has been previously stated in the EGARCH model we will only include the lagged returns of that particular country for which we are applying the model in each case (thus, not testing for the interdependence). The constant term has not been included in equations to avoid the dummy variable trap.

The concern was expressed about error variances not being constant over time, which would lead to obtaining inefficient estimates, if there actually is a time varying variance. Therefore, the assumption is made that $\varepsilon_t \sim N(0, \sigma_t^2)$ which implies that error terms follow a normal distribution with mean zero and σ_t^2 being the time varying conditional variance. Nevertheless, this is a quite unrealistic assumption since hardly any time series could be found that would nicely follow the normal distribution, and as we later show, our case is not an exception either. Therefore, to address this problem the econometric package used for our analysis automatically applies quasi-maximum likelihood estimation (QMLE) of the parameters, which is valid under non-normality.

Then, specifically, in the GARCH(1,1) model the conditional variance, σ_t^2, would depend on the first lag of its own and the first lag of the squared error:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2 \qquad \text{(2a)}$$

Where γ_1 is an ARCH parameter, δ_1 - a GARCH parameter, and γ_0 is a constant.

Moreover, we also expand our scope of study in another direction, although, many other researchers limited themselves to modeling seasonal patterns only in mean returns. We take a step further and also examine the presence of them in variation of volatility. Due to our intentions to account for seasonal trends (both, daily and monthly effects) in volatility of returns, we also include dummies in the conditional variance part of the equation as the following:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2 + g_M D_{M_t} + g_T D_{T_t} + g_W D_{W_t} + g_{TH} D_{TH_t} + g_F D_{F_t} \tag{2b}$$

and

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2 + g_1 D_{1_t} + g_2 D_{2_t} + \ldots.. + g_{12} D_{12_t} \tag{2c}$$

Respectively, in the case of a more general GARCH(2,2) specification, from which we start our analysis, the variance is modeled based on two lags instead of one, however, the inclusion of dummies in this case was neglected due to the convergence problems:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 \varepsilon_{t-2}^2 + \delta_1 \sigma_{t-1}^2 + \delta_2 \sigma_{t-2}^2 \tag{2d}$$

3.3.2 EGARCH specification

EGARCH process differs from GARCH in a way it models the time varying variance. The assumption of error term following the normal distribution remains, though, for easier reference we change the denotation – $\varepsilon_t \sim N(0, h_t)$, where h_t now is a time varying conditional variance of the error term. In the simplest form of EGARCH(1,1) it is modeled in the following way:

$$\ln(h_t) = \gamma_1 \varepsilon_{t-1} + \theta_1 \left(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}| \right) + \beta_1 \ln(h_{t-1}) \tag{3a}$$

Where β measures the persistence in volatility, while the magnitude effect is judged by the term θ. The value of γ determines whether the leverage effect is present in the stock market (if $\gamma_1 \neq 0$, then the impact is asymmetric). The advantage of this model comes from the fact that the logarithmic formulation assures always non-negative h_t. This could be the problem otherwise, because other parameters can possibly take negative values.

The introduction of the exponential GARCH model again allows us testing for the seasonal patterns in the volatility of returns. Thus the latter conditional variance equation (3a) needs to be enhanced by including dummy variables for both analyzed types of seasonality:

$$\ln(h_t) = g_M D_{M_t} + g_T D_{T_t} + g_W D_{W_t} + g_{TH} D_{TH_t} + g_F D_{F_t} + \gamma_1 \varepsilon_{t-1} + \theta_1 \left(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}| \right) + \beta_1 \ln(h_{t-1}) \tag{3b}$$

and

$$\ln(h_t) = g_1 D_{1_t} + g_2 D_{2_t} + ... + g_{12} D_{12_t} + \gamma_1 \varepsilon_{t-1} + \theta_1 \left(|\varepsilon_{t-1}| - E|\varepsilon_{t-1}| \right) + \beta_1 \ln(h_{t-1}) \tag{3c}$$

Conclusion: considering both models, if all the coefficients to dummy variables are observed to be zero, this would imply that no difference exists among index returns and their volatility across days of the week or months of the year. In other words, no seasonality effects would be encountered in the stock markets of countries analyzed.

4 Preliminary Statistics

In this section our intention is to review the statistical characteristics of the indices return variables for all of the three Baltic States. The reasoning for doing so is to provide supporting information which would justify our choice of the models and later would allow evaluating whether these models were reasonably well specified, so that the results are reliable.

4.1 Review of stock market indices returns

A first look at the statistics presented in the table below (Table 1) shows that on average, stock market mean returns for all Baltic countries were positive. From this follows a straightforward conclusion that on average the stock markets have been quickly growing over the selected period of seven years. The presented figures reveal that approximated growth in indices have equaled 0.1% per day over the observed period. After a quick glance at the numbers, one might conclude that the Latvian stock exchange yielded the highest average daily returns among the three markets – a fact which is clearly illustrated in Figure 1 in Appendix 1.

Table 1 – Statistical characteristics of returns on the Baltic States' stock market indices

	N	Mean	St. Dev.	Skewness	Kurtosis	Skewness - Kurtosis joint test[2]	ARCH-LM[3]	Portmanteau (Q-Statistics)[4]
OMX Tallinn returns	1825	0.09863	0.97155	0.22317	9.72114	0.0000	19.959*** 0.0000	114.4175*** 0.0000
OMX Riga returns	1825	0.10061	1.55472	-1.24951	24.41572	0.0000	499.962*** 0.0000	413.0828*** 0.0000
OMX Vilnius returns	1825	0.08738	0.89652	-0.69648	15.03786	0.0000	11.009*** 0.0009	159.9980*** 0.0000

[2] The normality test with the null hypothesis stating that tested variables follow the normal distribution (the table presents *p* values of the test)

[3] The test for ARCH effects in the returns (the table presents test statistics and *p* values)

[4] The test for white noise: checking for the existence of autocorrelations. The null hypothesis states that autocorrelation coefficients equal zero (again, in the table we present Q test statistics and *p* values)

Next, the table also presents information on skewness and kurtosis of the returns. The kurtosis of a normal distribution is equal to 3. From what we see above, the kurtosis for all three markets is significantly larger than this value, meaning that the distribution of these series is peaked and its tails are fatter than the tails of a normal distribution. “In other words, it means that large observations occur more often than one would expect in a normally distributed variable” (Savva et al., 2004). The kurtosis values are quite high for all three markets and it is reasonable to conclude that these markets are subject to more radical and hasty investor behavior and extreme trading.

We can also look at the skewness of the returns. The skewness of a normally distributed variable is zero. A value different from zero tells us which daily returns are more usual in the economy. Estonian stock market returns have a positive skewness attributed to them, which shows that positive market price movements are more common than negative, while a negative skewness for Latvia and Lithuania tells us precisely the opposite for their corresponding stock markets.

A graphical illustration of the skewness and kurtosis is shown in Appendix 1 in Figures 2-4. A thin line is drawn on the graphs which represents a normally distributed variable for easier comparison. One might then immediately notice the abnormally high peak around the mean, a steeper decline, and somewhat fatter tails. All these indicate that there is less “average” observations, and more extreme ones – i.e. the distribution exhibits large kurtosis. It has already been noted, however, that kurtosis’s peak is slightly exaggerated. This is due to the nature of the stock markets – no trading occurs on holidays, or some other rare occasions when trading does not happen, thus zero returns are reported over these days. Based on previous studies performed on other markets, we decided not to exclude them from our analysis as well. An abnormal skewness, albeit less obvious, can be noticed from the graphs as well, and is represented by a small shift of the whole figure to the left or right from zero on the X-axis.

In addition to the logical conclusions presented above, we also conducted an individual and joint skewness/kurtosis normality test (only the joint test results are reported). As expected, the test strongly rejects the hypothesis for normality. Summing up, the initial findings show that the returns are not normally distributed; instead they are leptokurtic – that is have the excessive kurtosis, and are skewed. Nevertheless, since our model uses the parameters’ estimation technique that works under non-normality, therefore, such characteristics of the returns does not pose threats to our analysis.

Next, the Lagrange Multiplier test for autoregressive conditional heteroskedasticity was conducted to determine whether the data sample exhibits ARCH effects, which would ultimately lead to the selection of a model. As it was initially expected for the financial time series, the test showed significant ARCH disturbance – the null hypothesis of no ARCH effects has been strongly rejected for all three stock markets. Consequently, this result implies that ARCH family model would be best suited for our analysis – hence our choice has been justified.

Finally, the table presents Portmanteau Q-test statistics for autocorrelations in residuals. To explain that, the first thing to be noted is that the desirable outcome after running a regression is to have the residuals in white noise as this would imply that the model was well specified, and the changes in the regressor can be explained by the independent variables included in the regression. One condition of the white noise is the absence of autocorrelation in residuals. Hence, the null hypothesis of the Q-test states that all autocorrelation values are zero; however, what we see from Table 1 is that our current time series is significantly autocorrelated because hypothesis has been strongly rejected. The usefulness of this test results is quite limited at this point, but they will serve as a benchmark and provide valuable insight further on, when we evaluate whether our proposed model specifications are successful in explaining variations in the returns on indices.

To conclude, we can take a look at the volatility of returns picture for a better understanding of stock market participants' behavior (Figures 5-7 in Appendix 1). It can be seen that Tallinn stock exchange experienced a higher volatility pattern in the first few years of the sample, and showed a steadier trend at the end of the examined period. Similar to Tallinn, Latvian market experienced higher volatility in the first half of the sample, including a period of extreme price movements in 2001-2002, and a much steadier and calmer market afterwards. Lithuanian stock exchange is characterized by a rather steady trend of moderate market fluctuations until the middle of 2005; the period afterwards is represented by increased market instability, and severe negative adjustments.

However, we consider the identification and explanation of the reasons for such volatility clustering to be outside the scope of our research. A thorough analysis on both, micro and macroeconomic, levels would be advisable if it was decided to accurately and justifiably divide the whole period into shorter time spans and then carry out separate examination. Currently, we are more interested in the volatility clustering patterns in general, which can also be observed from the graphs. The existence of such trends indicates the autoregressive movements in the sample, which further supports the choice of ARCH family model for our study.

4.2 Preliminary recognition of seasonal trends

By examining Table 2, we can take a closer look at the daily information. It is clear that the mean returns in general are positive for all days of the week, except for Mondays, which yield negative mean returns for Latvian and Lithuanian stock markets. The lowest mean return for all stock markets taken together is also observed on Mondays. What is interesting to note is that this is not an unexpected result – there is a quite well known speculative saying that “bad news come out on weekends”. In general, the reality of Mondays having negative or at least lower returns than on the other days of the week is encountered in most papers on seasonality. On the other hand, the highest mean returns are observed on Tuesdays for OMX Tallinn (0.1361), Fridays for OMX Riga (0.2056), and Thursdays for OMX Vilnius (0.1542).

It is also seen that kurtosis for Mondays in Lithuanian market and Mondays and Fridays for Estonian market are much higher than kurtosis values for the remaining days of the week. This could indicate that in returns on these days there are less “average” values and more extreme ones. A notably higher Monday kurtosis for Lithuania might indicate that investors tend to make relatively radical decisions on this day. Latvian market exhibits higher kurtosis levels for all days, meaning that the extreme market movements are much more common in this economy.

Table 2 – Statistical characteristics of returns (daily)

OMX Tallinn returns	N	Mean	St. Dev.	Kurtosis	Skewness
Monday	365	0,043869	1,063164	12,624800	0,307396
Tuesday	365	0,136146	0,939737	7,303218	0,458597
Wednesday	365	0,084007	1,021095	6,774637	-0,131338
Thursday	365	0,109041	0,855983	5,661583	-0,160878
Friday	365	0,120091	0,967452	12,792130	0,625632
OMX Riga returns	**N**	**Mean**	**St. Dev.**	**Kurtosis**	**Skewness**
Monday	365	-0,032812	1,547003	25,401880	-2,271528
Tuesday	365	0,112413	1,334559	18,117310	-0,632578
Wednesday	365	0,037324	1,464329	18,977080	-1,426365
Thursday	365	0,180568	1,725049	26,883430	-0,983033
Friday	365	0,205572	1,666882	24,017660	-0,950730
OMX Vilnius returns	**N**	**Mean**	**St. Dev.**	**Kurtosis**	**Skewness**
Monday	365	-0,021238	0,969166	36,872540	-3,243307

Tuesday	365	0,063384	0,906273	6,595861	0,376020
Wednesday	365	0,097246	0,834021	4,520549	-0,009372
Thursday	365	0,154223	0,891134	6,486264	-0,284968
Friday	365	0,143269	0,870109	7,195772	0,639661

OMX Riga shows negative skewness for all days of the week. This fact tells that the left tail of the probability distribution is fatter than the right one, meaning that on average negative daily returns happen more often than positive. Lithuanian and Estonian markets exhibit skewness with both positive and negative signs for different days of the week, which indicates that in general some days of the week have positive return, while others tend to bring negative returns. Without stepping into a more detailed discussion, it could be noted that Tuesdays and Fridays for both Lithuanian and Estonian markets have positive skewness – in other words, on these days the return is more often positive than negative.

Similar analysis could be carried out after an examination of the monthly returns statistics in Table 3. The highest average monthly return is observed in February for the Estonian stock market (0.2383), July for the Latvian (0.2764), and September for the Lithuanian (0.2359). On the other hand, the lowest mean return is encountered for all of the Baltic States on the same month, namely, in May for Estonia (-0.0388), Lithuania (-0.0754), and for Latvia (-0.1403). There is a reasonable and probable explanation for the observed decrease in returns for the period of May, June and July (except for Latvia) – all listed companies announce their financial results by that time, therefore, the pessimistic trends could possibly be influenced by this as investors decide to hold the good performers and desperately dump the non-performers. Otherwise, it is very difficult to draw any justified conclusions on that or find country specific events, that would cause such patterns, without getting a very detailed description of micro and macro environment affecting the analyzed stock markets.

Table 3 – Statistical characteristics of returns (monthly)

OMX Tallinn returns	N	Mean	St. Dev.	Kurtosis	Skewness
January	155	0,135463	0,890713	4,354634	-0,00396
February	141	0,238282	1,287012	9,485322	1,207888
March	156	0,14163	0,918216	10,04131	1,1327
April	148	0,068771	1,088699	9,385645	-1,41141
May	157	-0,03884	0,889408	6,543902	0,159609
June	150	-0,01441	0,876108	7,083387	-0,84521
July	153	-0,01426	0,666049	10,08953	-1,20392
August	157	0,117129	1,071536	16,84916	2,066438
September	149	0,012283	1,299759	5,5899	-0,66889

October	155	0,113687	0,932268	4,341845	0,429554
November	151	0,229649	0,859039	3,326028	0,177829
December	153	0,202994	0,669578	3,416555	0,047921
OMX Riga returns	**N**	**Mean**	**St. Dev.**	**Kurtosis**	**Skewness**
January	155	0,081981	0,927943	5,48515	0,123566
February	141	-0,11912	0,955231	21,50756	-1,75873
March	156	0,220043	1,244155	7,753758	-0,46818
April	148	0,105677	0,8575	4,662658	0,160373
May	157	-0,14028	1,243863	11,43367	-1,20977
June	150	0,085467	1,123641	10,69469	0,211144
July	153	0,276405	1,798886	10,73165	1,873964
August	157	0,207596	2,967693	12,825	-1,75792
September	149	-0,00115	2,061279	16,94761	-2,97526
October	155	0,072383	1,747029	17,13102	0,72407
November	151	0,217203	1,260417	12,15248	0,700452
December	153	0,184427	0,954605	9,399838	1,624603
OMX Vilnius returns	**N**	**Mean**	**St. Dev.**	**Kurtosis**	**Skewness**
January	155	0,179314	0,791319	6,665091	0,841395
February	141	0,06861	0,742117	6,051817	-0,38373
March	156	0,166279	0,69409	4,804632	0,313432
April	148	0,164853	0,993514	4,777543	0,757496
May	157	-0,07543	0,81662	5,159603	0,069311
June	150	-0,02236	0,93443	5,694014	0,381802
July	153	0,050826	0,632224	6,23876	0,722756
August	157	0,064866	0,947351	7,962106	-0,0484
September	149	0,235859	1,209156	4,900507	0,082117
October	155	-0,05329	0,927757	5,113415	-0,79739
November	151	0,168799	0,810853	6,229358	-0,4267
December	153	0,107985	1,067987	58,26686	-5,87381

Monthly kurtosis analysis yields similar results as the daily analysis. All kurtosis values are higher than 3, meaning that the distributions have “fat” tails. It is worth mentioning that only one month has a relatively higher kurtosis score for Estonia and Lithuania – August and December respectively, while for Latvia, all months have a reasonably similar kurtosis. Again, this indicates that the Latvian stock market experiences extreme investment decisions throughout the year, while this effect is mainly limited to one month in Estonia and, especially, in Lithuania – kurtosis score in December is almost 9 times higher than the average of the remaining months.

Skewness analysis gives an inconclusive picture. A noteworthy observation is that of extreme values of skewness for different months. August is associated with more upturns for Estonia, while December has more downturns in Lithuania – but still giving a positive return.

5 Empirical Findings

Before continuing with a review of the empirical results obtained after implementation of the models described in our methodology section, it is necessary, as has already been stated, to evaluate the effectiveness of the various model specifications applied. We do so by comparing the results of statistical tests, used on the return variables before the regressions, with those observed for the residuals that were estimated after performing the regressions.

Firstly, the issue of non-normality that was notable in the probability distribution of stock indices returns, as expected, has not been solved – this is seen from both the p-values of the joint Skewness / Kurtosis test and by comparing the individual changes in skewness and kurtosis. However, the latter outcome shall not be considered as a source of threat to the reliability of the results.

Secondly, we have also implemented the ARCH-LM test and checked whether our models were able to at least partially decrease the presence of ARCH effects in the residuals. Again, after comparing the results from Table 1 with those presented in each table within Appendix 2, we see that due to the reasons that we could not possibly solve, there remains significant conditional heteroskedasticity in error terms. For the latter an explanation could be provided based on the results of the tests used to determine the significance of higher order ARCH/GARCH (or EARCH/EGARCH) terms in the model, as these showed significance of very high order terms. Due to this, it would be reasonable to expect better outcome in higher order models. However, the complicated estimation procedure in our circumstances already prevented from convergence in parameter estimates when the order was increased to 3.

Lastly, however, what is more important, the results of the Portmanteau Q-test show that the issue of autocorrelations in residuals has been partially solved for models of Tallinn and Vilnius. Regarding the former, the null hypothesis of zero values for autocorrelation cannot be rejected in most model specifications, while Vilnius shows a significant improvement in the Q-statistic value. Nevertheless, the opposite happens in the models applied for Riga, as the situation seems to worsen. Considering this fact, results for the Latvian stock market should be treated with critical judgment.

In the following subsections with the help of empirical results the stated hypotheses are tested and a brief interpretation of the results is presented. Additionally, if observed, similarities in the results for different countries are emphasized.

5.1 Hypothesis 1

Baltic stock markets exhibit calendar anomalies (day-of-the-week, month-of-the-year) in stock indices returns.

Some background information regarding calendar anomalies has been provided in the literature review section. The existence of this phenomenon by itself contradicts the fundamental theory of financial markets efficiency. However, judging from research done in this field, the seasonal patterns in the stock returns and their volatility are not uncommon in many markets, and due to the fact that Baltic States are regarded to have emerging financial markets, this would imply a weaker form of efficiency, and, hence, higher chance of observing such trends.

The models which we apply in our study are designed in such a way that the null hypothesis on seasonal dummy variables, if rejected, supports our first hypothesis that calendar anomalies do actually exist in this region.

Concerning day of the week effects in all three markets, we analyze the results of GARCH specifications. First, we start with the more general GARCH (2,2) model (Table 6). The results show that all three countries experience a significant positive Friday effect. This effect is strongest in OMX Riga, with approximately double magnitude (0.1942) than that of the two other markets and is significant at 1%. The observed effect is weaker in Vilnius and Tallinn at 5% significance level. Another noteworthy observation is that the Lithuanian market exhibits a strong negative Monday effect; however, this is not encountered in the other markets.

The application of a more constrained filter of GARCH (1,1) (Tables 4-5), shows roughly the same results, but with improved significance scores. For example, the negative Monday effect, which is observed in OMX Vilnius, becomes significant at 5%, as opposed to 10% with a more general filtering. The same pattern, but with stronger coefficients, is observed in EGARCH (Table 10) model specification as well – Friday effect becomes significant for all countries at 1%. A question might be raised regarding the increasing and, more rarely, decreasing significance scores, but we dismiss it as a pure speculation based on different model specifications. We have no intention on claiming that one filter is better than another, except that the exponential GARCH model additionally addresses the probable issue of leverage effects.

The summary of the observed daily market anomalies in the mean returns is as follows (only those supported by all three models are reported): positive Tuesday and Friday effects for OMX Tallinn, positive Tuesday, Thursday and Friday effects for OMX Riga, and positive Wednesday and Friday and negative Monday effects for OMX Vilnius.

The same logic as above can be applied to the identification of monthly seasonal patterns in the mean returns of the three markets. A positive September trend is observed in all three countries (Tables 7-9). In addition, both OMX Tallinn and OMX Riga (and OMX Vilnius too, under the EGARCH filtering (Table 11)) show a significant positive November effect. EGARCH specification also indicates a positive April and December effects in both Tallinn and Riga, as well as a positive January movement in all three markets. The only negative effect was identified in February in Tallinn under the exponential GARCH specification.

The summary is as follows (once again, only the results persisting in all three models are specified): significant positive trends in August, September and November in the Tallinn stock exchange, positive March, April, September and November movements in Riga, and positive January, March and September effects in Vilnius. For any further statistics readers are kindly advised to look at the respectful tables in Appendix 2.

Conclusion: following the discussion above, we presented evidence for the existence of persistent calendar trends in the mean returns, hence our first hypothesis is claimed to be true. It is also worth mentioning that our findings in large part are consistent with previous research – most notably the January (for example see Lucey and Whelan (2004)) and Monday effects (Jacobs and Levy (1988), Gamble (1993), etc), as well as end-of-the-week, also known as Friday effect (Cross (1973) and others).

5.2 Hypothesis 2

Volatility of returns on Baltic stock market indices follows seasonal trends.

Tests for the presence of calendar patterns in the conditional volatility show a less inspiring picture. While GARCH model specification identifies some persistent seasonal trends in market volatility, the corresponding coefficients are estimated to be extremely high (Tables 5 and 8), which raises suspicion to the reliability of the scores. We believe that the problem lies within the unpleasant property of the ARCH-type models themselves, which are known for unpredictable behavior and weak convergence; as well as in our proposed model specification – it contains over 20 estimators, which puts a heavy strain on the basic model.

In this situation we prefer a cautious approach in interpreting the results. After examining the estimators, according to common sense, we believe that EGARCH filter's produced results are more reliable, hence we base our analysis on them alone. Based on this filter, we try to draw a careful conclusion that both Vilnius and Tallinn stock markets exhibit neither daily nor monthly calendar trends in return volatility. Hence, we reject the hypothesis of seasonal volatility patterns in index returns for these two countries. The reasons for it might be any of, but not restricted to, the following: small market size, young market age, small number of market participants, or simply that the markets are more efficient in terms of dealing with risk.

OMX Riga, on the other hand, according to EGARCH model, showed persistent both daily and monthly patterns in the conditional volatility. Tuesday is estimated to have a strong negative effect on the stock return volatility, significant at 5%. Continual significant monthly patterns are observed in May, August, and October at 10% and in July at 5% level. Still, we prefer to refrain from making brash statements on the existence of deterministic patterns in the Latvian stock market volatility, and hence our conclusions are subject to further debate.

Conclusion: According to the results obtained, we reject the hypothesis for the existence of any seasonal patterns in stock market volatility for Tallinn and Vilnius, and accept it for Riga; however, as noted above, this is subject for further discussion and perhaps more detailed analysis when many other relevant factors are included as explanatory variables in the models.

5.3 Hypothesis 3

There is a significant leverage effect in the Baltic stock markets.

The leverage effect refers to the asymmetric response of the markets to various shocks, and, if present, shows whether positive or negative events can have a higher impact on the stock market. A general belief among the researchers is that the leverage effect is usually negative, and it is supported by many papers (for example Black (1976), Nelson (1991), Savva *et al.* (2004)). In our analysis, the extent of this effect is captured by the EGARCH model specification, namely by the γ_1 estimator.

Our results show that for both OMX Tallinn and OMX Riga no leverage effect is visible, i.e. the hypothesis of no asymmetric effects is strongly accepted. Regarding OMX Vilnius, one might speculate as to whether a negative leverage effect in fact exists (p-value of 0.11), but we are still unable to reject the null hypothesis even at 10%.

It must be said, however, that despite the fact that this conclusion is not on par with our original expectations, it does not contradict previous research. The abovementioned work by Savva *et al.* (2004), while identifying the presence of negative leverage effect in most of the countries in their sample, concluded that no significant effects were observed in both Luxembourg and Denmark. The true reasons behind it are left unanswered. A logical explanation suggests that these markets, as well, as our analyzed markets, are more symmetric in reacting towards news, disregarding whether they are positive or negative. This, however, is not presented as a final statement, but rather as an invitation for further discussion and research.

Conclusion: No statistically significant leverage effects were identified, hence we reject this hypothesis.

5.4 Hypothesis 4

Significant interdependence between the three stock exchanges is present.

The issue and importance of interdependence between the markets has been thoroughly explained in the literature review section. Tables 4 through 9 in the Appendix summarize the estimation findings with the use of GARCH (1/1) and (2/2) specifications and address the issue of interdependence through testing for significant terms of the lagged returns of neighboring countries predicting the returns in each of the analyzed states.

The main observation is as follows: Estonian and Lithuanian stock markets are found to be very interrelated based on the daily estimators. Each regression done on these two stock markets included significant lags of another one. According to GARCH (1,1) specification, Latvian stock market seems to be less influential itself, but nevertheless quite dependent on the second order lag of OMX Vilnius. A more general GARCH filter, however, identifies the Latvian market as strictly independent from the other two.

Using monthly estimators in the formula presents a somewhat different picture, the returns being mostly dependent on the home stock market’s lag instead of its neighbor. Still, familiar trends can be noticed, such as Lithuanian market movements are significantly dependent on the events in OMX Tallinn, and OMX Riga being influenced by corresponding fluctuations in the Lithuanian market of the second order lag. OMX Tallinn, however, is shown as highly independent.

Despite the inability to draw a precise relationship matrix due to different results obtained from different model specifications, it can be undoubtedly said that interdependence and contagion effects are noticed between the three markets. We are inclined towards the following causal relationship: OMX Tallinn and OMX Vilnius are believed to be mutually interdependent and fluctuations in either of the markets propagate towards another crosswise. Latvian stock market is to some extent less influential, but nevertheless closely related to its neighbors, especially to Lithuania.

Conclusion: Instead of acting as purely individual entities, the markets are found to function as parts of a larger mechanism and shocks in any of them are bound to have substantial spillover effect towards the other two. With this in mind, the hypothesis is accepted and interrelation effects are identified.

6 Discussion of the results

An insight into the results achieved by our empirical study has been provided in the last section; however, the situation could be improved by identifying what bounds together the seemingly distinct questions that were asked during this study.

Together with the results obtained while testing for the interdependence between the stock markets we have drawn open to doubt conclusions because under different model specifications the results had a tendency to vary between some boundaries. However, putting these results in the perspective of those attained while testing for Hypotheses 1-2 and also the preliminary statistics, we observe that more similarities exist between Vilnius and Tallinn than any other pair from this small region. Furthermore, primarily, by including the lagged returns of neighboring countries into the regression it was our intention to not just increase the explanatory power of the models but also to set a base argument for further analysis of similarities (or absence of them) in seasonal trends on the stock markets. It was our expectation that interdependence leads to similar trends, however, what we see from the results is more likely the opposite – weak interdependence and substantially different patterns in stock market behavior.

7 Conclusions

Based on the example set by similar researches that were performed in many other regions around the world in the financial markets that could already be characterized as developed, or yet only emerging, throughout our study so far we have also, to a large extent, avoided speculating on the implications of the results of statistical analysis of financial time series of Baltic States' stock market indices returns. Such approach could be assessed as much positively as negatively.

As for an argument supporting our position we could take the fact that seasonal anomalies in the patterns of financial assets returns have attracted too much criticism and skeptical opinions since they first were encountered. This is not surprising, taking into account that the existence of the identified phenomenon strongly challenges the fundamental financial markets theory on efficiency. Moreover, it has been widely regarded that no rational explanations could possibly be found to interpret such abnormal repetitive trends; hence, the results have to be either unreliable or inconsistent. While the debate is still hot and ongoing, some compromises have already been achieved concerning the two most common effects: positive in January and negative on Monday. The former, for example, is usually explained by tax laws, as many investors try to dump non-performing stocks in December so to save in taxes, and as a result, prices catch a steeper upwards trend in January. As for the latter, it is thought that investors on Mondays are likely to react to the news published on late Friday as well as during the weekend.

Nevertheless, the failure to identify the implications of the results also poses threats since the relevance of the research itself becomes questionable. However, we are of the opinion that this study of the Baltic States' stock markets should not be regarded as a final product but rather as a framework on which further analysis, considering micro and macro factors of the economy as explanatory variables, shall be applied.

All things considered, we can conclude on what questions remain unanswered after our statistical study. The absence of the leverage effect in all three states contradicts findings in many other European markets and the causes of this remain unknown. Concerning the patterns in returns and volatility, the results were recovered, however, the usage of smaller recent periods' samples could show whether the move towards higher efficiency occurred as the markets gradually developed over time.

8 References

Balaban, Ercan. “Day of the Week Effects: New Evidence from an Emerging Stock Market”. The Central Bank of the Republic of Turkey, Discussion Paper 9410 (1994).

Baltic OMX Group. 2006. OMX AB. 4 Jan. 2006. <http://www.baltic.omxgroup.com>

Berg, Lennart. “Deterministic seasonal volatility in a small and integrated stock market: the case of Sweden." Finnish Economic Papers 16.2 (2003).

Berges, Angel, John McConnell, and Gary Schlarbaum. “The turn of the year in Canada.” Journal of Finance 39.1 (1984): 185–92.

Berument, Hakan, and Halil Kiymaz. (2001). “The day of the week effect on stock market volatility.” Journal of Economics and Finance 25 (2001): 181-193.

Black, Fisher. “Studies of Stock Market Volatility Changes,” Proceedings of the American Statistical Association, Business and Economic Statistics Section (1976): 177-81

Bollerslev, Tim (1986), “Generalised autoregressive conditional heteroskedasticity.” Journal of Econometrics 52 (1986): 307-27.

Brown, Philip, et al. “Stock return seasonalities and the tax loss selling hypothesis: analysis of the arguments and Australian evidence.” Journal of Financial Economics 12.1 (1983): 105–23.

Cross, Frank. “The Behavior of Stock Prices on Fridays and Mondays.” Financial Analysts Journal 29 (1973): 67-69.

Draper, Paul, and Krishna Paudyal, 1997, “Microstructure and Seasonality in the UK Equity Market.” Journal of Business Finance & Accounting 24.7-8 (1997): 1178-1204

Dornbusch, Rudiger, Yung Chul Park, and Stijn Claessens. “Contagion: Understanding How It Spreads”, World Bank Research Observer 15.2 (2000):177-97.

Engle, Robert F. “Autoregressive conditional heteroskedasticity with estimates of the variance of U.K inflation.” Econometrica 50 (1982): 987-1008.

Engle, Robert F. “Statistical Models for Financial Volatility.” Financial Analysts Journal 49 (1993): 72-78.

Fama, Eugene F. “The behavior of stock market prices.” Journal of Business 38 (1965): 34-105.

Fama, Eugene F. “Efficient Capital Markets: A Review of Theory & Empirical Work.” Journal of Finance (1970): 383-417.

Franses, Philip H., and Richard Paap. “Modelling Day-of-the-Week Seasonality in the S&P 500 index.” Applied Financial Economics 10 (2000): 483-8.

French, Kenneth R. “Stock Returns and the Weekend Effect.” Journal of Financial Economics 8 (1980): 55-69.

Gamble, Ralph. “The January effect and intergenerational transfers”, Quarterly Review of Economics and Finance 33 (1993): 295–304.

Gardeazabal, Javier and Marta Regulez. “A Factor Model of Seasonality in Stock Returns.” Working Paper 17th June, 2002.

Hamilton, James D. Time Series Analysis. Princeton: Princeton University Press, 1994.

Jacobs, Bruce I., and Kenneth N. Levy. "Calendar Anomalies: Abnormal Returns at Calendar Turning Points." Financial Analysts Journal Nov-Dec (1988): 28-39.

Jarrett, Jeffrey, and Eric Kyper. “Evidence on the seasonality of stock market prices of firms traded on organized markets.” Applied Economics Letters 12 (2005): 537–43.

Lucey, Brian M., and Shane Whelan. “Monthly and semi-annual seasonality in the Irish equity market 1934–2000.” Applied Financial Economics 14 (2004): 203–8

Mandelbrot, Benoit. “The variation of certain speculative prices.” Journal of Business 36 (1963): 394-419.

Masson, P. “Contagion: monsoonal effects, spillovers, and jumps between multiple equilibria.” IMF Working Paper 142 (1998).

Nelson, Daniel B. “Conditional Heteroskedasticity in Asset Returns: A New Approach.” Econometrica 59.2 (1991): 347-70.

Ogden, Joseph P. “Turn of the month evaluations of liquid profits and stock returns; a common explanation of the monthly and January effects.” Journal of Finance 45 (1990): 1259–72.

Pandey, Indra. M. “Seasonality in the Malaysian Stock Market: 1992-2002”, Journal of Financial Management and Analysis 15.2 (2002): 37-44.

Pajuste, Anete, Gatis Kepitis, and Peter Hogfeldt. “Risk factors and predictability of stock returns in Central and Eastern Europe.” Emerging Markets Quarterly 4 (2000): 7-25.

Rogalski, Richard. J. “New Findings Regarding Day-of-the-Week Returns over Trading and Non-Trading Periods: A Note.” Journal of Finance 35 (1984): 1603-14.

Sarma, Salakan. N. “Stock Market Seasonality in an Emerging Market.” Vikalpa: The Journal for Decision Makers 3 July-Sept (2004): 35-41

Savva, Christos S., Denise R. Osborn, and Len Gill. (2004). “The Day of the Week Effect on Stock Market Volatility using EGARCH Framework.” University of Manchester, Working Paper (First draft: April 2004, Revised: January 2006).

Stock, James H., and Mark W. Watson. Introduction to Econometrics. Boston: Pearson Education, 2003.

Scheicher, Martin. “The Comovements of Stock Markets in Hungary, Poland and the Czech Republic.” International Journal of Finance and Economics 6.1 (2001): 27-39.

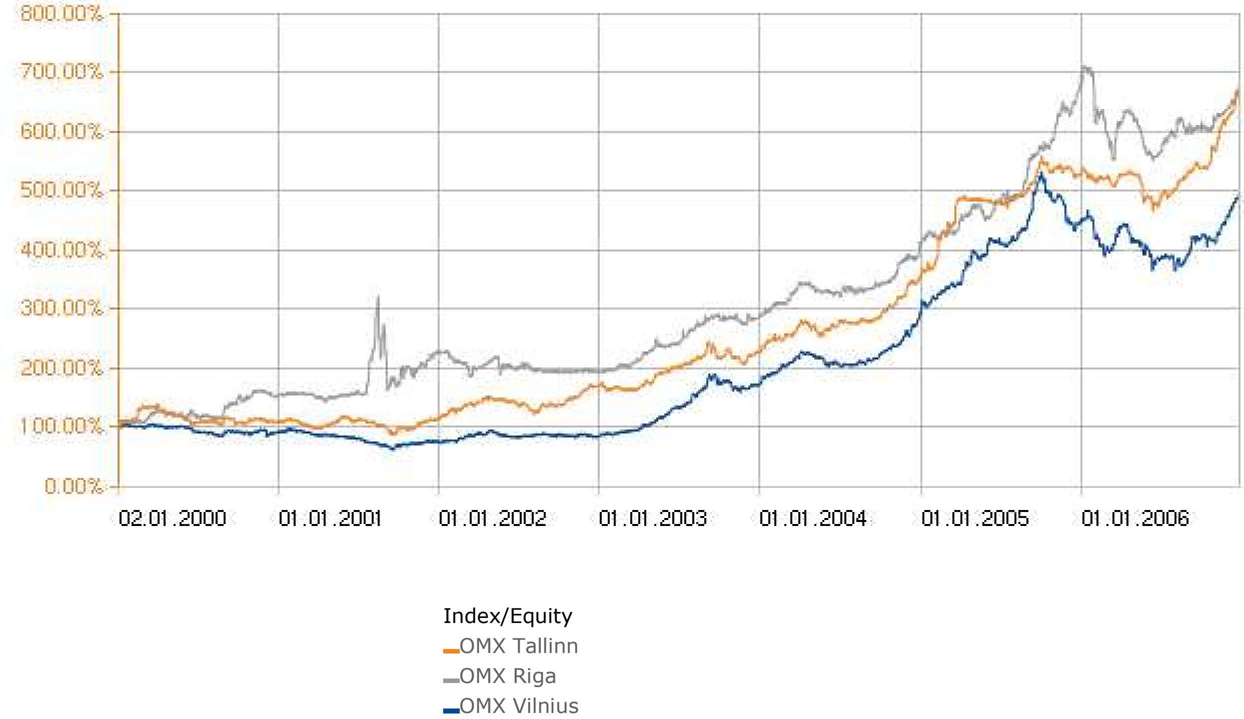
The Mathworks. 2004. The Mathworks, Inc. 4 Jan. 2006. <http://www.mathworks.com>

Tse, Yiuman, Chunchi Wu, and Allan Young. “Asymmetric Information Transmission between a Transition Economy and the U.S. Market: Evidence from the Warsaw Stock Exchange.” Global Finance Journal 14.3 (2003): 319-32.

Yakob, Noor A., Diana Beal, and Sarath Delpachitra. “Seasonality in the Asia Pacific Stock Markets.” Journal of Asset Management 6.4 (2005): 298-318.

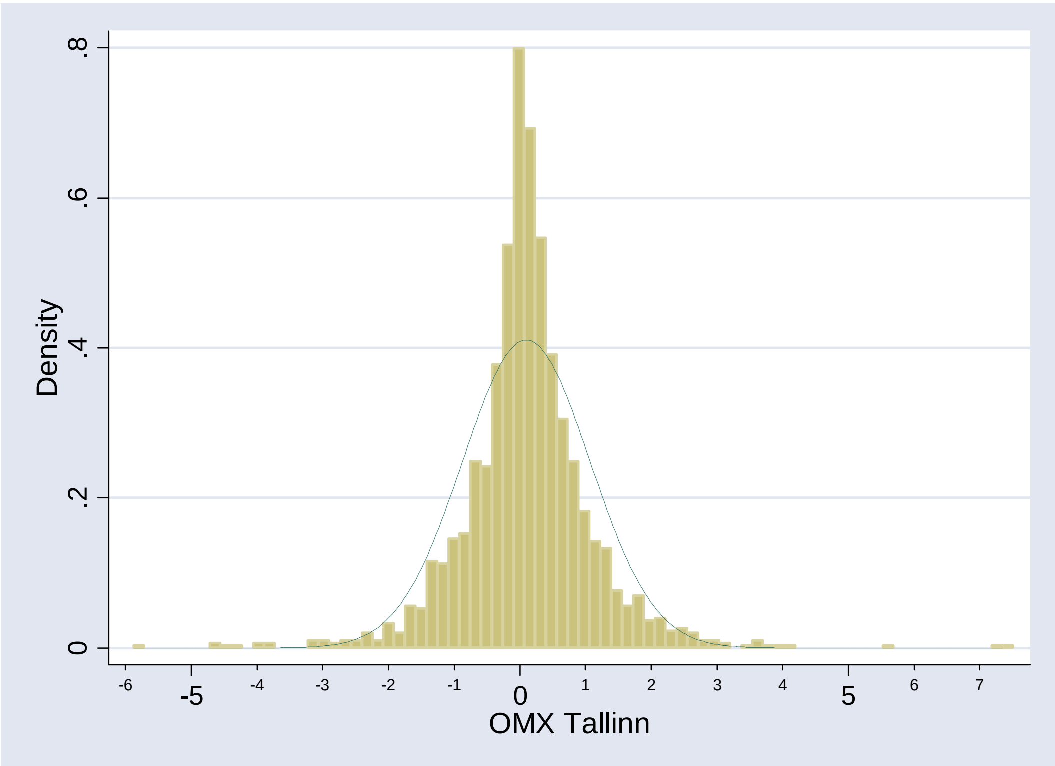
9 Appendix 1 – Figures

Figure 1 – Baltic Stock Market Indices



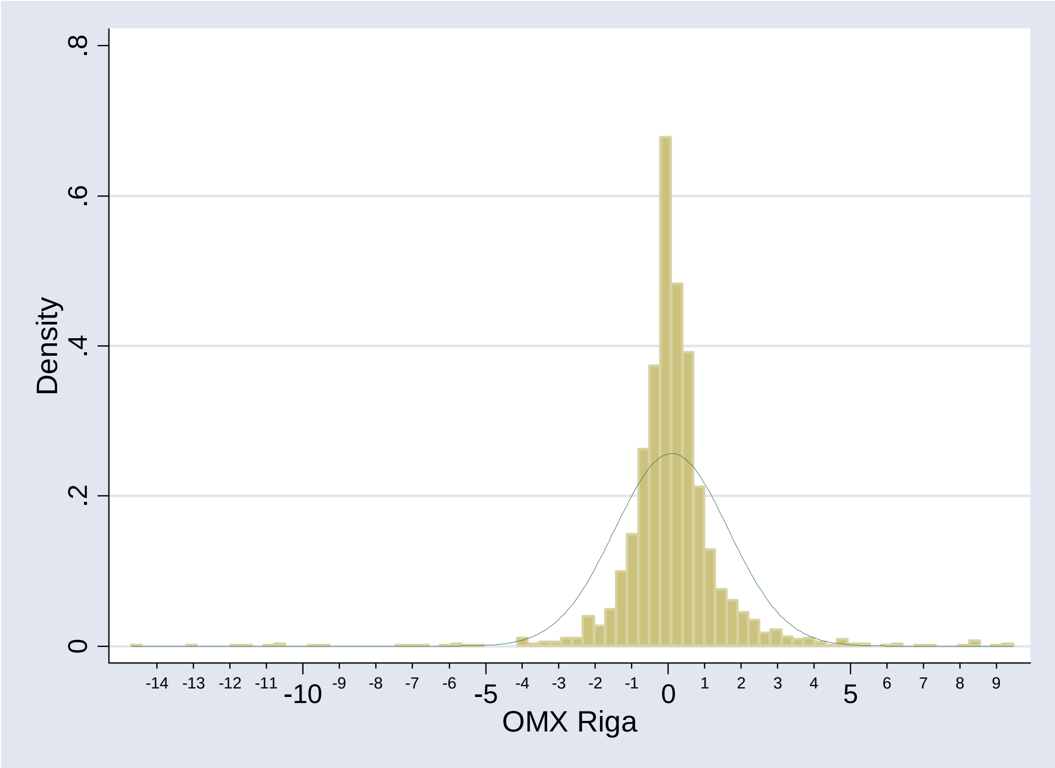
Source: Baltic OMX Group

Figure 2 - OMX Tallinn returns density plot



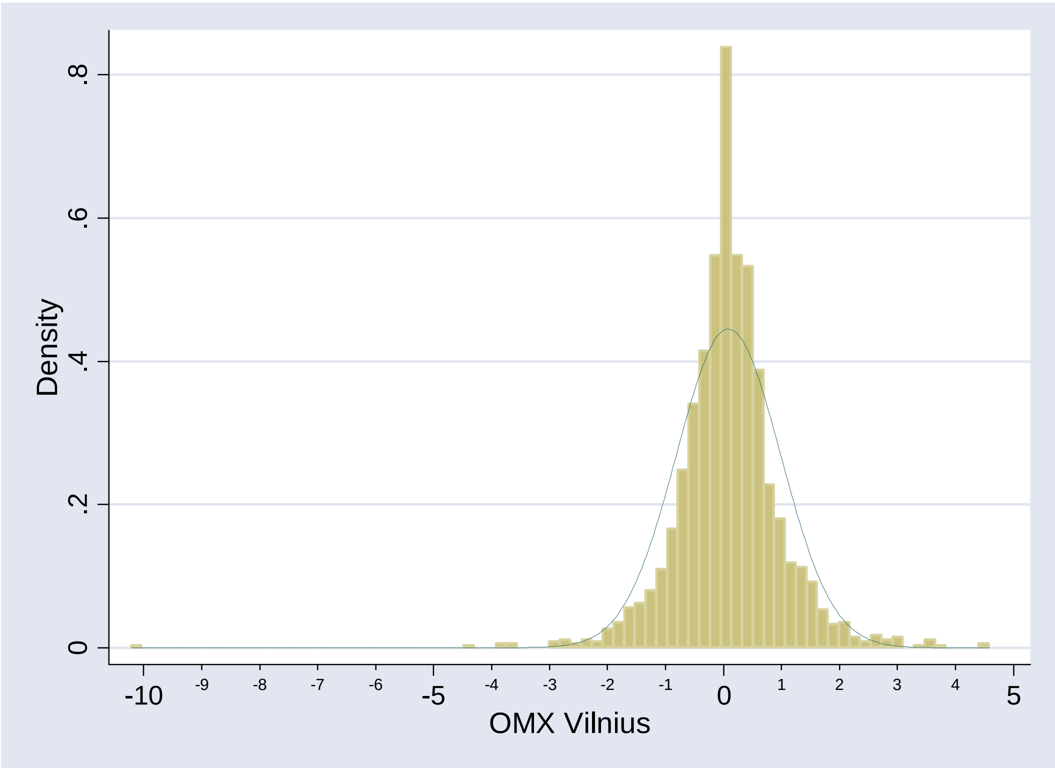
Line represents that of a normal distribution
Composed by authors based on OMX daily data (2006)

Figure 3 - OMX Riga returns density plot



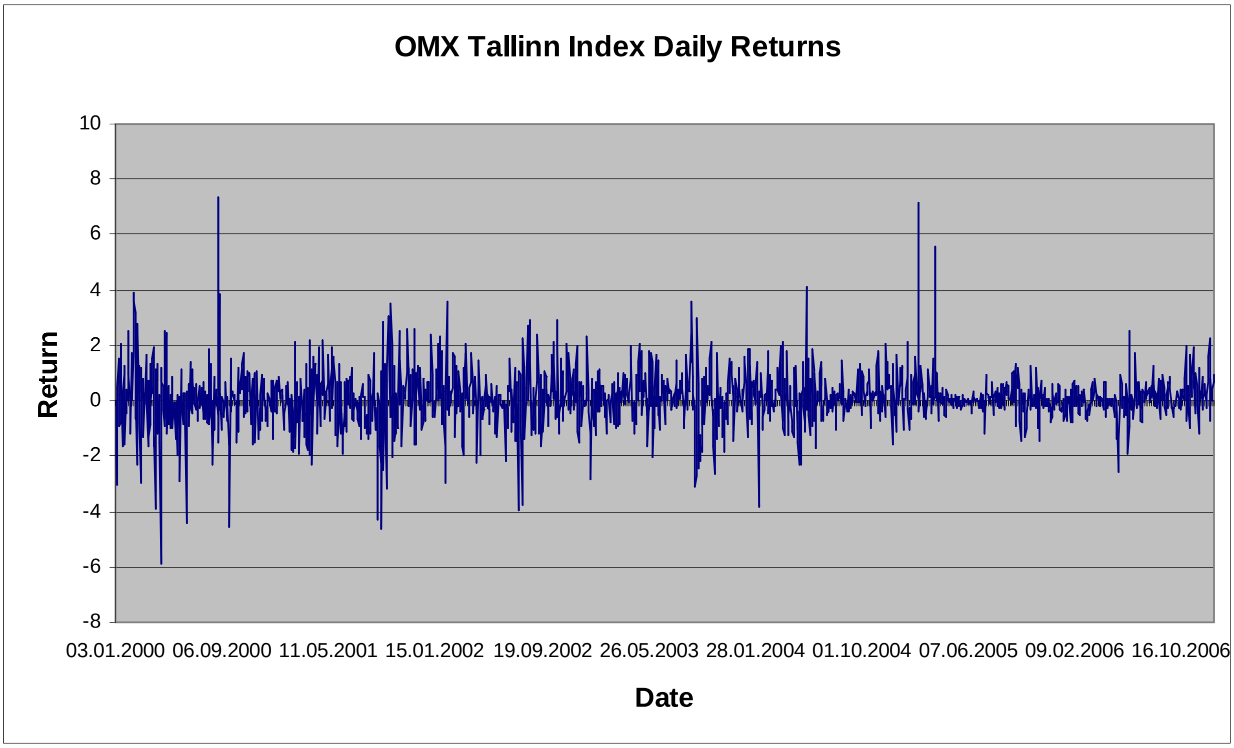
Line represents that of a normal distribution
Composed by authors based on OMX daily data (2006)

Figure 4 - OMX Vilnius returns density plot



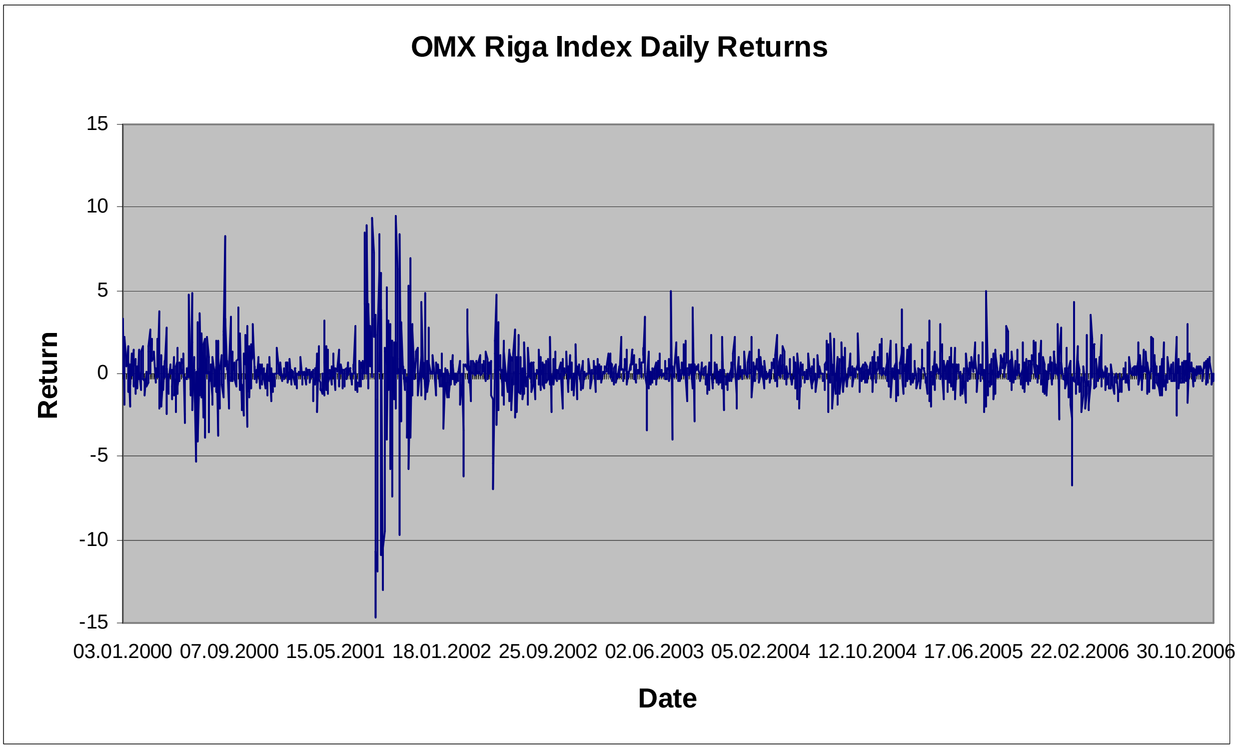
Line represents that of a normal distribution
Composed by authors based on OMX daily data (2006)

Figure 5 - OMX Tallinn Index Daily Returns



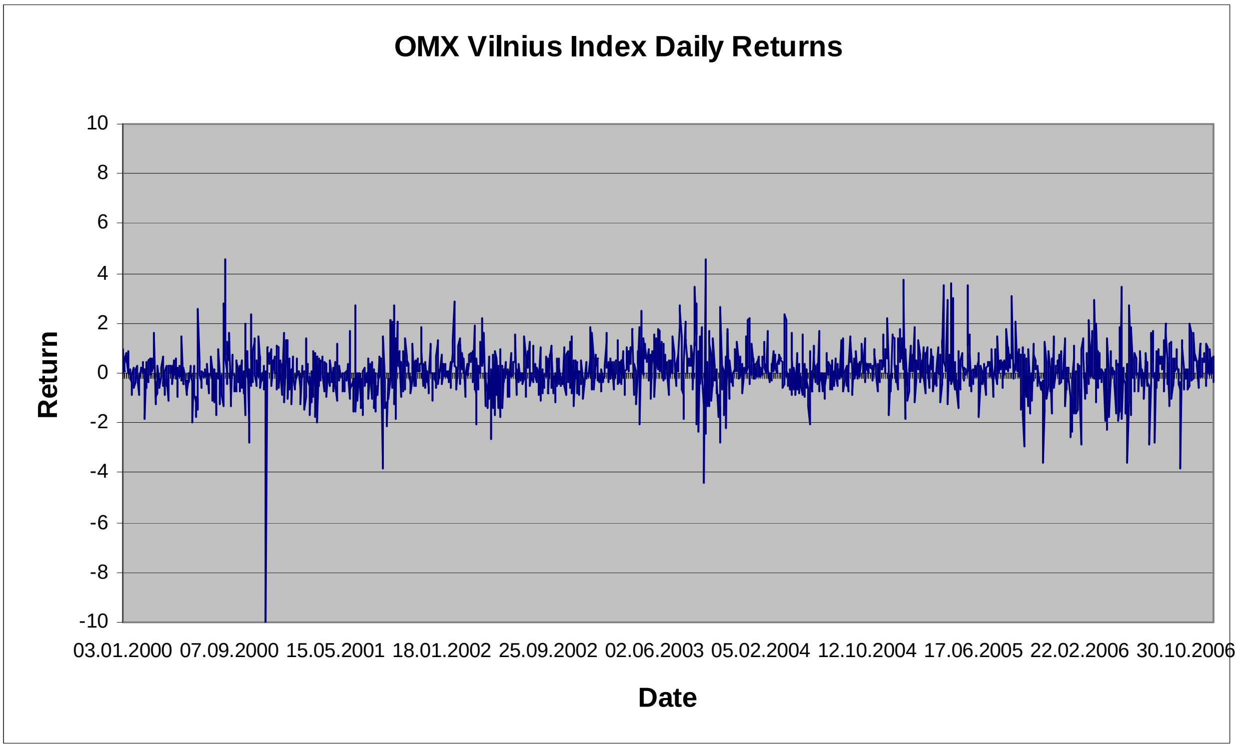
Composed by authors based on OMX daily data (2006)

Figure 6 - OMX Riga Index Daily Returns



Composed by authors based on OMX daily data (2006)

Figure 7 - OMX Vilnius Index Daily Returns



Composed by authors based on OMX daily data (2006)

10 Appendix 2 – Empirical results

Table 4 – GARCH(1,1) – daily patterns in return equation

	Tallinn				Riga				Vilnius			
	Coef.	Std. Err.	p		Coef.	Std. Err.	p		Coef.	Std. Err.	p	
a_M	-0.0400	0.0404	0.3230		-0.0505	0.0566	0.3720		-0.0961	0.0486	0.0480	**
a_T	0.0833	0.0394	0.0340	**	0.0847	0.0473	0.0730	*	0.0320	0.0418	0.4450	
a_W	0.0268	0.0428	0.5310		-0.0010	0.0675	0.9880		0.0934	0.0430	0.0300	**
a_{TH}	0.0582	0.0389	0.1340		0.1410	0.0565	0.0130	**	0.1069	0.0440	0.0150	**
a_F	0.0801	0.0344	0.0200	**	0.1770	0.0518	0.0010	***	0.1203	0.0505	0.0170	**
t_1	0.2023	0.0305	0.0000	***	0.0198	0.0246	0.4210		0.0438	0.0227	0.0540	*
t_2	0.0113	0.0293	0.7000		0.0119	0.0246	0.6280		0.0335	0.0201	0.0960	*
t_3	-0.0378	0.0259	0.1450		0.0118	0.0285	0.6790		0.0268	0.0208	0.1980	
t_4	0.0621	0.0269	0.0210	**	0.0321	0.0283	0.2560		0.0226	0.0229	0.3230	
r_1	0.0314	0.0179	0.0780	*	-0.0689	0.0319	0.0310	**	0.0066	0.0183	0.7180	
r_2	0.0132	0.0147	0.3700		0.0206	0.0328	0.5300		0.0262	0.0190	0.1670	
r_3	0.0178	0.0157	0.2560		0.0216	0.0279	0.4390		0.0071	0.0155	0.6490	
r_4	-0.0044	0.0163	0.7860		-0.0341	0.0271	0.2080		0.0068	0.0143	0.6340	
v_1	0.0352	0.0178	0.0480	**	0.0448	0.0349	0.1990		0.1446	0.0293	0.0000	***
v_2	0.0131	0.0190	0.4920		0.0548	0.0273	0.0450	**	0.0551	0.0297	0.0640	*
v_3	0.0140	0.0176	0.4260		0.0422	0.0277	0.1280		0.0108	0.0264	0.6820	
v_4	0.0208	0.0164	0.2050		0.0167	0.0238	0.4820		0.0197	0.0244	0.4200	
γ_0	0.0065	0.0039	0.0990	*	0.0924	0.0513	0.0720	*	0.2461	0.1143	0.0310	**
γ_1	0.1214	0.0224	0.0000	***	0.2225	0.0990	0.0250	**	0.1737	0.0455	0.0000	***
δ_1	0.8893	0.0180	0.0000	***	0.7383	0.1090	0.0000	***	0.5126	0.1329	0.0000	***
Wald chi2	109.16		0.0000	***	74.54		0.0000	***	110.00		0.0000	***
log-lik.	-2295.02				-2702.19				-2273.36			
Mean	0.0226				0.0154				-0.0016			
St. Dev.	0.9543				1.5520				0.8772			
Skewness	0.3636				-1.2093				-0.5534			
Kurtosis	9.6088				24.9757				14.7251			
Sk./Kurt. test			0.0000	***			0.0000	***			0.0000	***
ARCH-LM	56.0020		0.0000	***	563.1140		0.0000	***	24.7450		0.0000	***
Q-Statistic	50.9598		0.1148		476.3868		0.0000	***	64.8024		0.0078	***

Table 5 – GARCH(1,1) – daily patterns in return and volatility equations

	Tallinn				Riga				Vilnius			
	Coef.	Std. Err.	p		Coef.	Std. Err.	p		Coef.	Std. Err.	p	
a_M	-0.0402	0.0392	0.3050		-0.0445	0.0504	0.3770		-0.0882	0.0461	0.0560	*
a_T	0.0821	0.0380	0.0310	**	0.0961	0.0422	0.0230	**	0.0373	0.0413	0.3660	
a_W	0.0247	0.0426	0.5620		0.0185	0.0581	0.7500		0.0863	0.0417	0.0390	**
a_{TH}	0.0592	0.0384	0.1230		0.1360	0.0541	0.0120	**	0.1042	0.0430	0.0150	**
a_F	0.0789	0.0374	0.0350	**	0.1759	0.0517	0.0010	***	0.1068	0.0457	0.0190	**
t_1	0.2022	0.0306	0.0000	***	0.0157	0.0236	0.5040		0.0460	0.0214	0.0310	**
t_2	0.0110	0.0295	0.7100		0.0158	0.0235	0.5000		0.0353	0.0203	0.0830	*
t_3	-0.0365	0.0261	0.1610		0.0133	0.0267	0.6180		0.0253	0.0192	0.1880	
t_4	0.0614	0.0270	0.0230	**	0.0272	0.0273	0.3190		0.0183	0.0196	0.3490	
r_1	0.0326	0.0176	0.0650	*	-0.0732	0.0310	0.0180	**	0.0039	0.0234	0.8690	
r_2	0.0125	0.0147	0.3950		0.0256	0.0310	0.4090		0.0255	0.0207	0.2200	
r_3	0.0174	0.0155	0.2620		0.0243	0.0278	0.3830		0.0061	0.0162	0.7060	
r_4	-0.0042	0.0169	0.8050		-0.0322	0.0266	0.2270		0.0044	0.0163	0.7880	
v_1	0.0359	0.0177	0.0420	**	0.0385	0.0287	0.1790		0.1459	0.0296	0.0000	***
v_2	0.0122	0.0194	0.5300		0.0551	0.0248	0.0260	**	0.0665	0.0281	0.0180	**
v_3	0.0133	0.0179	0.4580		0.0300	0.0229	0.1910		-0.0011	0.0262	0.9660	
v_4	0.0214	0.0162	0.1870		0.0215	0.0229	0.3480		0.0246	0.0244	0.3140	
g_M	6.2772	43.2294	0.8850		-11.9599	1.9256	0.0000	***	1.2893	0.9487	0.1740	
g_T	0.3902	2.2659	0.8630		-12.6551	21.1099	0.5490		-2.2355	17.8100	0.9000	
g_W	10.9621	.	.		0.2436	1.0871	0.8230		0.3714	0.7595	0.6250	
g_{TH}	-14.5418	1.6801	0.0000	***	-1.7542	0.7437	0.0180	**	-2.0274	0.7387	0.0060	***
g_F	9.3051	11.8850	0.4340		-0.5992	2.6341	0.8200		0.5709	0.7374	0.4390	
γ_1	0.1235	0.0233	0.0000	***	0.2226	0.0746	0.0030	***	0.1816	0.0525	0.0010	***
δ_1	0.8875	0.0188	0.0000	***	0.7316	0.0843	0.0000	***	0.5590	0.1561	0.0000	***
Wald chi2	107.06		0.0000	***	81.64		0.0000	***	111.71		0.0000	***
log-lik.	-2294.34				-2691.07				-2258.54			
Mean	0.0233				0.0102				0.0008			
St. Dev.	0.9543				1.5522				0.8773			
Skewness	0.3640				-1.2147				-0.5586			
Kurtosis	9.6096				25.0571				14.8191			
Sk./Kurt. test			0.0000	***			0.0000	***			0.0000	***
ARCH-LM	56.1880		0.0000	***	567.7200		0.0000	***	24.6440		0.0000	***
Q-Statistic	50.8331		0.1171		478.9439		0.0000	***	66.7073		0.0051	***

Table 6 – GARCH(2,2) – daily patterns in return equation

	Tallinn				Riga				Vilnius			
	Coef.	Std. Err.	p		Coef.	Std. Err.	p		Coef.	Std. Err.	p	
a_M	-0.0424	0.0395	0.2830		-0.0386	0.0525	0.4610		-0.0916	0.0476	0.0550	*
a_T	0.0818	0.0389	0.0350	**	0.0768	0.0454	0.0910	*	0.0318	0.0411	0.4390	
a_W	0.0312	0.0440	0.4780		-0.0151	0.0780	0.8470		0.0919	0.0465	0.0480	**
a_{TH}	0.0633	0.0398	0.1120		0.1398	0.0635	0.0280	**	0.1102	0.0458	0.0160	**
a_F	0.0897	0.0359	0.0130	**	0.1942	0.0635	0.0020	***	0.1141	0.0480	0.0180	**
t_1	0.2001	0.0310	0.0000	***	0.0158	0.0272	0.5600		0.0461	0.0221	0.0360	**
t_2	0.0095	0.0287	0.7420		0.0187	0.0231	0.4180		0.0359	0.0215	0.0960	*
t_3	-0.0368	0.0263	0.1610		0.0081	0.0273	0.7680		0.0270	0.0213	0.2040	
t_4	0.0656	0.0268	0.0140	**	0.0217	0.0285	0.4480		0.0195	0.0222	0.3800	
r_1	0.0346	0.0177	0.0500	**	-0.0934	0.0457	0.0410	**	0.0058	0.0173	0.7350	
r_2	0.0112	0.0149	0.4500		0.0136	0.0303	0.6540		0.0279	0.0188	0.1380	
r_3	0.0139	0.0168	0.4080		0.0167	0.0306	0.5850		0.0054	0.0163	0.7410	
r_4	-0.0048	0.0160	0.7640		-0.0300	0.0268	0.2620		0.0088	0.0136	0.5170	
v_1	0.0401	0.0182	0.0270	**	0.0411	0.0339	0.2260		0.1478	0.0295	0.0000	***
v_2	0.0131	0.0190	0.4900		0.0548	0.0350	0.1180		0.0597	0.0304	0.0500	**
v_3	0.0100	0.0189	0.5990		0.0364	0.0361	0.3130		0.0141	0.0267	0.5970	
v_4	0.0205	0.0165	0.2130		0.0180	0.0250	0.4710		0.0156	0.0249	0.5320	
γ_0	0.0046	0.0032	0.1520		0.0208	0.0404	0.6070		0.3274	0.0739	0.0000	***
γ_1	0.1930	0.0637	0.0020	***	0.3246	0.0995	0.0010	***	0.1558	0.0554	0.0050	***
γ_2	-0.0982	0.0871	0.2600		-0.2682	0.0806	0.0010	***	0.0503	0.0570	0.3780	
δ_1	1.0257	0.2442	0.0000	***	1.1617	0.8042	0.1490		0.5118	0.1908	0.0070	***
δ_2	-0.1117	0.2151	0.6030		-0.2291	0.6876	0.7390		-0.1357	0.0822	0.0990	*
Wald chi2	108.68		0.0000	***	74.00		0.0000	***	107.69		0.0000	***
log-lik.	-2292.56				-2683.68				-2272.14			
Mean	0.0198				0.0193				-0.0025			
St. Dev.	0.9546				1.5614				0.8772			
Skewness	0.3622				-1.2517				-0.5475			
Kurtosis	9.5662				25.5138				14.7356			
Sk./Kurt. test			0.0000	***			0.0000	***			0.0000	***
ARCH-LM	56.5700		0.0000	***	596.3500		0.0000	***	25.1580		0.0000	***
Q-Statistic	51.2911		0.1088		530.9032		0.0000	***	65.7194		0.0064	***

Table 7 – GARCH(1,1) – monthly patterns in return equation

	Tallinn				Riga				Vilnius			
	Coef.	Std. Err.	p		Coef.	Std. Err.	p		Coef.	Std. Err.	p	
a_1	0.0467	0.0914	0.6100		0.0723	0.0583	0.2150		0.0963	0.0545	0.0770	*
a_2	-0.0617	0.1791	0.7300		-0.0598	0.0442	0.1760		0.0255	0.0498	0.6090	
a_3	0.0631	0.0479	0.1880		0.3309	0.1165	0.0050	***	0.1352	0.0553	0.0140	**
a_4	0.0248	0.0412	0.5470		0.1287	0.0508	0.0110	**	0.1025	0.0863	0.2350	
a_5	0.0027	0.0350	0.9390		-0.1084	0.0759	0.1530		-0.0445	0.0560	0.4270	
a_6	-0.0453	0.0348	0.1930		0.0859	0.0602	0.1530		0.0068	0.0709	0.9240	
a_7	-0.0046	0.0391	0.9070		-0.3124	0.3809	0.4120		0.0129	0.0387	0.7390	
a_8	0.1352	0.0642	0.0350	**	0.1029	0.1298	0.4280		-0.0073	0.0793	0.9270	
a_9	0.1128	0.0594	0.0580	*	0.1128	0.0679	0.0960	*	0.1945	0.0747	0.0090	***
a_{10}	0.0848	0.0598	0.1560		0.0671	0.0770	0.3840		-0.0351	0.0694	0.6130	
a_{11}	0.1530	0.0633	0.0160	**	0.1439	0.0637	0.0240	**	0.1637	0.1121	0.1440	
a_{12}	0.0783	0.0506	0.1210		0.0952	0.0702	0.1750		0.0057	0.1138	0.9600	
t_1	0.1940	0.0305	0.0000	***	0.0185	0.0256	0.4690		0.0486	0.0249	0.0510	*
t_2	0.0071	0.0309	0.8190		0.0186	0.0262	0.4780		0.0339	0.0216	0.1170	
t_3	-0.0446	0.0269	0.0980	*	0.0124	0.0313	0.6930		0.0364	0.0238	0.1260	
t_4	0.0483	0.0278	0.0820	*	0.0287	0.0291	0.3240		0.0185	0.0206	0.3700	
r_1	0.0282	0.0179	0.1160		-0.0929	0.0336	0.0060	***	0.0088	0.0162	0.5880	
r_2	0.0122	0.0147	0.4060		0.0104	0.0311	0.7390		0.0238	0.0167	0.1540	
r_3	0.0202	0.0159	0.2060		0.0055	0.0273	0.8420		0.0059	0.0151	0.6980	
r_4	-0.0027	0.0155	0.8600		-0.0399	0.0262	0.1270		0.0037	0.0145	0.7980	
v_1	0.0275	0.0173	0.1120		0.0386	0.0273	0.1580		0.1348	0.0292	0.0000	***
v_2	0.0097	0.0174	0.5790		0.0590	0.0275	0.0320	**	0.0468	0.0286	0.1020	
v_3	0.0119	0.0163	0.4650		0.0364	0.0246	0.1380		0.0004	0.0260	0.9870	
v_4	0.0133	0.0168	0.4290		0.0254	0.0241	0.2920		0.0141	0.0242	0.5590	
γ_0	0.0061	0.0041	0.1350		0.1015	0.0396	0.0100	***	0.2535	0.1165	0.0300	**
γ_1	0.1287	0.0294	0.0000	***	0.2862	0.1134	0.0120	**	0.1707	0.0498	0.0010	***
δ_1	0.8847	0.0207	0.0000	***	0.6866	0.0943	0.0000	***	0.5050	0.1341	0.0000	***
Wald chi2	121.39		0.0000	***	83.83		0.0000	***	117.91		0.0000	***
log-lik.	-2291.45			***	-2693.65			***	-2274.74			***
Mean	0.0194				0.0356				-0.0020			
St. Dev.	0.9552				1.5702				0.8762			
Skewness	0.3382				-1.1735				-0.6182			
Kurtosis	9.6665				25.4700				15.0676			
Sk./Kurt. test			0.0000	***			0.0000	***			0.0000	***
ARCH-LM	52.0240		0.0000	***	600.9790		0.0000	***	23.8550		0.0000	***
Q-Statistic	48.2862		0.1729		536.3668		0.0000	***	61.7335		0.0153	**

Table 8 – GARCH(1,1) – monthly patterns in return and volatility equations

	Tallinn				Riga				Vilnius			
	Coef.	Std. Err.	p		Coef.	Std. Err.	p		Coef.	Std. Err.	p	
a_1	0.0901	0.0758	0.2350		0.0796	0.0603	0.1870		0.0966	0.0566	0.0880	*
a_2	0.0452	0.0996	0.6500		-0.0450	0.0511	0.3790		0.0157	0.0533	0.7680	
a_3	0.0911	0.0578	0.1150		0.2747	0.0837	0.0010	***	0.1547	0.0585	0.0080	***
a_4	0.0203	0.0496	0.6820		0.1445	0.0593	0.0150	**	0.1024	0.0822	0.2130	
a_5	0.0034	0.0377	0.9270		-0.1165	0.0752	0.1210		-0.0397	0.0572	0.4880	
a_6	-0.0411	0.0590	0.4860		0.1030	0.0578	0.0750	*	-0.0087	0.0676	0.8970	
a_7	-0.0115	0.0506	0.8200		0.1390	0.1094	0.2040		-0.0036	0.0418	0.9310	
a_8	0.1324	0.0610	0.0300	**	0.0912	0.0983	0.3540		-0.0111	0.0751	0.8830	
a_9	0.1057	0.0541	0.0510	*	0.1412	0.0675	0.0370	**	0.1878	0.0728	0.0100	***
a_{10}	0.0862	0.0538	0.1090		0.0412	0.0752	0.5830		-0.0334	0.0643	0.6040	
a_{11}	0.1469	0.0666	0.0270	**	0.1446	0.0713	0.0420	**	0.0995	0.0658	0.1310	
a_{12}	0.0726	0.0481	0.1310		0.1064	0.0672	0.1140		-0.0038	0.1001	0.9700	
t_1	0.2080	0.0290	0.0000	***	0.0168	0.0262	0.5210		0.0550	0.0202	0.0060	***
t_2	0.0150	0.0287	0.6000		0.0163	0.0254	0.5200		0.0352	0.0192	0.0670	*
t_3	-0.0439	0.0269	0.1030		0.0146	0.0299	0.6250		0.0221	0.0193	0.2530	
t_4	0.0484	0.0266	0.0690	*	0.0211	0.0267	0.4290		0.0074	0.0179	0.6800	
r_1	0.0233	0.0191	0.2220		-0.0772	0.0301	0.0100	***	0.0103	0.0155	0.5090	
r_2	0.0090	0.0162	0.5780		0.0263	0.0283	0.3510		0.0180	0.0144	0.2120	
r_3	0.0215	0.0171	0.2080		0.0271	0.0267	0.3100		0.0134	0.0133	0.3140	
r_4	0.0037	0.0177	0.8350		-0.0314	0.0262	0.2310		0.0114	0.0138	0.4070	
v_1	0.0276	0.0187	0.1410		0.0163	0.0246	0.5070		0.1254	0.0292	0.0000	***
v_2	0.0022	0.0189	0.9070		0.0389	0.0227	0.0860	*	0.0547	0.0272	0.0450	**
v_3	0.0166	0.0155	0.2850		0.0285	0.0221	0.1970		-0.0050	0.0253	0.8420	
v_4	0.0074	0.0173	0.6670		0.0122	0.0219	0.5770		0.0293	0.0232	0.2050	
g_1	-0.4705	1.6025	0.7690		0.7718	0.6891	0.2630		0.0052	0.3358	0.9880	
g_2	-2.7173	1.5093	0.0720	*	-3.3970	0.6244	0.0000	***	-1.5366	0.2934	0.0000	***
g_3	-11.0145	59.4922	0.8530		1.5117	0.5650	0.0070	***	-0.0081	0.3273	0.9800	
g_4	-3.1235	2.0712	0.1320		0.0161	0.6314	0.9800		0.8831	0.3249	0.0070	***
g_5	-2.4228	3.5032	0.4890		1.1135	0.6080	0.0670	*	0.1757	0.3268	0.5910	
g_6	-3.9626	9.8102	0.6860		0.6740	0.6889	0.3280		0.5624	0.3435	0.1020	
g_7	-2.0645	1.7514	0.2380		2.5257	0.6428	0.0000	***	-0.4147	0.3020	0.1700	
g_8	-1.2725	1.4541	0.3820		1.4467	0.6330	0.0220	**	0.6443	0.3530	0.0680	*
g_9	-2.0739	1.4777	0.1600		0.8158	0.6957	0.2410		0.5996	0.3126	0.0550	*
g_{10}	-1.3600	1.5460	0.3790		1.1026	0.6225	0.0770	*	0.5163	0.3603	0.1520	
g_{11}	-1.9672	1.7505	0.2610		0.3440	0.6950	0.6210		0.4137	0.3566	0.2460	
g_{12}	-17.4645	7.5366	0.0200	**	0.8831	0.5982	0.1400		1.2679	0.7695	0.0990	*
γ_1	0.1186	0.0460	0.0100	***	0.1891	0.0629	0.0030	***	0.2403	0.0458	0.0000	***
δ_1	0.8807	0.0412	0.0000	***	0.7503	0.0750	0.0000	***	0.3339	0.0913	0.0000	***

Wald chi2	126.23		0.0000	***	84.87		0.0000	***	109.63		0.0000	***
log-lik.	-2275.27			***	-2646.32			***	-2221.86			***
Mean	0.0058				-0.0011				0.0061			
St. Dev.	0.9538				1.5527				0.8766			
Skewness	0.3306				-1.2414				-0.6436			
Kurtosis	9.6151				25.4147				15.1864			
Sk./Kurt. test			0.0000	***			0.0000	***			0.0000	***
ARCH-LM	54.6640		0.0000	***	575.8290		0.0000	***	22.2060		0.0000	***
Q-Statistic	49.5992		0.1421		482.1450		0.0000	***	62.5626		0.0128	**

Table 9 – GARCH(2,2) – monthly patterns in return equation

	Tallinn				Riga				Vilnius			
	Coef.	Std. Err.	p		Coef.	Std. Err.	p		Coef.	Std. Err.	p	
a_1	0.0544	0.0944	0.5650		0.0661	0.0619	0.2860		0.0919	0.0533	0.0850	*
a_2	-0.0489	0.1624	0.7630		-0.0625	0.0428	0.1440		0.0249	0.0491	0.6120	
a_3	0.0905	0.0618	0.1430		0.3217	0.1155	0.0050	***	0.1430	0.0572	0.0120	**
a_4	0.0300	0.0416	0.4710		0.1262	0.0512	0.0140	**	0.1086	0.0903	0.2290	
a_5	-0.0002	0.0366	0.9960		-0.1029	0.0747	0.1680		-0.0468	0.0542	0.3880	
a_6	-0.0433	0.0329	0.1870		0.0738	0.0581	0.2040		0.0076	0.0718	0.9160	
a_7	-0.0124	0.0436	0.7750		-0.2734	0.2924	0.3500		0.0135	0.0392	0.7300	
a_8	0.1492	0.0714	0.0370	**	0.1271	0.1422	0.3720		-0.0021	0.0768	0.9790	
a_9	0.0991	0.0512	0.0530	*	0.1135	0.0662	0.0870	*	0.1900	0.0752	0.0120	**
a_{10}	0.0816	0.0622	0.1900		0.0736	0.0841	0.3810		-0.0378	0.0685	0.5810	
a_{11}	0.1545	0.0657	0.0190	**	0.1305	0.0651	0.0450	**	0.1554	0.1253	0.2150	
a_{12}	0.0832	0.0542	0.1250		0.0892	0.0702	0.2040		0.0197	0.1032	0.8480	
t_1	0.1778	0.0461	0.0000	***	0.0182	0.0256	0.4770		0.0485	0.0239	0.0420	**
t_2	0.0155	0.0350	0.6570		0.0258	0.0280	0.3560		0.0346	0.0222	0.1190	
t_3	-0.0351	0.0270	0.1940		0.0060	0.0317	0.8510		0.0361	0.0244	0.1380	
t_4	0.0457	0.0276	0.0970	*	0.0309	0.0299	0.3010		0.0170	0.0212	0.4210	
r_1	0.0257	0.0179	0.1510		-0.0817	0.0314	0.0090	***	0.0064	0.0160	0.6890	
r_2	0.0121	0.0149	0.4170		0.0119	0.0327	0.7160		0.0254	0.0169	0.1320	
r_3	0.0157	0.0161	0.3320		0.0091	0.0274	0.7390		0.0039	0.0162	0.8100	
r_4	-0.0027	0.0160	0.8680		-0.0399	0.0269	0.1370		0.0060	0.0140	0.6710	
v_1	0.0310	0.0195	0.1120		0.0394	0.0289	0.1740		0.1387	0.0291	0.0000	***
v_2	0.0063	0.0181	0.7290		0.0537	0.0241	0.0260	**	0.0513	0.0294	0.0820	*
v_3	0.0099	0.0177	0.5780		0.0392	0.0257	0.1280		0.0051	0.0265	0.8490	
v_4	0.0163	0.0172	0.3430		0.0249	0.0221	0.2590		0.0109	0.0253	0.6670	
γ_0	0.0131	0.0079	0.0950	*	0.1879	0.0661	0.0040	***	0.3225	0.0671	0.0000	***
γ_1	0.1295	0.0312	0.0000	***	0.2636	0.0943	0.0050	***	0.1512	0.0628	0.0160	**
γ_2	0.1243	0.0332	0.0000	***	0.2905	0.1080	0.0070	***	0.0473	0.0556	0.3960	
δ_1	-0.1130	0.0251	0.0000	***	-0.1129	0.0537	0.0360	**	0.5423	0.1634	0.0010	***
δ_2	0.8833	0.0225	0.0000	***	0.5207	0.1100	0.0000	***	-0.1526	0.0740	0.0390	**
Wald chi2	118.89		0.0000	***	82.97		0.0000	***	115.65		0.0000	***
log-lik.	-2286.69			***	-2690.79			***	-2273.23			***
Mean	0.0161				0.0318				-0.0037			
St. Dev.	0.9538				1.5647				0.8762			
Skewness	0.3331				-1.1845				-0.6114			
Kurtosis	9.6334				25.3940				15.1102			
Sk./Kurt. test			0.0000	***			0.0000	***			0.0000	***
ARCH-LM	47.4380		0.0000	***	585.9040		0.0000	***	23.9910		0.0000	***

Q-Statistic	45.0845		0.2677		511.8266		0.0000	***	62.4943		0.0130	**

Table 10 – EGARCH(1,1) – daily patterns in return and volatility equations

	Tallinn				Riga				Vilnius			
	Coef.	Std. Err.	p		Coef.	Std. Err.	p		Coef.	Std. Err.	p	
a_M	-0.0413	0.0400	0.3010		-0.0430	0.0385	0.2650		-0.0912	0.0457	0.0460	**
a_T	0.0952	0.0382	0.0130	**	0.1092	0.0458	0.0170	**	0.0380	0.0896	0.6710	
a_W	0.0347	0.0389	0.3720		0.0360	0.0478	0.4520		0.1085	0.0111	0.0000	***
a_{TH}	0.0731	0.0442	0.0990	*	0.1822	0.0574	0.0010	***	0.0660	0.0467	0.1570	
a_F	0.1075	0.0416	0.0100	***	0.1967	0.0068	0.0000	***	0.1647	0.0388	0.0000	***
t_1	0.1896	0.0313	0.0000	***								
t_2	0.0300	0.0283	0.2900									
t_3	-0.0390	0.0295	0.1850									
t_4	0.0854	0.0294	0.0040	***								
r_1					-0.0486	0.0011	0.0000	***				
r_2					0.0419	0.0057	0.0000	***				
r_3					0.0347	0.0093	0.0000	***				
r_4					-0.0316	0.0118	0.0070	***				
v_1									0.1752	0.0676	0.0100	***
v_2									0.0521	0.0436	0.2330	
v_3									0.0172	0.0777	0.8250	
v_4									0.0418	0.0333	0.2100	
g_M	0.3272	0.2595	0.2070		-0.2735	0.2760	0.3220		0.2678	0.3538	0.4490	
g_T	0.0431	0.2350	0.8540		-0.4443	0.2143	0.0380	**	-0.1937	0.2825	0.4930	
g_W	0.2175	0.2698	0.4200		-0.0733	0.2559	0.7750		-0.1456	0.2036	0.4740	
g_{TH}	-0.1813	0.1438	0.2070		0.2565	0.1568	0.1020		-0.0479	0.1180	0.6850	
g_F	0.3778	0.3092	0.2220		-0.2646	0.3160	0.4020		0.0295	0.2045	0.8850	
γ_1	0.0005	0.0219	0.9820		0.0082	0.0247	0.7410		-0.0594	0.0376	0.1140	
θ_1	0.2155	0.0288	0.0000	***	0.3542	0.0636	0.0000	***	0.3287	0.0608	0.0000	***
β_1	0.9790	0.0073	0.0000	***	0.9521	0.0195	0.0000	***	0.7403	0.0804	0.0000	***
Wald chi2	73.81		0.0000	***	5122.21		0.0000	***	3954.26		0.0000	***
log-lik.	-2289.25				-2706.11				-2269.93			
Mean	0.0208				0.0050				0.0048			
St. Dev.	0.9560				1.5440				0.8849			
Skewness	0.3478				-1.2742				-0.5882			
Kurtosis	9.6226				24.9122				14.9314			
Sk./Kurt. test			0.0000	***			0.0000	***			0.0000	***
ARCH-LM	42.1110		0.0000	***	543.1960		0.0000	***	28.3540		0.0000	***
Q-Statistic	53.6003		0.0737	*	426.0920		0.0000	***	66.0274		0.0059	***

Table 11 – EGARCH(1,1) – monthly patterns in return and volatility equations

	Tallinn				Riga				Vilnius			
	Coef.	Std. Err.	p		Coef.	Std. Err.	p		Coef.	Std. Err.	p	
a_1	0.1390	0.0711	0.0510	*	0.1059	0.0539	0.0490	**	0.1254	0.0667	0.0600	*
a_2	-0.0428	0.0200	0.0320	**	-0.0523	0.0523	0.3170		0.0211	0.0603	0.7260	
a_3	0.0589	0.0627	0.3480		0.3061	0.0428	0.0000	***	0.1793	0.0589	0.0020	***
a_4	0.0359	0.0005	0.0000	***	0.1701	0.0534	0.0010	***	0.0988	0.1260	0.4330	
a_5	-0.0087	0.0358	0.8090		-0.1294	0.0807	0.1090		-0.0818	0.0572	0.1530	
a_6	-0.0142	0.0326	0.6630		0.0937	0.0258	0.0000	***	-0.0547	.	.	
a_7	0.0289	0.0396	0.4650		0.1622	0.0461	0.0000	***	0.0208	0.0435	0.6330	
a_8	0.1100	0.0528	0.0370	**	0.0401	0.0909	0.6590		-0.0347	0.0825	0.6740	
a_9	0.1602	0.0607	0.0080	***	0.1666	0.0655	0.0110	**	0.1551	0.0823	0.0590	*
a_{10}	0.1176	0.0616	0.0560	*	0.0850	0.0756	0.2610		0.0229	0.0639	0.7200	
a_{11}	0.1674	0.0663	0.0120	**	0.2070	0.0611	0.0010	***	0.1142	0.0661	0.0840	*
a_{12}	0.0986	0.0530	0.0630	*	0.1363	0.0678	0.0440	**	0.1682	0.1107	0.1290	
t_1	0.1930	0.0296	0.0000	***								
t_2	0.0233	0.0076	0.0020	***								
t_3	-0.0389	0.0048	0.0000	***								
t_4	0.0340	.	.									
r_1					-0.0806	0.1189	0.4980					
r_2					0.0108	0.0068	0.1110					
r_3					0.0227	0.0582	0.6970					
r_4					-0.0468	0.0498	0.3480					
v_1									0.1478	0.0480	0.0020	***
v_2									0.0474	0.0237	0.0450	**
v_3									0.0015	0.0262	0.9550	
v_4									0.0395	0.0252	0.1170	
g_1	0.0247	0.0442	0.5770		0.0492	0.0722	0.4950		0.0219	0.1701	0.8980	
g_2	0.0347	0.0433	0.4230		-0.0318	0.0416	0.4450		-0.3158	0.2084	0.1300	
g_3	-0.0125	0.0691	0.8560		0.1269	0.0657	0.0530	*	-0.0285	0.1493	0.8490	
g_4	-0.0598	0.0472	0.2050		-0.0055	0.0509	0.9130		0.3986	0.2536	0.1160	
g_5	-0.0119	0.0512	0.8160		0.0688	0.0600	0.2510		0.0683	0.1611	0.6720	
g_6	-0.0458	0.0526	0.3830		0.0868	0.0701	0.2160		0.2398	0.2104	0.2540	
g_7	-0.0683	0.0525	0.1930		0.2295	0.0988	0.0200	**	-0.2076	0.1630	0.2030	
g_8	0.0343	0.0545	0.5290		0.1336	0.0776	0.0850	*	0.3053	0.2345	0.1930	
g_9	-0.0427	0.0491	0.3850		0.0534	0.0672	0.4270		0.3181	0.2316	0.1700	
g_{10}	-0.0244	0.0478	0.6100		0.1092	0.0635	0.0860	*	0.1905	0.2091	0.3620	
g_{11}	-0.0387	0.0463	0.4040		-0.0011	0.0526	0.9840		0.2310	0.1662	0.1650	
g_{12}	-0.0655	0.0535	0.2210		0.0636	0.0598	0.2870		0.5219	0.6375	0.4130	
γ_1	-0.0139	0.0186	0.4540		0.0023	0.0267	0.9310		-0.0593	0.0374	0.1130	
θ_1	0.2045	0.0333	0.0000	***	0.3947	0.0645	0.0000	***	0.4119	0.0759	0.0000	***
β_1	0.9777	0.0091	0.0000	***	0.9233	0.0261	0.0000	***	0.5161	0.2291	0.0240	**
Wald chi2	57067.45		0.0000	***	12687.81		0.0000	***	270.96		0.0000	***
log-lik.	-2265.21				-2669.95				-2240.71			

Mean	0.0085				0.0024				0.0055			
St. Dev.	0.9560				1.5581				0.8838			
Skewness	0.3325				-1.2848				-0.6745			
Kurtosis	9.8382				25.5611				16.0027			
Sk./Kurt. test			0.0000	***			0.0000	***			0.0000	***
ARCH-LM	40.1170		0.0000	***	604.5390		0.0000	***	20.4660		0.0000	***
Q-Statistic	48.9575		0.1556		500.3821		0.0000	***	65.0321		0.0074	***