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CALENDAR ANOMALIES IN THE BALTIC STOCK MARKETS

Bachelor's Thesis

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1. INTRODUCTION

1.1. Background of the Study

The concept of efficient capital market has been perhaps the most dominant topic in the academic literature of finance since the 1960s. Typically, efficient capital markets refer to a situation where *prices fully reflect all available information*, which is the famous line from the Efficient Market Hypothesis (EMH). After its infancy, the EMH turned into a huge success. More impressively, a vast amount of empirical findings emerged supporting the hypothesis.

However, the theory soon began to face both theoretical and empirical challenges. As on example of contradicting findings, studies started to record consistent abnormal returns based on seasonal patterns. For example, studies by French (1980), Gibbons and Hess (1981) and Keim and Stambaugh (1984) discovered the average returns in the USA to be significantly negative on Monday and significantly positive on Friday. Rozeff and Kinney (1976) were the first ones to discover the abnormally high returns in January studying the performance of the New York Stock Exchange.

Undoubtedly, these seasonal patterns in returns are clear contradictions to the EMH as prices should follow a random walk and not be predictable based on certain time periods. Thus, it should be impossible for an investor to continuously earn abnormal returns based on some seasonal patterns.

Since the first anomaly studies emerged, a vast array of calendar anomalies have been discovered in various markets. The anomalies have often been reported to weaken, diminish or even reverse over time. This has been an incentive to shift focus on emerging markets, especially during the last two decades. However, the Baltic markets have gotten very little attention.

1.2. Objective, Limitations and Structure of the Study

This bachelor's thesis will analyze the efficiency of the Baltic (Estonia, Latvia and Lithuania) stock exchanges through calendar anomalies. The study concentrates on the month-of-the-year and the day-of-the-week effects. Other seasonal anomalies are excluded from the analysis. The data covers the time period between January 3, 2000 and October 31, 2008. The time period is divided into two sub-periods which will be analyzed separately, as is the whole sample period. The first sub-period ends on May 31, 2004.

The rest of the paper is organized as follows. Section 2 examines the basic concepts of the efficient market hypothesis and introduces the calendar anomalies. Section 3 showcases the used test methodology and data. Section 4 goes through the empirical results while the last chapter concludes and gives suggestion for further research.

2. THEORETICAL BACKGROUND

2.1. Market Efficiency

To describe efficient capital markets it is first beneficial to contrast them with perfect capital markets. Perfect capital markets are frictionless; there are no transaction costs, taxes or constraining regulations and all assets are fully divisible and marketable. There is also perfect competition on securities market which means that all participants are price takers. Markets are informationally efficient; information is costless and received simultaneously by all individuals. When these conditions are fulfilled, both product and securities markets are allocationally and operationally efficient. In an allocationally efficient market prices are determined in a way that equates the risk adjusted marginal rates of return for all producers and savers and scarce savings are optimally allocated to lucrative investments in a way that benefits everyone. Operational efficiency refers to the cost of transferring funds. In perfect capital markets transaction costs are assumed to be zero and markets are perfectly liquid. (Copeland et. al, 2005 353-354)

Capital market efficiency is much less restrictive than the concept of perfect capital markets discussed above. In an efficient capital market prices fully and instantly reflect all available relevant information, which means that when assets are traded the prices are precise signals for capital allocation. For example, capital markets are still efficient if markets are not frictionless. Prices still fully reflect all available information if securities trader has to pay brokerage fee or if a particular asset cannot be divided into thousand parts and auctioned off. Moreover, there doesn’t have to be perfect competition in the product market to have efficient capital markets. In case of a monopoly, the efficient capital market determines a specific security price that fully reflects the present value of the abnormally high returns. In other words, we can have inefficiencies in the product markets and still have efficient capital market. It is also not necessary to have costless information in efficient capital markets.
(Copeland et. al, 2005 354)

The efficient market hypothesis has been the underlying proposition of finance nearly four decades. It assumes that stock prices adjust rapidly to the arrival of new information, and thus, current prices fully reflect all available information. The basic theoretical case for EMH lies on three main assumptions: investors are assumed to be rational and hence to value securities rationally, to the extent that some investors are not rational, their trades are random and thus cancel each other without affecting prices, and finally, to the extent that investors are irrational similarly, their influence on prices is eliminated by rational arbitrageurs (Shleifer 2000, 2). Thus, the EMH has a plain message for average investors: they cannot hope to consistently beat the market, and resources used to analyzing, picking and trading securities are useless. Rather, the EMH prompts the investor to passively hold the market portfolio and forget active management.

Fama (1970) formalized the theory, organized the empirical evidence, and divided the EMH into three subhypotheses which identify three main levels of financial market efficiency. Each level is based on a different outlook of what type of information is actually understood to be significant when prices are said to “fully reflect all relevant information”. The weak-form EMH states that current stock prices fully reflect all historical information. The semi-strong EMH asserts that prices fully reflect not only the historical information but also all public. Finally the strong-form EMH contends that stock prices reflect all information from historical, public, and private sources, so not even an insider can achieve abnormal returns.

2.2. Behaviouristic View on Market Efficiency

Traditional finance tries to explain and understand financial markets with models that assume agents to act rationally. That is, after receiving new information they adjust their beliefs correctly according to Bayes’ law and given their beliefs, make choices that are consistent with the expected utility theory (Barberis & Thaler, 2003). Behavioral finance typically refers to studies that reject one or more of the underlying axioms behind the modern finance theory which is built on neoclassical framework. One of those rejected axioms is exactly the full rationality of agents. The classical framework is of course highly appealing because of its simplicity. However, there is an extensive amount of evidence which suggests that individual trading behavior is not easily comprehended in this framework.

Specifically, behavioral finance has two building blocks: cognitive psychology and the limits to arbitrage. Cognitive refers to how people think. There is a huge psychology literature documenting that people make systematic errors in the way that they think: they are overconfident, they put too much weight on recent experience, etc. Their preferences may also create distortions. Behavioral finance uses this body of knowledge, rather than taking the arrogant approach that it should be ignored. Limits to arbitrage refers to predicting in what circumstances arbitrage forces will be effective, and when they won't be. (Ritter 2003)

It is difficult to sustain that people, investors in particular, are fully rational. Many investors react to irrelevant information in forming their demand for securities. They trade on noise rather than information and hardly pursue the passive strategies expected of uninformed market participants by the EMH. Of course, the EMH does not rely solely on the rationality of individual investors as it was assumed that their random trades cancel each other out. However, it is exactly this argument that the behavioral theories reject completely. Psychological evidence shows precisely that people do not deviate from rationality randomly. Rather, most deviate in the same way. Thus, investor sentiment reflects the common judgements errors made by substantial number of investors, rather than uncorrelated mistakes. (Shleifer 2000, 10-12)

According to EMH, even if sentiment is correlated across unsophisticated investors, the arbitrageurs (who perhaps are not subject to psychological biases) should take the opposite position and bring the prices back to fundamental values. In contrast to the efficient market theory, the central argument of behavioral finance states that real-world arbitrage is risky and therefore limited. The effectiveness of arbitrage relies decisively on the availability of close substitutes for securities whose price is potentially affected by noise trading. To terminate risks, those who sell or sell short overpriced securities must be able to buy the same or essentially the same securities that are not overpriced. For some derivative securities close substitutes are usually available, although arbitrage might still require notable trading. For example, the S&P

500 Index futures typically sell at a price close to the underlying basket of stocks, because if the future sells at a different price from the basket, an arbitrageur can buy the cheaper one and sell the more expensive against it thus locking a safe profit. However, in many cases securities do not have obvious substitutes. An arbitrageur who expects the stocks as a whole to be overpriced cannot sell short stocks and buy a substitute portfolio since such a portfolio does not exist. Instead, the arbitrageur can simply sell or reduce exposure to stocks in the hope of above-market return. However, this arbitrage is no longer even approximately riskless. (Shleifer 2000, 13-14)

Even when individual securities have better substitutes than does the market as a whole, fundamental risk still remains a significant deterrent for arbitrage. First, such substitutes may not be perfect, even for individual stocks. An arbitrageur betting on relative price movements then bears the idiosyncratic risk that the news about the securities he is short will be surprisingly good or the securities he is long surprisingly bad. For example, arbitrageur is convinced that the shares of Ford are expensive relative to those of General Motors and Chrysler. If he sells short Ford and purchases some combination of GM and Chrysler, he may be able to remove the general risk of automobile industry, but remains exposed to the possibility that Ford does surprisingly well and GM or Chrysler do surprisingly poorly, which leads to arbitrage losses. With imperfect substitutes, arbitrage becomes risky. (Shleifer 2000, 14)

There is a further important source of risk for an arbitrageur, which he confronts even with perfect substitutes. The risk comes from the possibility that mispricing becomes worse before it disappears. Even with fundamentally identical securities, the expensive one can become even more expensive and the cheap one even cheaper. Even if it is absolutely certain that the prices of the two securities ultimately converge, the trade may lead to temporary losses for an arbitrageur. If the arbitrageur can maintain his positions through such losses, he can still count on a positive return from his trade, but sometimes he cannot maintain his positions through the losses. Arbitrage is again limited when arbitrageurs need to worry about financing and maintaining their positions where price divergence worse before it gets better. As a consequence, the arbitrage-based theoretical case for efficient market is limited as well. (Shleifer 2000, 14-15)

At first, behavioral finance was widely rejected by mainstream academia. Later the attitudes have become more tolerant. Critics admit that the biases and anomalies exist but tend to question the impact and importance of these. Lo (2005) stated that "While all of us are subject to behavioral biases from time to time, (traditional economic theorists) disciples argue that market forces will always act to bring prices back to rational levels, implying that the impact of irrational behavior on financial markets is generally negligible, and, therefore, irrelevant."

One of the most rigorous critics of behavioral finance has been Eugene Fama, the father of the EMH. Fama (1998) criticised behavioral finance especially for the following reasons. First, he argued that the discovered anomalies were just as often due to underreaction as overreaction and found this even split to be a "Pyrrhic victory for market efficiency". Second, he stated that anomalies tend to disappear over time or when different methodology is used. He also accuses that behavioral finance does not explain the big picture and the behavioral school has not provided a competing theory, which itself would be rejectable by empirical tests.

2.3. Calendar Anomalies

Calendar anomalies are the best-known stock market anomalies and a vast amount of studies has recorded these seasonal patterns in returns starting from late 1970s. According to Brooks (2004) calendar anomalies can be loosely defined as the tendency of financial asset returns to display systematic patterns at certain times of day, week, month or year.

Bildik (2004) asserts that calendar anomalies indicate either market inefficiencies or inadequacies in the underlying asset pricing model and reminds that recorded anomalies tend to disappear, reverse or fade over time, as discovered by e.g. Schwert (2001). Bildik sees these changes as enhanced market efficiency as rational traders take advantage of anomalous behaviour. However, if anomalies still exist both statistically and economically, there must be some other factors that are effective. An anomaly is not economically significant if the return behaviour is not definite enough for a rational trader to make profits in trading it. Brooks (2004) relates to this and reminds that although calendar anomalies at first glance might imply market inefficiency, this might not be true for two reasons. First, it is likely that the small average excess returns might not generate net gains when employed in a trading system due to transaction costs. Therefore, under “modern” definition of market efficiency (e.g. Jensen 1978), these markets would not be classified as inefficient. And second, the apparent differences in returns on different time periods might be attributable to time-varying stock market risk premiums.

2.3.1. Day-of-the-Week Effect

Day-of-the-week effect refers to situations where the returns for certain days of the week constantly offer higher returns, while the opposite is true for other days. The most common finding has been the high returns on Friday and low ones on Monday. The first ones to record this phenomenon in the USA were Cross (1973) and French (1980). Gibbons and Hess (1981) confirmed the day of the week effect with their sample between 1962-1978. Keim and Bamstaugh (1984) also confirmed the results using the same S&P 500 Index as French, but extending his sample period from 1953-1977 to 1928-1982.

Jaffe and Westerfield (1985) expanded their study from the US markets to also include Australian, Canadian, Japanese and UK markets with a dataset of 1950-1983, and found significant daily variations in the returns. They found the mean returns for the US, UK and Canadian markets to be negative on Mondays, but for the Japanese and Australian market the lowest returns were recorded on Tuesdays. Condoyanni et al. (1987) explored the national stock exchanges of Australia, Canada, France, Japan, Singapore and the USA between 1969-1984. The results indicated a significant traditional day of the week anomaly for the US markets. Data for Canada did not only show significantly negative returns on Mondays but also for Tuesdays. The results for Australia, France, Japan and Singapore also indicated negative returns for Tuesdays, thus partially affirming the results of Jaffe and Westerfield (1985). The results for the

UK were similar to the US markets. After examining the correlation between the stock markets, Condoyanni et al. suggested that reason behind the different kind of anomalies could be time-lag. However, this does not sound absolutely convincing, since the results for the UK and US markets were similar. However, the dominant position of the US markets in the global markets and the growing integration of markets displayed clearly.

No theoretical explanation has satisfied the researchers. However, various explanations have been studied. Gibbons and Hess (1981) and Kleim and Stambaugh (1984) suggested that settlement procedures and measurement errors in returns caused by irregular trading could cause the effect. Maberly (1988), Damodaran (1989) and more recently Copeland et al. (2005) find that firms tend to inform bad news on Fridays and weekend and suggest that the negative Monday effect might be the result of the delay announcement of bad news. Miller (1988) argues that the negative returns over weekends are due to the increased amount of sell orders. He further explains the phenomenon by arguing that especially individual investors evaluate their portfolios during weekends, and the balancing tends to occur via selling investments that are realized expendable immediately as the market opens.

2.3.2. Month-of-the-Year Effect

Differences in returns based on month have been well documented since the anomalies literature exploded in the 70s and 80s. They are also the most common and interesting anomalies, since profiting from it doesn’t require day trading from the investor. The standard month of the year effect was the negative returns of December and positive returns of January. In their study, Rozeff and Kinney (1976) were the first ones to document the January Effect. They studied the equal-weighted NYSE index from 1904 to 1974 and discovered that the average return in January was 3.48 percent, when the average returns for the remaining months were 0.42 percent. Ho (1990) studied the daily returns of eight Asian Pacific stock markets between 1975 and 1987 and found a significant January effect in six of them.

More recently, Mehdian and Perry (2002) explored the US markets with a dataset covering the time period of 1964-1998. They used three different indices: Dow Jones Composite, NYSE Composite and the S&P 500. They found the January effect to be significant in all three indices in a 1964-1987 sample period. After 1987 the still positive January returns were no longer statistically significant. Tonchev and Kim (2004) examined the month-of-the-year effect in the Czech Republic, Slovakia and Slovenia from 1999 to 2003. They found weak monthly variations in the Czech markets with the returns of January and May being the highest and June returns to be the lowest. However, no evidence of month of the year effect was found in the Slovakian or Slovenian markets.

Various arguments have been suggested to explain monthly patterns in returns. The tax-loss selling hypothesis (Branch (1977) and Dyl (1977)) argues that investors are more willing to sell their stocks at the end of the tax year to realise capital losses and thus reducing the amount under taxation. If the tax year ends in December, investors will sell at the end of the year to reduce tax liability and buy in January, which causes the well-recorded January effect. Rozeff and Kinney (1976) introduced the so called information release hypothesis which claims that firms release their news or make announcements at the end of the fiscal year which causes returns to be higher subsequently. According to window dressing hypothesis, at the end of the year professional fund managers sell stocks that have performed poorly during the year to polish them out of reports (Lakonishok et al. 1991).

3. TEST METHODOLOGY AND DATA

3.1. Index Descriptions

To test the particular calendar anomalies, the main indices of the markets are used: OMX Tallinn, OMX Riga and OMX Vilnius.

OMX Tallinn, OMX Riga and OMX Vilnius are all-share total return indices which include all the shares listed on the main and secondary lists on the Tallinn, Riga and Vilnius Stock Exchanges with exception of the shares of the companies where a single shareholder controls at least 90% of the outstanding shares. The base date for the OMX Tallinn is June 3, 1996 and for OMX Riga and OMX Vilnius December 31, 1999. The index values are disseminated in real time. (OMX Nordic Exchange)

3.2. Data and Descriptive Statistics

The data consist of daily closing values of the countries' main indices OMH Tallinn, OMX Riga and OMX Vilnius during January 2000 – October 2008. No earlier data for Latvia and Lithuania was available. Logarithmic returns are used and calculated according to the following formula:

$$R_{it} = \ln\left[\frac{P_t}{P_{t-1}}\right] \quad (1)$$

Where R_{it} is the change in the index in question, P_t is the last value of the index on day *t* and P_{t-1} the last value of the index on day *t-1*.

Table 1 Descriptive Statistics

Table 1 reports the descriptive statistics for the OMX Tallinn, OMX Riga and OMX Vilnius index returns. The statistics are based on daily logarithmic returns. ** indicates statistical significance at the 0.01 level and * at 0.05. Non-trading weekdays are excluded from the data.

Country	N	Mean	Std.Dev.	Skewness	Kurtosis	Bera-Jarque
Estonia						
2000-2008	2235	0.0432	1.1170	0.1250	14.7343	12828.50**
Latvia						
2000-2008	2278	0.0505	1.5860	-0.9023	19.4724	26063.72**
Lithuania						
2000-2008	2215	0.0435	1.2139	-0.8602	27.6217	56223.13**
Estonia						
2000-2004	1116	0.0871	1.1789	0.8561	14.964	6792.25**
Latvia						
2000-2004	1135	0.0968	1.8649	-1.0944	18.0364	10918.84**
Lithuania						
2000-2004	1109	0.0798	1.0326	-1.4064	21.0426	15408.02**
Estonia						
2004-2008	1119	-0.00001	1.0504	-0.939	13.6089	5411.97**
Latvia						
2004-2008	1143	0.00045	1.2481	-0.2031	12.4917	4298.53**
Lithuania						
2004-2008	1106	0.00072	1.3713	-0.5591	27.2097	27067.43**

Table 3 shows that the Latvia has the highest daily return with 0.0505 percent for the whole sample period and it also features the highest daily volatility with 1.2139 percent. Latvia also has the highest mean returns and volatility in the first sub-period. However, in the second one, Lithuania has the highest returns and volatilities, 0.00072 and 1.2481. The returns have dropped significantly in the second sub-period, due to the still raging financial crisis.

High kurtosis statistics indicate that distributions are substantially more peaked than the normal distribution which has a kurtosis of three. Skewness measures the extent to which the distribution is not symmetric around its mean and naturally normal distribution is not skewed. The time series for each market deviate from these figures significantly which causes the Bera-Jarque statistics to be extremely high, and thus the null hypothesis of normally distributed returns is rejected. (Brooks 2004, 179)

3.3. Test Methodology

In order to test whether seasonalities exist in the returns, both calendar anomalies are studied separately using the ordinary least squares (OLS) regression with dummy variables. It is suggested by Brook (2004, 537) as a simple way of detecting seasonalities in stock returns. The objective is to test whether daily (or monthly) returns are statistically different from each other. For detecting a possible day of the week effect, the following regression model is constructed (e.g. Brusa and Liu 2004):

$$R_t = \gamma_0 + \sum_{1}^{4} \gamma_i D_{it} + \varepsilon_t \qquad (2)$$

Where R_t is the return on day *t* for each country's index examined separately, D_{it} is dummy variable taking value of one for the returns which occur on day *i*, and zero otherwise, γ_0 is the intercept which measures the mean returns for Monday, and the coefficients from γ_1 to γ_4 measure the difference between the mean return of Monday and other days of the week, and ε_t is the random error term.

The model is tested for the null hypothesis of

$$H_0 : \gamma_i = 0 \text{ for i=1,…,4} \qquad (3)$$

against the alternative hypothesis that all days of the week are not equal. In case there is no day-of-the-week effect, the coefficients for dummy variables are not significantly different from zero meaning that the return on day *i* is not different from Monday's return. Hypothesis is evaluated using the F-test.

Similarly, the following model is used for the month-of-the-year effect (e.g. Tonchev and Kim 2004):

$$R_t = \gamma_0 + \sum_{1}^{11} \gamma_i D_{it} + \varepsilon_t \qquad (4)$$

where R_t is the return on month *t* for each country's index examined separately, D_{it} is dummy variable taking value of one for the returns which occur on month *i*, and zero otherwise, γ_0 is the intercept which measures the mean returns for January, and the coefficients from γ_1 to γ_{11} measure the difference between the mean return of January and other months of the year, and ε_t is the random error term.

The model is tested for the null hypothesis

$$H_0 : \gamma_i = 0 \text{ for i=1,…,11} \qquad (5)$$

against the alternative hypothesis that all months are not equal. If there is no month-of-the-year effect, the coefficients for dummy variables are not significantly different from zero meaning that the return on month *i* is not different from January's return. Again, F-test is employed for testing the hypothesis.

Brooks (2004, 55-56) introduces the assumptions behind the linear regression model: variance of the error terms must be constant, the error terms are statistically independent and are uncorrelated and the error term follow the normal distribution.

To test the series for autocorrelation, we employ the popular Durbin-Watson statistic. It is calculated as follows:

$$DW = \frac{\sum_{t=2}^{n} (e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \qquad (6)$$

Where e_t is the residual for time period *t* and e_{t-1} is the residual for time period *t-1*.

When the DW-statistic get the value of two there is no autocorrelation in the residuals. When is has a value of zero, there is perfect positive autocorrelation in the residuals and a statistic of four corresponds to the case where there is perfect negative autocorrelation. The DW does not follow a standard statistical distribution but there are critical values based on number of observations and explanatory variables excluding the constant. In this case as an approximate, we don't reject the null hypothesis of no autocorrelation unless the DW is outside a 1.5-2.5 boundary. (Brooks 2004, 160, 163-164)

For detecting of heteroskedasticity (variance of the error terms is not constant), we employ White's heteroskedasticity test.

The White estimator is

$$Est.Asy.\text{var}. = \frac{1}{n}\left(\frac{x'x}{n}\right)^{-1}\left(\frac{1}{n}\sum_{i=1}^{n} e_i^2 x_i x_i^{'}\right)\left(\frac{x'x}{n}\right)^{-1} \qquad (7)$$

where e_i is the *i*th least squares residual, can be used as an estimate of the asymptotic variance of the least squares estimator.

The White test is very general. To carry it out, we need not to make any specific assumptions about the nature of the heteroskedasticity. Although this characteristic is a virtue, it is, at the same time, a potentially serious shortcoming. The test may reveal heteroskedasticity, but it may instead simply identify some other specification error. White test is also nonconstructive. If we reject the null hypothesis of no heteroscedasticity, then the results of the test gives no indication what to do next. The test statistic is asymptotically distributed as a chi square with degrees of freedom equal to the number of slope coefficients, excluding the constant. (Greene 2003, 222-223)

In addition to F-tests applied with dummy-variables, we employ a non-parametric Kruskal-Wallis (KW) test for testing the equality of changes. Non-parametric tests provide additional information regarding robustness of the statistical results held by t-tests where the data does not fit the normal distribution (Bildik, 2004).

Kruskal-Wallis statistic is:

$$H = \frac{12}{n(n+1)} \sum_{k=1}^{k} \frac{(T_k)^2}{n_k} - 3(n+1) \qquad (7)$$

where *k* is the number of groups, n_k is the number of observations for each group, *n* is the total number of observations, and T_k is the sum of ranks received by the returns in the k_{th} group. The statistic follows closely the chi square distribution with k-1 degrees of freedom. (Koutinnoudis and Wang 2002)

4. EMPIRICAL RESULTS

4.1. Day-of-the-Week Effect

Table 2 reports the mean returns and volatilities on each day for each period and market. For the whole sample period, Estonia has the highest returns on Tuesday (0.0797%), Latvia on Friday (0.1377%) and Lithuania on Thursday (0.1339%). Similarly, the highest standard deviations the three indices were on Monday (1.2822%), Thursday (1.7072%) and also Monday (1.3912) for Lithuania.

In the first sub-period, Estonia has the highest mean returns on Thursday (0.1033%) while volatility is the highest on Monday (1.5057%) as it is for the whole sample period. Latvia has negative returns on Monday (-0.0455), while highest returns (0.2319%) and volatility (2.0793%) is displayed on Thursdays. Lithuania has also negative Monday returns (-0.0445%) and the highest returns on Thursdays (0.2044%). Volatility is highest on Monday (1.1941%)

In the second sub-period the returns were significantly lower. Estonia's returns peak on Tuesday (0.0593%), while Latvia has the highest returns on Friday (0.1413%) and Lithuania also on Friday (0.0772%). Similarly, highest volatilities were on Friday (1.1326%), Tuesday (1.5083%) and Monday (1.5720%). To get information about the statistical significance of the differences, we next examine the results of the regression analysis.

Table 2. Summary Statistics for Day-of-the-Week Effect

Table 2 reports summary statistics for the day-of-the-week effect. The statistics are based on daily logarithmic returns.

	Monday	Tuesday	Wednesday	Thursday	Friday
2000-2008					
Estonia					
N	440	449	452	448	446
Mean.	0.0055	0.0797	0.0228	0.0437	0.0635
St.Dev.	1.2822	1.0388	1.1007	1.0586	1.0946
Latvia					
N	455	456	459	457	451
Mean.	-0.0653	0.0106	0.0478	0.1223	0.1377
St.Dev.	1.5940	1.5111	1.4859	1.7072	1.6208
Lithuania					
N	434	447	442	444	448
Mean.	-0.0107	0.0131	0.0104	0.1339	0.0697
St.Dev.	1.3912	1.2121	1.2595	1.1213	1.0644
2000-2004					
Estonia					
N	222	223	225	223	223
Mean.	0.0857	0.1003	0.0537	0.1033	0.0927
St.Dev.	1.5057	1.0436	1.2254	0.9998	1.057
Latvia					
N	229	227	228	227	224
Mean.	-0.0455	0.0928	0.0725	0.2319	0.1342
St.Dev.	1.8516	1.5127	1.7524	2.0793	2.0765
Lithuania					
N	221	224	218	220	226
Mean.	-0.0445	0.0492	0.1296	0.2044	0.0624
St.Dev.	1.1941	0.9936	0.9327	0.9717	1.0423
2004-2008					
Estonia					
N	218	226	227	225	223
Mean.	-0.0761	0.0593	-0.0077	-0.0154	0.0344
St.Dev.	1.0019	1.0359	0.9632	1.1129	1.1326
Latvia					
N	226	229	231	230	227
Mean.	-0.0854	-0.0708	0.0235	0.0142	0.1413
St.Dev.	1.2853	1.5083	1.1682	1.2300	0.9882
Lithuania					
N	213	223	224	224	222
Mean.	0.0243	-0.0233	-0.1055	0.0646	0.0772
St.Dev.	1.5720	1.3990	1.5043	1.2492	1.0888

Table 3. The Day-of-the-Week Effect – Whole Sample Period

Table 3 reports the regression results for the whole sample period for every market. ** indicates statistical significance at the 0.01 level and ** at 0.05. P-values are in parentheses. F-test tests the null hypothesis of equal means. Kruskal-Wallis (KW) is the non-parametric equivalent of the F-test, Durbin-Watson (DW) tests for autocorrelation and White's test for heteroscedasticity. The T-statistics are based on Newey-West HAC consistent standard errors.

	Estonia		**Latvia**		**Lithuania**	
	Value	*T-stat.*	*Value*	*T-stat.*	*Value*	*T-stat.*
Monday: γ_0	0.0055	0.0901	-0.0653	-0.8752	-0.0107	-0.1633
		(0.9282)		(0.3815)		(0.8703)
Tuesday: γ_1	0.0742	1.0436	0.0759	0.7733	0.0238	0.3056
		(0.2968)		(0.4394)		(0.7599)
Wednesday: γ_2	0.0173	0.2214	0.1131	1.1933	0.0212	0.2295
		(0.8248)		(0.2329)		(0.8185)
Thursday: γ_3	0.0382	0.4856	0.1876	1.8984	0.1446	1.7690
		(0.6273)		(0.0578)		(0.0770)
Friday: γ_4	0.0580	0.7813	0.2031	2.1864*	0.0804	1.0025
		(0.4347)		(0.0289)		(0.3162)
F-test	0.3192		1.2549		1.0365	
	(0.8653)		(0.2856)		(0.3869)	
KW	3.4593		8.3989		8.2278	
	(0.4841)		(0.0780)		(0.0836)	
White	4.2098		1.2533		2.9666	
	(0.3784)		(0.8693)		(0.5634)	
DW	1.6451		1.8464		1.7951	

Results in the table 3 show that the null hypothesis of equal coefficients is not rejected in any of the three markets as F-statistic and Kruskal-Wallis remain insignificant. However, Latvia has a significant Friday's coefficient γ_4 at 0.05 level measuring and a nearly significant Thursday coefficient γ_3. We report no day-of-the-week effect for the whole sample period. White statistics gives no evidence of heteroscedasticity and according to Durbin-Watson, there is no significant autocorrelation.

Table 4. The Day-of-the-Week Effect – First Sub-Period

Table 4 reports the regression results for the first sub-period for every market. ** indicates statistical significance at the 0.01 level and * at 0.05. P-values are in parentheses. F-test tests the null hypothesis of equal means. Kruskal-Wallis (KW) is the non-parametric equivalent of the F-test, Durbin-Watson (DW) tests for autocorrelation and White's test for heteroscedasticity. The T-statistics are based on Newey-West HAC consistent standard errors.

	Estonia		**Latvia**		**Lithuania**	
	Value	*T-stat.*	*Value*	*T-stat.*	*Value*	*T-stat.*
Monday: γ_0	0.0857	0.8495	-0.0455	-0.3740	-0.0445	-0.5553
		(0.3958)		(0.7085)		(0.5788)
Tuesday: γ_1	0.0146	0.1208	0.1383	0.9223	0.0937	0.9125
		(0.9038)		(0.3565)		(0.3617)
Wednesday: γ_2	-0.0321	-0.2503	0.1180	0.7940	0.1741	1.8354
		(0.8024)		(0.4274)		(0.0667)
Thursday: γ_3	0.0176	0.1396	0.2774	1.6921	0.2489	2.5738*
		(0.8890)		(0.0909)		(0.0102)
Friday: γ_4	0.0070	0.0607	0.1797	1.1974	0.1069	0.9997
		(0.9516)		(0.2314)		(0.3177)
F-test	0.0639		0.6628		1.7977	
	(0.9925)		(0.6179)		(0.1270)	
KW	1.4558		1.9062		8.4576	
	(0.8344)		(0.7530)		(0.0762)	
White	8.9935		3.2768		1.8795	
	(0.0613)		(0.5126)		(0.7579)	
DW	1.6288		1.7686		1.8150	

Results in table 4 indicate that there is no reason to suspect the null hypothesis of equal coefficients although Thursday's coefficient γ_3 is positively significant at 0.05 in Lithuania. Durbin-Watson indicates no remarkable autocorrelation for any market and White statistic remains insignificant at 0.05 level indicating no significant heteroscedasticity.

Table 5. The Day-of-the-Week Effect – Second Sub-Period

Table 5 reports the regression results for the second sub-period for every market. ** indicates statistical significance at the 0.01 level and * at 0.05. P-values are in parentheses. F-test tests the null hypothesis of equal means. Kruskal-Wallis (KW) is the non-parametric equivalent of the F-test, Durbin-Watson (DW) tests for autocorrelation and White's test for heteroscedasticity. The t-statistics are based on Newey-West HAC consistent standard errors.

	Estonia		**Latvia**		**Lithuania**	
	Value	*T-stat.*	*Value*	*T-stat.*	*Value*	*T-stat.*
Monday: γ_0	-0.0761	-1.1107	-0.0854	-0.9897	0.0243	0.2294
		(0.2669)		(0.3225)		(0.8186)
Tuesday: γ_1	0.1355	1.7801	0.0145	0.1184	-0.0475	-0.3976
		(0.0753)		(0.9057)		(0.6910)
Wednesday: γ_2	0.0684	0.7601	0.1089	0.8679	-0.1298	-0.8164
		(0.4474)		(0.3856)		(0.4145)
Thursday: γ_3	0.0607	0.6470	0.0995	0.8811	0.0404	0.3011
		(0.5178)		(0.3784)		(0.7634)
Friday: γ_4	0.1106	1.1790	0.2267	2.0615*	0.0529	0.4355
		(0.2387)		(0.0395)		(0.6633)
F-test	0.5408		1.2009		0.6562	
	(0.7058)		(0.3087)		(0.6226)	
KW	2.8674		10.1503**		2.7922	
	(0.5803)		(0.0380)		(0.5932)	
White	1.3404		7.3839		2.5952	
	(0.8545)		(0.1169)		(0.6277)	
DW	1.6695		2.0260		1.7856	

Table 5 reports no significant F-statistics to suggest the rejection of the null hypothesis. Latvia, though, has positively significant Friday's coefficient γ_4 at 0.05 level and Kruskal-Wallis is significant at 0.05 level also. We cannot confirm the day-of-the-week effect for Latvia in the second sub-period, but there is some indication of that. White and Durbin-Watson statistics give no confirmation of significant heteroscedasticity or autocorrelation.

4.2. Month-of-the-Year Effect

Table 6 shows the daily mean returns and standard deviation for each month in the three markets. In the whole sample period, Estonia has the highest daily returns in December (0.2153%). The negative returns of October (-0.1377%) is also notable and in the same month the volatility is also highest (1.4706%). Latvia has the highest returns in July (0.2423%) and volatility in August (2.6481%). May has negative mean returns of -0.1411 percent. In Lithuania, the highest returns occur in January (0.1436%) and lowest in October (0.1974%) with the highest volatility of 1.9827 percent.

In the first sub-period Estonia has the highest returns in January (0.2855%) and lowest in September (-0.1505) in which the volatility is also highest (1.6684%). Latvia's highest mean returns are in July (0.3955%) while lowest occur in September (-0.2075). Volatility is highest in August (3.8655%). Lithuania has the highest mean returns in January (0.2612%) and lowest in December (0.1180%). Highest volatility occurs in September (1.6213%).

Estonia's highest mean returns in the second sub-period take place in December (0.2301%) while lowest return (-0.3368%) and volatility (1.7017%) in October. Latvia has the highest returns in December (0.1311) and lowest in February (-0.1879%). Volatility is highest in October (2.0467%). Lithuania's highest daily mean returns are in December (0.2359%) and lowest in October (0.3453%) in which the daily volatility is also highest (2.5094%). Next, the statistical significance of the deviations is examined.

Table 6. Summary Statistics for the Month-of-the-Year-Effect

Table 6 reports summary statistics for the month-of-the-year effect. The statistics are based on daily logarithmic returns.

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
2000-2008												
Estonia												
N	195	177	194	182	192	180	197	195	191	200	173	159
Mean.	0.1654	0.1311	0.1179	0.0168	-0.0298	0.0143	-0.0723	0.0987	-0.0786	-0.1377	0.1245	0.2153
St.Dev.	1.2957	1.4439	1.0376	1.0741	0.8625	0.8544	0.8193	1.0660	1.3870	1.4706	0.9276	0.7305
Latvia												
N	194	182	196	184	201	191	198	201	191	201	173	166
Mean.	0.0999	-0.0909	0.1439	0.0988	-0.1411	0.0702	0.2423	0.1594	-0.1591	0.0364	0.0654	0.0758
St.Dev.	1.1684	1.3068	1.2697	0.9023	1.1997	1.2512	1.6369	2.6481	1.9783	2.1306	1.2956	1.1116
Lithuania												
N	192	174	189	186	194	186	190	196	187	197	166	158
Mean.	0.1436	0.0926	0.1262	0.0744	-0.0100	-0.0017	0.0386	0.0690	0.0631	-0.1974	0.0794	0.0657
St.Dev.	0.9743	0.9640	0.8089	1.6459	1.1118	0.9855	0.7779	0.9957	1.4379	1.9827	0.9559	1.2562
2000-2004												
Estonia												
N	108	98	108	102	107	79	89	86	84	91	85	79
Mean.	0.2855	0.1920	0.0795	0.0951	0.0196	-0.0783	-0.0573	0.1031	-0.1505	0.1009	0.2026	0.2003
St.Dev.	1.5081	1.3343	0.9114	1.3000	0.9908	0.9953	0.7671	1.4016	1.6684	1.0961	0.9639	0.7139
Latvia												
N	108	101	109	102	111	84	89	89	84	91	85	82
Mean.	0.1562	-0.0132	0.2744	0.0768	-0.1088	0.0523	0.3955	0.3256	-0.2075	0.0992	0.0832	0.0171
St.Dev.	1.0265	0.7654	1.2417	1.0046	1.5089	1.4431	2.1451	3.8655	2.6070	2.2376	1.5518	1.1811
Lithuania												
N	107	98	105	106	108	84	86	87	80	89	83	76
Mean.	0.2612	0.1653	0.1758	0.1832	-0.0304	-0.0742	0.0520	0.0519	0.0604	-0.0180	0.1534	-0.1180
St.Dev.	0.8127	0.8259	0.6761	0.9655	0.9426	0.9273	0.8772	1.1081	1.6213	1.0196	0.8453	1.5945
2004-2008												
Estonia												
N	87	79	86	80	85	101	108	109	107	109	88	80
Mean.	0.0163	0.0556	0.1661	-0.0831	-0.0919	0.0866	-0.0847	0.0952	-0.0221	-0.3368	0.0491	0.2301
St.Dev.	0.9575	1.5747	1.1809	0.6816	0.6676	0.7225	0.8633	0.7035	1.1231	1.7017	0.8901	0.7508
Latvia												
N	86	81	87	82	90	107	109	112	107	110	88	84
Mean.	0.0291	-0.1879	-0.0196	0.1261	-0.1811	0.0842	0.1173	0.0274	-0.1211	-0.0156	0.0481	0.1331
St.Dev.	1.3282	1.7647	1.2925	0.7612	0.6461	1.0840	1.0503	0.8654	1.2999	2.0467	0.9964	1.0431
Lithuania												
N	85	76	84	80	86	102	104	109	107	108	83	82
Mean.	-0.0045	-0.0011	0.0642	-0.0698	0.0156	0.0581	0.0275	0.0826	0.0651	-0.3453	0.0054	0.2359
St.Dev.	1.1335	1.1161	0.9498	2.2511	1.2989	1.0317	0.6892	0.9010	1.2918	2.5094	1.0550	0.8023

Table 7. The Month-of-the-Year Effect – Whole Sample Period

Table 7 reports the regression results for the whole sample period for every market. ** indicates statistical significance at the 0.01 level and * at 0.05 and. P-values are in parentheses. F-test tests the null hypothesis of equal means. Kruskal-Wallis (KW) is the non-parametric equivalent of the F-test, Durbin-Watson (DW) tests for autocorrelation and White's test for heteroscedasticity. The t-statistics are based on Newey-West HAC consistent standard errors.

	Estonia		Latvia		Lithuania	
	Value	*T-stat.*	*Value*	*T-stat.*	*Value*	*T-stat.*
January: γ_0	0.1654	1.4968	0.0999	1.2392	0.1436	1.6081
		(0.1346)		(0.2154)		(0.1080)
February: γ_1	-0.0343	-0.1943	-0.1908	-1.7556	-0.0509	-0.4398
		(0.8460)		(0.0793)		(0.6601)
March: γ_2	-0.0475	-0.3615	0.0440	0.3176	-0.0174	-0.1641
		(0.7178)		(0.7508)		(0.8697)
April: γ_3	-0.1486	-1.0696	-0.0011	-0.0112	-0.0692	-0.5153
		(0.2849)		(0.99119		(0.6064)
May: γ_4	-0.1952	-1.4044	-0.2410	-2.0726*	-0.1535	-1.2543
		(0.1603)		(0.0383)		(0.2099)
June: γ_5	-0.1511	-1.1685	-0.0297	-0.2931	-0.1452	-1.1897
		(0.2427)		(0.7695)		(0.2343)
July: γ_6	-0.2377	-1.7474	0.1425	0.8736	-0.1049	-0.8826
		(0.0807)		(0.3824)		(0.3775)
August: γ_7	-0.0667	-0.4792	0.0596	0.3033	-0.0746	-0.6112
		(0.6319)		(0.7617)		(0.5412)
September: γ_8	-0.2440	-1.5365	-0.2590	-1.3141	-0.0805	-0.4561
		(0.1246)		(0.1889)		(0.6484)
October: γ_9	-0.3030	-1.7365	-0.0635	-0.4274)	-0.3410	-2.0750*
		(0.0826)		(0.6692)		(0.0381)
November: γ_{10}	-0.0409	-0.2790	-0.0345	-0.2597	-0.0642	-0.4912
		(0.7803)		(0.7951)		(0.6233)
December: γ_{11}	0.0499	0.3877	-0.0241	-0.2112	-0.0779	-0.6219
		(0.6983)		(0.8328)		(0.5341)
F-test	1.8380*		1.1560		1.0288	
	(0.0431)		(0.3130)		(0.4176)	
KW	21.0610*		14.9414		12.6394	
	(0.0327)		(0.1852)		(0.3175)	
White	33.3473**		60.9876**		35.5616**	
	(0.0005)		(0.0000)		(0.0002)	
DW	1.6617		1.8570		1.8058	

Table 7 reports regression results for the whole sample period. It shows a significant F-statistic at 0.05 level in Estonia and this is supported by a significant Kruskall-Wallis statistic at 0.05 level, although no coefficient is significant at the required level. This is possible because F-test is a joint test so that even if all the t-statistics are insignificant, the F-statistic can be highly significant. So although the slope coefficients from γ_1 to γ_{11} remain insignificant, there is enough deviation among the groups for the F-statistic to be significant.

Latvia has a negatively significant coefficient γ_4 and Lithuania has at 0.05 a significantly negative coefficient γ_9 at 0.05 level. However, F- and Kruskal-Wallis statistics are not significant and the null hypothesis of equal coefficients is not rejected. Table 7 also reports the White and Durbin-Watson statistics for detecting heteroscedasticity and autocorrelation. White statistic is significant at 0.01 level which confirms that residuals are heteroscedastic in the total sample period in every regression. Durbin-Watson statistic indicates that there is no evidence of significant autocorrelation.

Table 8 reports the results for the first sub-period and suggests that there is no month-of-the-year effect in any market. January's returns are positively significant at 0.05 level in Estonia and at 0.01 level in Litnuania. Lithuania also has positive coefficients coefficients γ_4, γ_5, γ_9 and γ_{11}. F-statistic and Kruskal-Wallis statistic are still not significant and the null hypothesis of equal coefficient remains effective for all the markets.

White statistics are significant at 0.01 level in Latvia and at 0.05 in Lithuania, but there is no heteroscedasticity in the Estonian regression. Durbin-Watson reports no significant autocorrelation.

Table 8. The Month-of-the-Year Effect – First Sub-Period

Table 8 reports the regression results for the first sub-period for every market. ** indicates statistical significance at the 0.01 level and * at 0.05. P-values are in parentheses. F-test tests the null hypothesis of equal means. Kruskal-Wallis (KW) is the non-parametric equivalent of the F-test, Durbin-Watson (DW) tests for autocorrelation and White's test for heteroscedasticity. The t-statistics are based on Newey-West HAC consistent standard errors.

	Estonia		Latvia		Lithuania	
	Value	*T-stat.*	*Value*	*T-stat.*	*Value*	*T-stat.*
January: γ_0	0.2855	2.1954*	0.1562	1.7493	0.2612	3.2839*
		(0.0283)		(0.0805)		(0.0011)
February: γ_1	-0.0935	-0.4480	-0.1694	-1.5166	-0.0958	-0.8343
		(0.6542)		(0.1297)		(0.4043)
March: γ_2	-0.2060	-1.3374	0.1182	0.6525	-0.0854	-0.8263
		(0.1814)		(0.5142)		(0.4088)
April: γ_3	-0.1904	-1.0203	-0.0794	-0.6753	-0.0780	-0.5861
		(0.3078)		(0.4996)		(0.5579)
May: γ_4	-0.2659	-1.4734	-0.2650	-1.5504	-0.2916	-2.1933*
		(0.1409)		(0.1213)		(0.0285)
June: γ_5	-0.3638	-2.0654	-0.1039	-0.7256	-0.3354	-2.2891*
		(0.0391)		(0.4682)		(0.0223)
July: γ_6	-0.3428	-2.1916	0.2393	0.7796	-0.2091	-1.2553
		(0.0286)		(0.4358)		(0.2096)
August: γ_7	-0.1824	-0.8776	0.1694	0.3706	-0.2092	-1.1868
		(0.3803)		(0.7110)		(0.2356)
September: γ_8	-0.4360	-1.7945	-0.3638	-1.0321	-0.2008	-0.8708
		(0.0730)		(0.3022)		(0.3841)
October: γ_9	-0.1846	-1.0037	-0.0570	-0.2552	-0.2791	-1.9978*
		(0.3157)		(0.7986)		(0.0460)
November: γ_{10}	-0.0829	-0.4519	-0.0730	-0.4688	-0.1078	-0.8864
		(0.6514)		(0.6393)		(0.3756)
December: γ_{11}	-0.0852	-0.5396	-0.1392	-0.8993	-0.3792	-2.2323*
		(0.5896)		(0.3687)		(0.0258)
F-test	1.0985		0.8051		1.2025	
	(0.3587)		(0.6351)		(0.2803)	
KW	11.4230		18.7478		14.6026	
	(0.4085)		(0.0658)*		(0.2014)	
White	19.3604		77.0492		20.8564	
	(0.0549)*		(0.0000)***		(0.0349)**	
DW	1.6501		1.7845		1.8371	

Table 9. Month-of-the-Year Effect – Second Sub-Period

Table 9 reports the regression results for the first sub-period for every market. ** indicates statistical significance at the 0.01 level and * at 0.05. P-values are in parentheses. F-test tests the null hypothesis of equal means. Kruskal-Wallis (KW) is the non-parametric equivalent of the F-test, Durbin-Watson (DW) tests for autocorrelation and White's test for heteroscedasticity. The t-statistics are based on Newey-West HAC consistent standard errors.

	Estonia		Latvia		Lithuania	
	Value	*T-stat.*	*Value*	*T-stat.*	*Value*	*T-stat.*
January: γ_0	0.0163	0.0926	0.0291	0.2022	-0.0045	-0.0284
		(0.9262)		(0.8398)		(0.9773)
February: γ_1	0.0393	0.1379	-0.2170	-1.0572	0.0034	0.0172
		(0.8903)		(0.2907)		(0.9863)
March: γ_2	0.1498	0.6994	-0.0487	-0.2410	0.0687	0.3697
		(0.4845)		(0.8096)		(0.7117)
April: γ_3	-0.0994	-0.5147	0.0970	0.6099	-0.0653	-0.2705
		(0.6069)		(0.5421)		(0.7868)
May: γ_4	-0.1082	-0.5400	-0.2101	-1.2804	0.0202	0.0977
		(0.5893)		(0.2007)		(0.9222)
June: γ_5	0.0703	0.3707	0.0552	0.3479	0.0626	0.3256
		(0.7109)		(0.7280)		(0.7448)
July: γ_6	-0.1010	-0.4682	0.0882	0.5748	0.0320	0.1845
		(0.6397)		(0.5656)		(0.8537)
August: γ_7	0.0789	0.4069	-0.0017	-0.0103	0.0871	0.4880
		(0.6842)		(0.9918)		(0.6256)
September: γ_8	-0.0384	-0.1807	-0.1502	-0.6487	0.0696	0.2693
		(0.8567)		(0.5167)		(0.7877)
October: γ_9	-0.3531	-1.3069	-0.0447	-0.2115	-0.3408	-1.2289
		(0.1915)		(0.8325)		(0.2194)
November: γ_{10}	0.0328	0.1489	0.0190	0.0902	0.0099	0.0436
		(0.8817)		(0.9281)		(0.9652)
December: γ_{11}	0.2138	1.0670	0.1041	0.5971	0.2404	1.3180
		(0.2862)		(0.5505)		(0.1878)
F-test	1.9371		0.7468		0.9551	
	(0.0314)		(0.6937)		(0.4862)	
KW	21.0165**		13.3615		12.9635	
	(0.0332)		(0.2704)		(0.2957)	
White	48.0213***		47.2321***		38.9017***	
	(0.0000)		(0.0000)		(0.0001)	
DW	1.7044		2.0399		1.8062	

Table 9 presents the regression results for the second sub-period and reports significant Kruskal-Wallis and F-statistics in Estonia. However, none of the coefficients is statistically significant at the required level, which is the case for Latvia and Lithuania also. Again, although the null hypothesis is rejected, we cannot draw definite conclusions on which is the true nature of the month-of-the-year effect.

The residuals exhibit heteroscedasticity in each regression as White statistic is significant at 0.01 level. Durbin-Watson does not give evidence to suspect a significant autocorrelation problem.

5. CONCLUSIONS

This bachelor's thesis has studied calendar anomalies in the Baltic stock markets during 2000-2008 using OMX Tallinn, Riga and Vilnius total returns indices. The objective was to examine weather the returns exhibit day-of-the-week or month-of-the-year effects using OLS regression with dummy variables.

We found no day-of-the-week effect in the three markets in the whole sample period or in neither of the two sub-periods. However, some days showed significant deviation, but the null hypothesis of equal returns among days was not rejected as F-statistic remained insignificant. In Latvia, Kruskal-Wallis was significant at 0.05 level in the second sub-period and the Friday's positive returns were significant both in the whole sample and second sub-period. Thus Friday has been a quite lucrative trading day in Latvia. Also, in the first sub-period Thursday's positive returns were nearly significant at 0.01 level in Lithuania. However, the null hypothesis still remained valid.

The results for the month-of-the-year effect were mixed and unpleasantly inconclusive. Although the null hypothesis of equal returns among groups was rejected in the whole sample period and the second sub-period in Estonia, no coefficient was statistically significant. This is possible due to the joint nature of the F-test. So although we recorded a significant deviation among months, we cannot clearly name a month-of-the-year effect. In the whole sample period in Estonia December was the best month with a daily return of 0.2153 percent and January was a close second with 0.1654 percent.

The null hypothesis was not even close to being rejected in Latvia and Lithuania, but some months exhibited significant deviations. For the whole sample period in Latvia, May's returns were significantly negative. In Latvia, October's negative returns were significant in the whole sample period and in the first sub-period January's returns were highly significant at 0.01 level, and May, June, October and December deviated negatively at 0.05 level. Still, the null hypothesis held.

Durbin-Watson statistics displayed no significant autocorrelation in any of the regressions. White statistics were insignificant in the day-of-the-week regressions but showed significant heteroscedasticity in all of the month-of-the-year regressions, excluding for Estonia in the first sub-period.

As for further research, other anomalies, such as turn-of-the-month, Halloween and holiday effect, could be included to the analysis. Securities could also be analyzed independently or they could be divided into groups based on, for example, their respective business sectors. Also, a different model or methodology could be employed. To further test the overall efficiency of the Baltic stock markets, various test for weak-form market efficiency could be used. It would also be interesting to try to construct various trading rules, and test if significant profit can be made as transaction costs are taken into account.

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